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Linn Emelie Schäffer

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Doctoral thesis

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of
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Faculty of Information Technology and Electrical
Engineering
Department of Electric Energy

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Preface

The presented research was carried out at the Department of Electric Energy (named Department of Electric Power Engineering until 2023) at the Norwegian University of Science and Technology (NTNU) and started in February 2020. My main supervisor has been Professor Magnus Korpås from NTNU. Dr. Arild Helseth from SINTEF Energy Research and Professor Tor Haakon Bakken from NTNU have been my co-supervisors.

The work was done as part of FME HydroCen, one of several Norwegian Centres for Environment-friendly Energy Research (FME). The work has been connected to work package 3 of HydroCen "Market and services", managed by SINTEF Energy Research. HydroCen is financed by the Norwegian Research Council and has several project partners from the Norwegian hydropower industry.

Acknowledgements

When I started this PhD, I thought three years would be a very long time but, in the end, it turned out that three years pass quite quickly. I am grateful that I have had the chance to spend these years investigating interesting and meaningful topics. It has been three exciting years, with ups and downs, where the feeling of brilliance never is far away from feeling discouraged. At times, I have had to remind myself that a PhD is an education to become a researcher. Nevertheless, it has first and foremost been a rewarding period, where I have had the opportunity to dive deep into my research, gain new knowledge and develop my skills.

I would describe my PhD as an independent journey, but one where I have never been alone. I have been lucky to have several people follow me on this journey. Especially, I would like to thank my team of supervisors, Magnus Korpås, Arild Helseth and Tor Haakon Bakken, for their excellent support and guidance throughout my PhD. Your academic competence, experience and encouragement have been essential to my research and personal development. I really appreciate your dedication and interest in my work, and each of your contributions and perspectives. I would also like to thank my IDUN-mentor Gro Klæboe, for encouraging and inspiring conversations. You should not be surprised if I come to you for advice also later in my career. The collaboration I have had with my two Master students, Asja Alic and Sofie Børresen, is also much appreciated. I am impressed by your accomplishments.

Thanks to all my colleagues and friends at the institute, I look back on three fun years with lots of new experiences - even with a pandemic on our hands. My fellow PhD students have made my everyday life the best it could be during this period. Always ready for a cup of coffee followed by good conversations, smiles and jokes – and a hug if needed. A special shout-out goes to the corner-office crew (present and previous): Mari Haugen, Aurora Flataker, Sigurd Bjarghov, Kasper Thorvaldsen, Kjersti Berg, Emil Dimanchev, Erik Bjørnerem, Christian Øyn Naversen and Dimitri Pinel, as well as our frequent office-guests Marthe Fogstad Dynge and Stine Fleischer Myhre. You all inspire me in your own way. Furthermore, I would like to thank all my supportive, smart and inspiring colleagues at SINTEF. I truly appreciate the great work environment we have together. An extra thanks to Mari for providing feedback on my thesis.

Finally, I want to thank my family and friends for their unlimited support and encouragement. Most of all I want to thank you for reminding me of all that life has to offer, and for changing my focus whenever I feel lost or unmotivated. Most importantly, thanks to my husband Andreas for letting me have my ups and downs without yielding an inch in your support. This journey would have been much harder without you by my side.

Summary

The transformation of the European power system to a climate-friendly one by 2050 involves a shift from fossil fuel generation to renewable energy sources. As a part of this transition, flexible assets are needed to balance out the increasing variability in electricity supply and demand to ensure stability in the system. Hydropower can be an enabler for the green transition because of the technology's unique ability to provide both short-term operational flexibility and long-term energy storage in the reservoirs. On the other hand, hydropower plants may negatively impact surrounding ecosystems in several ways. To mitigate the negative impacts of hydropower, environmental regulations are normally defined in the licences of hydropower plants. Environmental regulations are necessary to protect local ecosystems and to respect the needs of other stakeholders. Nevertheless, such regulations may reduce the operational flexibility of the hydropower plants and are therefore also associated with a cost.

Good utilisation of renewable energy resources contributes to lower system costs and security of supply. To achieve efficient use of water for power generation, hydropower producers rely on decision support tools to schedule the short- and long-term operation of hydropower plants and reservoirs. Accurate representation of environmental constraints in hydropower scheduling models is required to make correct assessments of the operational flexibility of hydropower plants and the influence of environmental regulations. Understanding the implications of environmental constraints on the operation of hydropower plants and their capability to provide flexibility to power systems is imperative to effectively plan the operation of hydropower-dominated power systems with high shares of variable renewable power generation.

The work conducted in this thesis investigates the implications of environmental constraints on flexible hydropower plants in stochastic scheduling models with long planning horizons. The impacts of different types of environmental constraints have been assessed from the perspective of a profit-maximising power producer operating in a competitive market and from a cost-minimising system perspective considering a wind- and hydropower-dominated region of a power system. A special emphasis was put on the modelling and evaluation of reservoir-filling constraints that are formulated as reservoir-level dependent discharge limitations (soft reservoir-filling constraints). The results are disseminated through five scientific papers, where three are published and two are under review at the present time. The publications constitute the core of this thesis and substantiate the discussions and results presented here.

The work in this thesis contributes to the overall understanding of environmental constraints on the operations of hydropower plants. Two stochastic optimisation models have been developed, one for the scheduling of a hydropower system from the perspective of a single producer and one for the scheduling of a wind- and hydropower-dominated region in a power system. The models are based on stochastic dynamic programming (SDP) and include non-convex reservoir-level dependent environmental constraints. The models are used to investigate the implications of environmental constraints on the operation of hydropower plants, the importance of including such constraints in the strategic scheduling of hydropower plants with reservoirs and, finally, the interplay between environmental constraints and reserve capacity requirements. Four different types of environmental constraints are considered in this thesis: a soft reservoir filling constraint (reservoir-level dependent discharge limitation), a reservoir ramping constraint, a minimum release constraint and a ramping constraint on discharge.

The findings imply that environmental constraints may have considerable impacts on seasonal reservoir management and that, under certain conditions, there is an economic benefit in planning for soft reservoir filling constraints (reservoir-dependent discharge limitations) in advance. Furthermore, the results show that reservoir-level dependent (i.e., state-dependent) constraints may induce a non-concave expected future profit function and significantly change the expected marginal value of storing water in some periods. The work also investigates and discusses the impacts of three different types of discharge constraints (i.e., reservoir-level dependent discharge limitations, minimum release requirements and ramping restrictions on discharge) on the available flexibility in a hydro-dominated region of a power system. The results show that the impacts on the capability to meet the demand for electricity and reserve capacities requirements depend on the characteristics of the environmental constraints, such as if the constraint mainly reduces the available power capacity or the amount of regulated energy production, and if the constraint includes state- and time-dependencies.

Contents

Abbreviations

aFRR	automatic Frequency Restoration Reserves
AR	Auto-Regressive
FCR	Frequency Containment Reserves
FME	Norwegian Centres for Environment-friendly Energy Research
HPF	Hydropower Production Function
IPBES	The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
LP	Linear Programming
mFRR	manual Frequency Restoration Reserves
MILP	Mixed Integer Linear Programming
NVE	The Norwegian Water Resources and Energy Directorate
RPM	Regulation Power Market
SDDiP	Stochastic Dual Dynamic integer Programming
SDDP	Stochastic Dual Dynamic Programming
SDP	Stochastic Dynamic Programming
SOS	Special Ordered Sets
SOS-2	Special Ordered Sets of type 2
TSO	Transmission System Operator
VAR	Vector Auto-Regressive
WEO	The World Energy Outlook
WFD	The Water Framework Directive

1 Introduction

This chapter presents an overview of the thesis. Section 1.1 provides the underlying motivation for the work, followed by the scope and assumptions of the thesis in Section 1.2. The main contributions of the work are summarised in Section 1.3, before the list of publications is presented in Section 1.4. Finally, an outline of the thesis is given in Section 1.5.

1.1 Motivation

The global community is unified in the commitment to limit the rise in global temperatures to 1.5-2 degrees Celsius compared to pre-industrial levels [1]. Yet, several studies show that current pledges fall short of what is required to reach these targets and point to the need to accelerate the transformation of the energy system towards low-carbon energy resources [2–4]. Such a transformation offers a chance to build a safer and more sustainable energy system but may also introduce threats to energy security, as pointed out in the latest World Energy Outlook (WEO) [5]. Investments in flexibility to balance out variations in electricity supply and demand is one of ten provided guidelines in the WEO to reinforce energy security.

Hydropower is foreseen as a key enabler for the green transition in many parts of the world because of the technology's operational flexibility. The potential to provide long-term energy storage and to rapidly adjust generation distinguishes hydropower from other renewable energy resources [6]. On the other hand, hydropower plants have negative impacts on surrounding ecosystems. Hydropower plants may, for example, alter the flow regime in regulated rivers, create barriers for fish migration due to the establishment of dams and impact terrestrial ecosystems [7, 8]. Coincident with the climate crises, the world faces a biodiversity crisis. Human actions have never before threatened more species with global extinction and, according to the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), land use changes have had the largest negative impact on nature since 1970, to which power production contributes substantially [9].

To limit the burden of hydropower on local ecosystems and communities, hydropower plants are usually subject to environmental regulations. In many countries, environmental regulations are given as terms in the licences which control the rights to operate hydropower plants. The terms in the licences are usually only revised periodically (often with a 30- to 50-year interval). In these processes, new environmental regulations may be imposed to align the licence terms with environmental policies (e.g., the European water framework directive [10]) and to adjust operations in accordance with new knowledge of environmental impacts and mitigation measures. More than 400 licences are liable for revision in Norway [11, 12], and there is considerable potential for ecological improvements in many of the affected watercourses [13]. It is expected that stricter environmental restrictions will be imposed on several of these hydropower plants during the revision of the licences, and especially on the plants that have been determined to have a high ecological priority by the Norwegian regulator (NVE) in [12].

Efficient operation of reservoir hydropower contributes to good utilisation of resources, lower system costs and security of supply in power systems. In the Nordic power system, liberalised markets contribute to efficient resource allocation by having power producers compete to deliver energy and balancing services. Environmental constraints on hydropower reduce the operational flexibility of the plants and are therefore associated with an economic cost in addition to the environmental benefits. Accurate representation of environmental regulation in the hydropower scheduling problem is therefore important to correctly assess the reduced operational flexibility associated with such constraints, and to ensure efficient utilisation of the hydropower resources.

On top of this, increasing shares of wind power, electrification and more cross-border transmission capacity are expected to result in higher requirements for reserve capacity in the Nordic power market [14]. The Nordic transmission system operators (TSOs) rely on flexible assets such as hydropower plants to handle imbalances in the power system. However, the Norwegian TSO, Statnett, has highlighted that several hydropower plants with a “high ecological priority” are also important contributors of flexibility services to the Nordic power system [14]. This may lead to trade-off situations where ecological and recreational needs are weighted against the need for a flexible and secure power supply. Understanding the flexibility potential and limitations of hydropower plants, including the implication of different types of environmental constraints, is therefore becoming increasingly important in the operational planning of hydro-dominated systems.

1.2 Scope and objective

This thesis models environmental constraints in hydropower scheduling models with a long (seasonal to yearly) planning horizon and examines the implications of the constraints on hydropower operations. Environmental constraints are necessary to mitigate the negative externalities of hydropower plants, but are also associated with reduced operational flexibility and an economic loss for the hydropower owner. Furthermore, flexible power generation and energy storage solutions are becoming increasingly vital in the changing European and Nordic power systems, where conventional thermal power plants are being phased-out and the share of unregulated, renewable generation is increasing. This also influences the hydro-dominated Nordic power system, which is expected to face higher requirements for reserve capacity in the coming years [14]. Reduced flexibility of the Norwegian hydropower fleet may therefore provide operational challenges since several of these plants deliver crucial flexibility services to the Nordic power system. Thorough evaluations and knowledge of the implications of environmental constraints on hydropower operations are therefore important, both for hydropower producers and for security of supply.

The work of this thesis is part of FME HydroCen, one of several Norwegian Centres for Environment-friendly Energy Research (FME). HydroCen is a research centre for hydropower technology with the main objective of enabling the Norwegian hydropower sector to meet complex challenges and exploit new opportunities through innovative technological solutions. The work is connected to work package 3, *Market and services*, and is part of a project that focuses on the impacts of environmental constraints and uncertainties. The project is highly relevant as more than 400 hydropower plants in Norway are liable for revision of licence terms and thereby may face new environmental regulations [12]. In a survey conducted as part of the project [15], several Norwegian hydropower producers reported challenges with handling complex environmental constraints in the scheduling of hydropower plants, as these constraints often cannot be included in scheduling tools with long planning horizons. The project is particularly relevant to the Nordic power system as hydropower constitutes about 50% of the total power generation in the system and two thirds of this comes from Norwegian plants [16]. In Norway, around 87% of the total yearly generation and 85% of the total generation capacity comes from hydropower [17].

The research presented in this thesis has been limited to the modelling of hydrologic environmental constraints on hydropower operations, and the impacts of such constraints on hydropower plant operations and power system areas with limited transmission capacity. Several environmental constraints are included in the papers, but the work especially considers constraints that include dependencies on the reservoir level (state-dependent constraints). Particularly, the implications of a soft reservoir filling constraint imposed on several Norwegian hydropower plants (also referred to as a maximum-discharge constraint in this work) are evaluated. In general, there has been a knowledge gap on the implications of these types of constraints and how to handle them in operational planning. The environmental constraints that are considered in the different parts of this thesis are: 1) soft reservoir filling constraints, 2) reservoir ramping constraints, 3) minimum release constraints and 4) flow ramping constraints.

The temporal and spatial scope is limited to the scheduling of systems comprising a hydropower cascade of up to two reservoirs over a long planning horizon (seasonal to yearly). The problem is formulated either from the profit-maximising perspective of a single hydropower producer or from a cost-minimising perspective for a limited area of a larger power system. Since the work focuses on environmental constraints with non-convex characteristics, solution algorithms that can handle non-convex problems have to be used. These algorithms usually have limited scalability and the spatial scope was restricted accordingly. The case studies and analyses are based on Norwegian topology, weather patterns and plant characteristics.

The following four research questions describe the starting point of the research:

1. How can state-dependent environmental constraints be modelled in stochastic medium-term hydropower scheduling models?
2. What are the operational and economic impacts of state-dependent environmental constraints on the operation of hydropower plants in cascaded hydro systems?
3. What are the implications of omitting state-dependent environmental constraints in the medium-term hydropower scheduling, or in other words, what are the consequences of not considering such constraints in the seasonal planning of the reservoir management?
4. What are the implications of environmental constraints on operational flexibility and security of supply in hydropower-dominated power systems?

To address research questions one, two and three, the perspective of a risk-neutral and price-taking operating agent is assumed, where all revenues are expected from selling power in the day-ahead (spot) market. This research considers single hydropower plants and small cascaded hydropower systems. Research question four broadens the scope to consider a renewable-based area of the Nordic power system with a weak transmission connection to the rest of the system. Two optimisation models have been developed to answer the research questions: 1) a medium-term hydropower scheduling model that optimises operation from the perspective of a risk-neutral price-taker in a competitive power market and 2) a cost-minimising scheduling model for optimal operation of wind- and hydropower plants in a region of a congested power system.

1.3 Contributions

The main contributions of this thesis are:

Identification of research gaps in the modelling of environmental constraints in hydropower scheduling (Paper I). A review of environmental constraints in hydropower scheduling and associated modelling challenges is provided.

An SDP-based modelling framework for medium-term hydropower scheduling considering a non-concave future profit function (Paper II). The implemented stochastic dynamic programming (SDP) model optimises the medium-term scheduling of a hydropower system with two reservoirs. Non-concave expected future profit functions are approximated as piecewise linear functions by the use of Special Ordered Sets (SOS) following the approach given in [18] for two-dimensional functions. To keep the number of mixed-integer linear programming (MILP) problems to a minimum, the proposed SDP algorithm checks if the calculated future value points are non-concave in either dimension and includes SOS in the decision problem if non-concave behaviour is detected.

Modelling of state-dependent and non-convex environmental constraints in medium-term hydropower scheduling (Paper II and III). State-dependent reservoir constraints in the form of soft reservoir constraints and reservoir ramping constraints are accurately treated in the SDP-based modelling framework. The environmental constraints depend on the state variables: reservoir volume, the weekly inflow and a variable indicating if the low-inflow period has ended.

Water values and optimal operation of hydropower systems considering environmental reservoir constraints in medium-term hydropower scheduling (Paper II and III). The water values and optimal operation of selected hydropower systems have been studied when considering soft reservoir filling constraints and reservoir ramping constraints in the medium-term hydropower scheduling model. The soft reservoir filling constraint is found to have a distinct impact on the water value curves and the optimal operation. The strategic and operational impacts of the environmental constraints are found to be sensitive to the expected power price and the configuration of the hydropower system.

The economic impacts of considering environmental reservoir constraints in medium-term hydropower scheduling (Paper III). Optimal short-term operations of hydropower systems are strongly impacted by the water values calculated in the medium- and long-term hydropower scheduling. The economic value of considering complex environmental constraints in medium-term scheduling has been assessed by simulating the operation of selected hydropower systems. Simulated optimal operation based on water values that consider environmental reservoir constraints has been compared to simulated operation based on water values not considering the constraints. Improved water values are found to reduce the economic cost of environmental constraints in some situations.

An SDP-based optimisation model for operation of hydropower-dominated renewable power systems considering reserve capacity requirements and environmental constraints (Paper IV and V). The implemented model optimises the operation of a wind- and hydropower-based region of a power system over long planning horizons. The objective is to minimise the system cost of meeting electricity demand and reserve capacity requirements while respecting physical and environmental constraints. State-dependent and non-convex environmental constraints are included, as well as spinning and non-spinning reserve capacity requirements.

The marginal costs of meeting electricity demand and reserve capacity requirements in hydropower-dominated renewable energy systems with environmental constraints on hydropower plants (Paper V). The influence of environmental constraints on the operation of a wind- and hydropower-dominated region of a power system has been studied. The available operational flexibility in renewable power systems can be strongly impacted by environmental constraints on hydropower plants. In particular, the effect of the environmental constraints on system costs, curtailment of load, provision of reserve capacity and the marginal costs of meeting electricity demand and reserve capacity requirements are considered.

1.4 List of publications

This PhD thesis is based on the papers listed below. The papers are given in full in the Publications chapter of this document. **Paper III** and **V** are currently under review, and modifications to the manuscripts should be expected.

Paper I L. E. Schäffer, A. Adeva Bustos, T. H. Bakken, A. Helseth and M. Korpås, "Modelling of environmental constraints for hydropower optimization problems – a review", *2020 17th International Conference on the European Energy Market (EEM)*, Stockholm, Sweden, 2020, pp. 1-7. DOI: 10.1109/EEM49802.2020.9221918

Paper II L. E. Schäffer, A. Helseth and M. Korpås, "A stochastic dynamic programming model for hydropower scheduling with state-dependent maximum discharge constraints", *Renewable Energy*, vol. 194, pp. 571-581, 2022. DOI: 10.1016/j.renene.2022.05.106

Paper III L. E. Schäffer, T. H. Bakken, A. Helseth and M. Korpås, "Optimal operation of hydropower systems with environmental constraints on reservoir management", under review in *Water Resour Manage.*, submitted March 2023.

Paper IV L. E. Schäffer, M. Korpås and A. Helseth, "Optimal operation of hydro-dominated power systems with environmental constraints",*2022 18th International Conference on the European Energy Market (EEM)*, Ljubljana, Slovenia, 2022, pp. 1-6. DOI: 10.1109/EEM54602.2022.9921058.

Paper V L. E. Schäffer, T. H. Bakken and M. Korpås, "Implications of environmental constraints in hydropower scheduling for a power system with limited grid and reserve capacity", under review in *Energy Syst.*, revised manuscript submitted April 2023.

Publications related to the work carried out in this thesis, but that are either outside the scope of the thesis or only contain a minor contribution from the candidate, are listed below. The two last papers are written as part of, or based on, Master student projects where the PhD candidate has been the co-supervisor. The last paper (Alic, 2023) uses an extension of the medium-term scheduling model developed in this PhD.

- A. Helseth, B. Mo, H. O. Hågenvik and L. E. Schäffer, "Hydropower scheduling with state-dependent discharge constraints – an SDDP approach", *Journal of Water Resources Planning and Management*, vol. 148, no. 11, 2022. DOI: 10.1061/(ASCE)WR.1943-5452.0001609.
- S. A. Børresen and L. E. Schäffer, "Evaluating modelling approaches for state-dependent environmental constraints in medium-term hydropower scheduling," *2022 18th International Conference on the European Energy Market (EEM)*, Ljubljana, Slovenia, 2022, pp. 1-6, DOI: 10.1109/EEM54602.2022.9921089.
- A. Alic, L. E. Schäffer, V. Trovato, M. Toffolon, "Optimal price-based scheduling of a pumped-storage hydropower plant considering environmental constraints", under review in *Energy Syst.*, submitted Nov. 2023.

1.5 Thesis structure

The thesis consists of five chapters. Chapter 1 has presented an overview of the thesis, describing the motivation, aim and scope of the work, as well as a summary of the main contributions. Chapter 2 contextualises the thesis by providing an introduction to the research area and a review of the state-of-the-art literature on the most relevant topics. A brief introduction to stochastic programming and some of the key modelling elements of this work are presented in Chapter 3, before the main results are discussed in Chapter 4. Finally, concluding remarks and suggestions for future work are given in Chapter 5.

2 Research context

This chapter places the research conducted as part of this PhD into the wider research context. First, Sections 2.1 and 2.2 give a brief introduction to hydro-dominated, renewable power systems and hydropower scheduling in liberalised markets. Then, Section 2.3 presents the most common environmental regulations on operations of hydropower, before Section 2.4 gives a more thorough review of environmental constraints in hydropower scheduling. The review is partly based on the literature review conducted in **Paper I** and extended during the course of this PhD.

2.1 Hydropower-dominated renewable power systems

The green shift is transforming power systems around the world towards partly—and in time, fully—renewable power systems, introducing new challenges for both power producers and system operators. One such challenge is to balance out fluctuations in renewable power generation to ensure system stability and security of supply. Hydropower-dominated systems, such as the Nordic power system, are exceptionally well positioned to integrate large shares of variable renewable power generation as hydropower plants can rapidly adjust production to balance out short-term fluctuations. Furthermore, water can be stored in the reservoirs for longer periods to balance out seasonal variations and longer periods with low generation from other renewable energy sources. It is well established that large amounts of wind power can be integrated into hydropower-dominated power systems (see e.g., [19, 20]), and coordinated day-ahead planning of wind and hydropower operations has been shown to ease congestion problems [21].

Nevertheless, to handle higher variability, efficient use of flexibility assets in the system is becoming increasingly important. In the Nordic (and European) power system, markets are used to ensure competition between power producers and balance the supply and demand of electricity. Power producers first trade to deliver energy in the day-ahead market before commitments can be adjusted closer to real-time in the intraday market. This trading is done on market platforms, such as Nord pool and EPEX SPOT. The transmission system operators (TSOs) are responsible for balancing out short-term imbalances in real-time. The TSOs acquire reserve capacity in advance to ensure that flexible resources can be activated when required. The requirements for reserve capacity are usually categorised depending on response time (e.g., from seconds to several minutes) and required duration (e.g., from minutes to several hours). Reserve capacity with short activation time is often referred to as spinning reserves since the units must be running to deliver on time. In the Nordic system, spinning reserves usually refer to Frequency Containment Reserves (FCR) and automatic Frequency Restoration Reserves (aFRR). Non-spinning reserve capacities can be slower to activate but may have a longer duration time. In the Nordic system, the Regulation Power Market (RPM) is used to procure non-spinning reserves, i.e., manual Frequency Restoration Reserves (mFRR). Non-spinning reserves are used to relieve the spinning-reserve capacity. An overview of the Nordic balancing markets is provided in [22].

Provision of reserve capacity has previously been considered in medium-term hydropower scheduling models (see e.g., [23–25]), and for hydro-dominated power systems with high penetration of wind power in [26]. Some short-term hydropower scheduling models also consider reserve capacity requirements in combination with environmental constraints on hydropower. A weekly hydropower scheduling model for the day-ahead and spinning reserve markets, which includes environmental constraints on the operation of hydropower, is presented in [27]. Similarly, environmental constraints on hydropower operations are included in the short-term power market model used to assess the benefits of exchanging spinning reserve capacity in the Nordic market in [28]. However, none of these studies include the implications of long-term operational planning, nor discuss the interplay between reserve capacity requirements and environmental regulations.

2.2 Hydropower scheduling in liberalised markets

This section provides a brief overview of the hydropower scheduling problem to place the research presented in this thesis in the broader field of hydropower scheduling. The hydropower scheduling problem optimises the use of water for electricity production from hydropower plants. This implies finding the perfect balance between when to use water for power production and when to store water for later use. Large reservoirs can store water over many seasons and may require planning horizons of up to several years to be considered in the scheduling. The problem is complicated by the many uncertain factors that impact the decisions, as well as the number of physical, technical and regulatory details of the hydropower systems. Uncertainty and variability in weather parameters, fuel costs, CO_2-prices, electricity demand and grid capacity are factors that impact the optimal use of hydropower resources and may necessitate a long planning horizon. The many details of the hydropower cascades, on the other hand, may require a fine time resolution and a large number of variables and constraints to be included in the problem formulation. Furthermore, the use of binary logic and non-linear terms may be necessary to accurately represent certain plant characteristics. The combination of uncertain variables, long planning horizons and a high level of detail causes the overall scheduling problem to grow in size, quickly making it intractable. For practical reasons, the problem is therefore often solved as a set of scheduling problems with varying levels of details and planning horizons [29, 30].

Hierarchies of hydropower scheduling models have been developed to determine the optimal scheduling of hydropower-dominated power systems in different parts of the world, such as Canada, Brazil and the Nordic region. A common approach is to solve the overall problem by dividing it into long-term, medium-term and short-term scheduling problems [31, 32]. Information about the uncertain variables is transferred from the longer planning horizons to the short-term scheduling where the operational decisions are refined by considering a higher level of physical detail. The scheduling approaches vary between geographical regions due to the different characteristics of the hydro-systems, market designs and regulations. However, the core principle of the scheduling hierarchies is the same: to transfer information about the uncertain future from the long-term models to the short-term models.

The following describes the hydropower scheduling hierarchy based on the Nordic approach. The Nordic power market was de-regulated to a competitive market in the 1990s [33]. In competitive power markets, individual consumers and producers place bids to buy or sell electricity through market platforms like Nord Pool. All the market participants try to maximise their own benefit. For power producers, this implies maximising profit by selling electricity at the highest price possible. The equilibrium between supply and demand, i.e., the market cross, determines which producers are obliged to deliver electricity, as well as the power price in each time step. In well-functioning power markets, such as the Nordic market, competition efficiently pushes the power prices down towards the marginal cost of producing electricity, as the power producers compete on price to be allowed to deliver electricity. Both central dispatch and competitive markets with perfect competition should provide the theoretical cost-optimal solution that maximises socioeconomic welfare. The Nordic hydropower scheduling hierarchy provides decision support to hydropower producers participating in competitive power markets [29]. The Nordic scheduling toolchain comprises both cost-minimising power system models (long-term) and profit-maximising, price-taker models (short- and medium-term). The toolchain is illustrated in Fig. 2.1.

2.2.1 The water value

The marginal value of storing water, the water value, is a central element in hydropower scheduling [32]. The water value represents the expected marginal

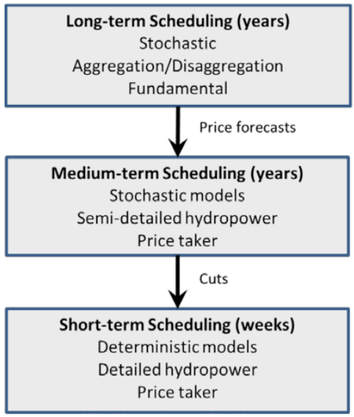


Figure 2.1: Illustration of the scheduling toolchain for the decentralised Nordic system. Source: [29].

value of storing water for later use rather than using it immediately, or in other words, the alternative cost of using water. For thermal power plants, the marginal cost of production is set by the fuel cost, while for variable renewable energy resources, the marginal cost is normally assumed to be zero as unregulated inflow, wind and solar radiation are free resources. For reservoir hydropower, on the other hand, the alternative cost of power production in each time step—the water value—represents the marginal cost of hydropower production. This might seem strange, but considering that water is a limited resource, the water values provide a means to constantly evaluate the current value of electricity production towards the expected future value. Simplified, this means that a hydropower producer only wants to dispatch generation when the power price is higher than the water value.

The ability to store water in the hydropower reservoirs creates a strong time coupling where the expected future cost or profit is a function of decisions forwards in time. Furthermore, since water often can be stored for long periods (up to several years), the calculation of the water values has to consider long planning horizons and uncertainties in different parameters such as inflow, power prices and demand/supply. The main goal of long- and medium-term hydropower scheduling is to calculate water values for use in short-term hydropower scheduling.

2.2.2 Long-term hydropower scheduling

Long-term hydropower scheduling models optimise the operation of the power system from a cost-minimising perspective based on fundamental modelling of production and consumption. This type of model may have a large spatial scope but with an aggregated representation of power production and consumption. An important feature of long-term modelling is to represent the multi-stage uncertainty of weather parameters such as inflow, wind, solar radiation and temperature. Operational decisions may be modelled down to an hourly resolution, while uncertainty normally is represented for a weekly resolution. Physical and technical details are often excluded or simplified to make the problem computationally tractable. The main challenge is to tackle the long-term uncertainty while sufficiently representing the physical characteristics of the hydropower plants and reservoirs. Methods for aggregation (and disaggregation) of the hydropower topology may therefore be used in these types of models. In addition to calculating water values for short-term scheduling models, long-term hydropower scheduling models are used to analyse future scenarios for the power system, expansion planning and price forecasting.

2.2.3 Medium-term hydropower scheduling

The medium-term scheduling problem is placed between the long- and short-term modelling in the scheduling hierarchy. The term covers a wide category of scheduling models with varying planning horizons, geographical scope and representation of details, see for example [29, 34]. The time-frame in long- and medium-term hydropower scheduling models can sometimes overlap as there is not one standard classification for the length of the planning horizon or the spatial scope. However, a common feature of the medium-term scheduling models is that they provide refined water values to the short-term scheduling problem based on a more detailed representation of the hydropower system and, sometimes, a finer time resolution.

In systems with central dispatch, the models have a cost-minimising perspective, while a profit-maximising objective often is used for liberalised markets. In the Nordic region, medium-term scheduling models take the perspective of a risk-neutral, profit-maximising hydropower producer. The system description normally covers a small geographical region or a single hydropower cascade. The hydropower producer is assumed to be an individual competitive participant in the power market who optimises the operation of the hydropower plants under a price-taker assumption. Power price forecasts are therefore one of the main inputs to the model and are normally provided through scenarios generated using a long-term scheduling model and other available resources.

2.2.4 Short-term hydropower scheduling

The short-term scheduling models are distinctively different from the long- and medium-term models. Short-term models normally only consider a planning horizon of one to two weeks but include much more details in the system description [35]. As with medium-term models, short-term models may follow a central dispatch approach (cost-minimising) or take the perspective of a profit-maximising hydropower producer. Common to both approaches is that the models rely on water values from the medium- or long-term models for information about the uncertain future. The water values are the only available information about the future, and the only signal to store water by the end of the planning horizon. In liberalised markets, such as the Nordic, the producer-centric short-term models are used for placing bids in the power markets and optimising production to fulfil the obligations to the markets after the market is cleared. The short planning horizon and limited geographical scope leave room to include a detailed system description including non-linear elements such as binary unit commitment, head-dependent production curves and complex environmental constraints.

2.3 Environmental regulation of hydropower operation

Negative external impacts are associated with the utilisation of all types of energy sources. Renewable energy sources generally contribute to reduced greenhouse gas emissions, but negative externalities are also often affiliated with the power plants [8]. Hydropower plants are built into the river at specific locations where the water resources are abundant and topography favourable for power production, thus the power plants strongly impact the river system and surrounding ecosystems. Hydropower projects may alter the flow regime downstream of the power plant, create barriers for fish migration, leave bypass river sections dry for longer periods and impact the terrestrial ecosystem [7]. Environmental concerns caused by the operation of hydropower plants are often related to the alteration of flow regimes in bypass sections and downstream the outlets [36–38], but can also be related to factors such as unnatural fluctuations in the water levels in the reservoirs [39, 40], changes in water temperature [41], poor water quality [42], gas saturation [43] and even greenhouse gas emissions from reservoirs [44].

Environmental constraints may be imposed to minimise and mitigate the environmental impacts of hydropower. In many countries, such constraints are defined in the terms of the licences of the hydropower plants and are revised periodically [45]. The environmental constraints defined in the licences have to balance the societal need for a reliable supply of electricity from hydropower while sustaining important environmental qualities in the rivers and lakes affected by hydropower operations [11]. The process of defining, and revising, licences is therefore often a time-consuming task, requiring thorough investigations of impacts on the power system and on the surrounding ecosystems [46].

A wide range of environmental constraints may be imposed on the operation of hydropower plants with the ambition of mitigating negative effects on surrounding ecosystems or to facilitate other water uses (e.g., recreational use or irrigation). Certain environmental constraints are designed for a specific purpose, and might therefore only be used in a few places, while other types of environmental constraints are frequently recommended and more generic in type. Frequently applied environmental constraints on hydropower plants in the Nordic countries aim to control the water level in the reservoir, the flow downstream of the plant or the flow in a bypass section. The most common categories of environmental constraints on hydropower operations in the Nordic region are discussed briefly in the following. Some of the discussed environmental constraints are illustrated in Fig. 2.2.

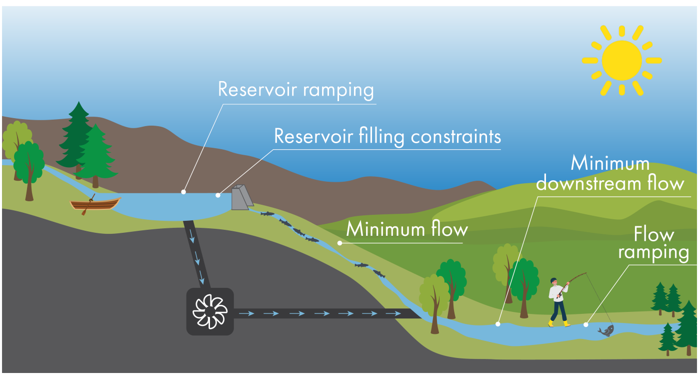


Figure 2.2: Illustration of different types of environmental constraints in a hydropower-regulated river.

2.3.1 Flow constraints

Flow constraints aim to preserve certain flow characteristics in the river downstream of the hydropower plant or in a bypass section. The most frequently used flow constraints in the Nordic countries are minimum flows and maximum ramping rates.

Minimum flows (also referred to as environmental flows, ecological flows and e-flows) are integrated into water policy and legislation in several countries and regions around the world [47], such as the implementation of the Water Framework Directive (WFD) [10, 48] in Europe. In Norway, minimum flows may not have been included in licences given 30-50 years ago but are expected to be included in the terms of most hydropower plants during the ongoing revision of the licences. Flow requirements can be given as direct requirements on release from the reservoir/plant or as conditions on flow at a certain point in the river downstream of the power plant (i.e., “downstream flow” in Fig. 2.2) or in a bypass section (i.e., “minimum flow” in Fig. 2.2). A large set of methods are available to set ecologically sound minimum flow regimes (see e.g., [49–52]). Traditionally, minimum flows were defined as constant minimum levels but recent environmental regulations include more dynamic release requirements like low flows, seasonal variations, artificial flood releases and inflow-dependencies [53, 54]. In extreme cases, release can be regulated as mandatory run-of-river operation [55], where the release has to be equal to the inflow for given periods.

Flow ramping constraints restrict the maximum rate of change in the release from hydropower plants, and are imposed to mitigate frequent and rapid fluctuations in the operation (often referred to as hydropeaking). Hydropeaking operations can have large environmental impacts downstream of the power plants compared to rivers exposed to traditional, base-load production [13,56]. Several studies propose ecologically acceptable flow regimes in downstream river sections exposed to hydropeaking operations [38, 57]. In Norwegian hydropower licences, ramping constraints have traditionally only been included as qualitative formulations to encourage smooth operation and not in quantitative terms. But recent studies have shown that hydropeaking occurs at a considerably high level in Nordic rivers [13, 58] and can increase with higher shares of variable renewable energy resources [59,60]. Consequently, more precise (quantitative) ramping constraints are expected to be included in the licence terms of several Norwegian hydropower plants after the licences are revised. In some recently revised licences, quantitative maximum ramping rates over a resolution of one hour or 30 minutes have been defined. More complex formulations of ramping constraints may include dependencies on daylight, discharge, the morphology of the river or the flow at a given point downstream of the outlet of the plant.

2.3.2 Reservoir constraints

Reservoir constraints restrict reservoir management directly or indirectly to preserve certain conditions in hydropower reservoirs. Such constraints may be imposed on hydropower plants to preserve ecologically important spawning grounds, reduce the risks of landslides and erosion along the shorelines, improve ice coverage and facilitate multiple water use (e.g., irrigation and recreational use) [11]. A few studies assess the impacts of hydropower operations on ecological conditions in reservoirs (see e.g., [39, 40]), but in general, less research investigates the implications of hydropower operations on the conditions in reservoirs than in rivers.

Short-term fluctuations in the water level in the reservoir can be mitigated by the use of reservoir ramping constraints. This type of constraint is less frequently applied than flow ramping constraints but may be imposed to preserve ecological conditions in the shoreline to ensure safe ice coverage in winter or to facilitate recreational use of the reservoir. Ecologically acceptable levels of variation in the water level of reservoirs have been proposed in [61].

Reservoir filling constraints (also called reservoir level constraints) are frequently used to reach certain target water levels in the reservoirs in certain periods. Minimum reservoir filling constraints can be used to ensure water supply (e.g., for ecological purposes, irrigation and drinking water) or to facilitate recreational use and tourism, while maximum reservoir filling constraints may be imposed as a flood-dampening measure. In many systems, hard reservoir level limits are unsuitable because of large seasonal variations in inflow. Instead, soft reservoir constraints can be used. Soft reservoir filling constraints are formulated as constraints on discharge that depend on the water level in the reservoir (these constraints are therefore also referred to as state-dependent maximum discharge constraints). Soft reservoir filling constraints are imposed on many hydropower plants in the Nordic region to accommodate tourism and recreational use of the reservoirs in the summer season. Such needs are also common in other parts of the world but are often met through different types of regulations, operating rules or agreements.

2.4 Environmental constraints in hydropower scheduling

Environmental regulations are often included as constraints in the hydropower scheduling problem, though some types of environmental constraints are more frequently applied than others. Several studies consider frequently applied environmental constraints like minimum flow and ramping constraints, while a few studies explore other environmental factors such as temperature limits [62] and water quality [63, 64]. In the following, the discussion is limited to flow, ramping and reservoir constraints.

Environmental constraints on hydropower are often associated with negative operational and economic impacts in addition to the intended environmental benefits. In general, all constraints reduce the operational flexibility of power production and are therefore associated with a cost. The costs associated with environmental constraints are usually a consequence of lower energy yield or that power production is shifted between hours. In addition, hydropower plants' ability to provide other types of services to the power system may be restricted. Economic assessments can be carried out to compare the environmental benefits to the associated costs. However, fair comparisons can be challenging to achieve as the environmental benefits are often difficult to quantify [65, 66].

Environmental constraints can be included in the short-, medium- and long-term scheduling problem, but the formulations of the constraints have to be adapted to the type of model and solution method that is used. In general, environmental constraints are frequently included in short-term scheduling models, as these models include a detailed description of the hydropower system. Furthermore, short-term models often allow for non-linear and non-convex terms in the modelling [35], making it possible to represent complex environmental constraints. On the other hand, medium- and long-term scheduling models are often based on linear programming and a convex model formulation, which makes it challenging to consider complex environmental constraints. Still, many types of environmental constraints can be included without difficulties in these types of models but may be excluded due to a general caution of adding constraints to the already computational heavy scheduling problems.

Exclusion or simplification of environmental constraints in medium-term hydropower scheduling may create an inconsistency between the water values (i.e., the strategic reservoir management) and the optimal decisions in the short-term scheduling. Over time, this may lead to sub-optimal operation, a loss in revenues for the hydropower producer and increased system costs. Furthermore, if environmental constraints are ignored in the long-term planning, important aspects in the development of hydro-dominated power systems may be underestimated or missed, potentially resulting in misleading analyses about and expectations for the future power system.

2.4.1 Flow constraints

Flow constraints refer to constraints that are used to control the flow in bypass sections or in the river downstream hydropower plants, such as minimum flow, minimum release and ramping constraints. Constant and dynamic (time-dependent) flow constraints are usually straightforward to include in most hydropower scheduling models. More complex formulations such as integral requirements, e.g., requirements to release a specific amount of water over a given period, and ramping constraints, create a time coupling that can be challenging to treat accurately in dynamic programming based models. Furthermore, more advanced formulations may include dependencies on the water level in the reservoir or inflow (i.e., state-dependencies) or non-linearities. Examples of non-linearities are flow ramping rates given as a function of the flow or logical conditions.

The operational and economic impacts of standard flow constraints are thoroughly assessed in the research literature. Several studies have found the costs of minimum flow constraints to increase (almost) linearly with the restrictiveness of the constraint and the costs of ramping constraints to increase quadratically with the restrictiveness of the constraint (see e.g., [62, 67–69]). Nevertheless, the costs associated with these constraints strongly depend on the hydropower system, the inflow conditions and the configuration of the power system [70, 71]. The costs of minimum flow constraints are, for example, found to increase with the level of price volatility [72, 73].

Minimum flow and ramping rates have been demonstrated to have a considerable impact on water values [74, 75]. Furthermore, the importance of considering such constraints in the calculation of the water value is assessed in [71] by combining a linear programming-based medium-term scheduling model and a more detailed short-term operational model. The results demonstrated a significant economic improvement under certain conditions but not for all the considered hydropower systems. Moreover, it is important to distinguish between system costs and the loss in revenues for a hydropower producer. If sufficient flexibility is available in a system, ramping constraints may not have a significant impact on system costs [76], even though the hydropower producer's revenues are considerably reduced.

The costs are a result of the different characteristics of the constraints. Minimum flow in a bypass section usually results in a direct energy loss proportional to the amount of water released. Minimum release requirements, on the other hand, do not result in a direct loss of energy if the water can be released through the turbines but may reduce the overall energy delivered due to reduced operational efficiency. On the contrary, ramping constraints may even increase total power production under certain conditions (see e.g., [67]). Nevertheless, the constraints are still associated with a cost, as hydropower generation may be shifted from peak to off-peak periods [77]. Furthermore, minimum release and ramping constraints also limit hydropower producers' ability to deliver services such as reserve capacity. Minimum release constraints force the hydropower plant to stay in operation, thereby limiting the capacity available for downwards regulating services, but potentially increasing the available supply of upwards regulation. In [78] the authors find a lower cost impact when including markets for regulating reserves due to an increase in the provision of upwards reserves. Ramping constraints, on the other hand, restrict the short-term operational flexibility of the plants and may therefore limit the supply of both upwards and downwards regulating services. Minimum flow requirements in bypass sections do not limit the short-term operational flexibility directly and are therefore not considered to limit the provision of reserve capacity.

2.4.2 Reservoir constraints

Reservoir constraints are normally not associated with a direct loss of water or energy, but the amount of available water may be restricted in certain periods. Consequently, power production may be reduced in certain periods and increased in others to compensate, changing the use of the reservoir for seasonal storage. Hard reservoir level constraints are normally included in hydropower scheduling models to control the water volume available for regulation, but limited research addresses the operational and economic impacts of *environmental reservoir constraints* for hydropower producers or for power system operations [79].

Nevertheless, some research considers the representation of more complex reservoir filling constraints in medium-term hydropower scheduling models. Complex reservoir filling constraints are applied in many systems when hard reservoir constraints are unsuitable due to practical considerations. Summer filling targets for tourism or recreational purposes can, for example, be demanding to reach because of large inflow variations. In such situations, hydropower producers would have to hold back water before the summer season to be sure to reach the hard constraint. This could increase the system costs as power production would be reduced in the low inflow period and the risk of spillage would increase in the high inflow period. To avoid such unwanted consequences, alternatives to hard constraints can be used. In the Nordic region, this is handled via regulation through the use of soft reservoir filling constraints, which implicitly restrict the water level in the reservoir in the summer, instead of explicitly like hard constraints. Alternatively, probabilistic constraints can be used to set aggregated upper and lower bounds for the reservoir filling, as is currently done by EDF in France [80]. A stochastic viability approach has also been found to yield promising results [80, 81].

Soft reservoir constraints are in practice discharge limitations that depend on the water level in the reservoir. Even though the constraints relax the target filling requirement, these constraints still impose intrusive restrictions on the operation of the system. The constraints may impact the seasonal flexibility of the hydropower plants less than hard reservoir constraints but may in return restrict the provision of energy and regulating services in certain periods. Furthermore, the constraints are challenging to apply in scheduling models that require a convex problem formulation as they include both logical conditions and dependencies on the water level (i.e., state dependencies) [15]. In [82] an advancement of the stochastic dual dynamic programming (SDDP) algorithm (SDDiP [83, 84]) is used to model a soft reservoir filling constraint in the medium-term scheduling of a multi-reservoir system in Norway. The study demonstrates a potential for improved scheduling by accurately treating this type of constraint compared to using a linear approximation. A tight linear approximation of the soft reservoir constraints is proposed and tested for two multi-reservoir hydropower systems in Norway in [85], with the approximation demonstrating a good economic performance. This was further investigated in a Master thesis connected to this PhD that compared the tight linear approximation to a traditional linear approximation and an accurate implementation by the use of SDP [86, 87]. The results revealed that the economic performance of the tight linear approximation is close to the accurate implementation for the considered hydropower plant. Furthermore, soft reservoir filling constraints, or discharge limitations that depend on the water level, can also be used to coordinate water use for hydropower production and irrigation, as demonstrated for a hydropower system in Chile in [88].

3 Optimal scheduling of hydropower systems with environmental constraints

Two stochastic optimisation models are developed and used as part of this PhD. The first is a medium-term hydropower scheduling model that optimises the operation of a hydropower system from the perspective of a profit-maximising producer under a price-taker assumption. This model is used in **Papers II** and **III**. The second is a hydropower scheduling model in the form of a fundamental, cost-minimising optimisation model that optimises the operation of a wind- and hydropower-dominated region of a power system over a long planning horizon. This model is used in **Papers IV** and **V**. The models are presented in **Paper II** and **Paper V**, respectively.

This chapter describes some of the key modelling aspects used as part of this work. Section 3.1 gives a brief introduction to stochastic programming, the use of dynamic programming methods to solve stochastic hydropower scheduling problems (Section 3.1.1) and modelling of non-concave (non-convex) expected future profit (cost) curves as piecewise linear approximations (Section 3.1.2). Section 3.2 presents two common techniques for modelling of uncertainty, Section 3.3 presents the most common constraint in the hydropower scheduling problem and the modelling of the environmental constraints is presented in Section 3.4. Finally, an overview of the solution framework is given in Section 3.5.

3.1 Stochastic programming for hydropower scheduling

Optimal operation of hydropower depends on a wide range of uncertain factors such as hydrology, weather parameters, fuel prices, electricity demand and faults. Furthermore, uncertainty may have to be considered for different time resolutions and planning horizons. In this thesis, uncertainty is considered on a weekly resolution over a one-year planning horizon for different stochastic parameters. The used producer-centric, medium-term hydropower scheduling model considers uncertainty in inflow and in the (exogenously given) power price, while the cost-minimising scheduling model for a hydro-dominated region of a power system considers uncertainty in inflow, wind power generation and temperature-dependent electricity demand. Both of the hydropower scheduling models are solved using stochastic dynamic programming (SDP).

Stochastic programming considers decision-making under uncertainty and is particularly useful when uncertain parameters significantly impact the costs associated with the decisions. Stochastic programming methods can be used to find the optimal solution when decisions have to be made before the outcome of the uncertainty is known. The idea is to consider the potential outcomes of the uncertain parameters when making the decisions, ensuring that the optimal decision is made given the possible outcomes. This implies that the optimal decision is not necessarily optimal for the actual realisation of the uncertain parameters but instead for the available information when the decision is made.

A two-stage stochastic optimisation problem is a decision process where a set of decisions, *the first-stage decisions*, have to be made before the uncertain parameters are revealed, while a second set of decisions, *the second-stage recourse decisions*, are made after the actual realisation of the uncertainty is known [89]. The objective is to minimise the total cost of the first- and second-stage decisions. Equation (3.1) describes the decision process, where the cost functions f_1 and f_2 represent the value of the first and second-stage decisions. In each stage t, y_t is a vector of the decision variables, x_t is a vector of the incoming state variables and z_t represents the uncertainty revealed at the beginning of each stage. The second term describes the expected value of the second-stage decisions given the possible realisations of the uncertain variables ($\mathbb{E}_{z_2 \in Z_2}[...]$).

$$\min_{y_1} \Big[f_1(x_1, y_1, z_1) + \mathop{\mathbb{E}}_{z_2 \in Z_2} \big[\min_{y_2} f_2(x_2, y_2, z_2) \big] \Big] \tag{3.1}$$

The solution space of the problem is bounded by the constraints in the sets $y_t \in \mathcal{Y}_t(x_t, y_t, z_t)$, where the state-variables in the second-stage is a function of the variables in the first-stage. The function $x_2 = \delta(x_1, y_1, z_1)$ describes the transition of the state variables from one stage to the next, where the state variables at the beginning of the second stage (x_2) are a function of the variables in the previous stage, namely the incoming state-variables (x_1), the made decisions (y_1) and the uncertainty (z_1). The state variables comprise all the information that is carried between the stages, describing the condition of the system in the given stage.

The two-stage stochastic problem described in Equation (3.1) can be generalised into a multi-stage formulation [89], where new information is revealed before every stage. In the two-stage formulation, the second term of the objective function represents the recourse decision after the uncertainty is revealed. However, this term can in itself comprise a sequence of decisions and stages, turning the problem into a multi-stage problem. The second term of the objective function thereby represents the future cost assuming optimal operation in all future stages.

The hydropower scheduling problem is a stochastic, multi-stage problem. The problem is defined by physical, technical and regulatory constraints, such as bounds on the reservoir level and discharge, efficiency curves for the power stations and environmental regulations. The primary decision variables are the amount of water to discharge from each reservoir in every time step, implicitly determining the power generation, reservoir level (storage) and spillage. Hydropower producers make operational decisions in a sequence, where updated information becomes available stage-wise and corrective actions can be made in the following stages. The option to store water in the reservoir is controlled by the water balance constraint, which couples the decisions in time. The water level in the reservoir is the main state variable in the hydropower scheduling problem, but other state variables can also be included, such as snow storage, accumulated inflow in previous stages or information about other stochastic parameters.

Stochastic problems are often solved by defining a set of potential realisations of the uncertain variables, referred to as scenarios. A probability is associated with each scenario, making it possible to calculate the expectation over the set of defined scenarios. As the decisions in each stage depend on the previous decisions, the size of the problem grows exponentially with the number of scenarios for each stage. Tractability is therefore a major challenge when solving multi-stage stochastic problems. A wide range of methods and approaches are used to solve multi-stage stochastic problems within the field of hydropower scheduling, see for example [90, 91]. The following gives a brief introduction to dynamic programming-based methods. These mature methods are frequently used to solve large hydropower scheduling problems and form the foundation of the models developed in this PhD.

3.1.1 Dynamic programming based methods

Dynamic programming (DP) decomposes the overall problem into smaller, stage-wise problems (often referred to as decision problems) that can be solved sequentially using backwards recursion. The method requires the state space to be discretised, and the decision problem is solved for each discrete state in every stage. Multi-stage, stochastic problems can be solved using stochastic dynamic programming (SDP) [92]. If the problem is stochastic, the problem is solved for each discrete state and stochastic realisation (scenario) in every stage. Using backwards recursion, the method iterates from the last stage T to the first stage. After solving the problem for each state and scenario in a stage (t+1), the expectation of the optimal solutions over all the scenarios is used to solve the previous stage (t), as given by (3.2).

$$g_t(x_t, y_t, z_t) = \min_{y_t} \Big[f_t(x_t, y_t, z_t) + V_{t+1}(x_{t+1}) \Big] \tag{3.2}$$

Where $g_t(...)$ is the total cost in stage t, $f_t(...)$ represents the cost of the immediate decisions and $V_{t+1}(...)$ is the expected future cost, i.e., $V_t(x_t) = \mathbb{E}\big[g_t(x_t, y_t, z_t)\big]$. The state variables are a function of the decisions in the previous stage $x_{t+1} = \delta(x_t, y_t, z_t)$.

The formulation in (3.2) assumes that the stochastic variables are uncorrelated between the stages. Temporal correlation can be considered by including an additional state variable (z), like given in [3.3].

$$g_t(x_t, y_t, z_t) = \min_{y_t} \Big[f_t(x_t, y_t, z_t) + V_{t+1}(x_{t+1}, z_t) \Big] \tag{3.3}$$

where $V_t(x_t, z_{t-1}) = \mathbb{E}_{z_t|z_{t-1}} \big[g_t(x_t, y_t, z_t) \big]$ and $\mathbb{E}_{z_t|z_{t-1}}$ is the expectation based on the conditional probability of moving to state z_t in a stage from state z_{t-1} in the previous stage. Inflow is often included as a state variable in hydropower scheduling models to represent the temporal persistence in the inflow series, but other hydrologic variables can also be used as discussed further in [93].

In hydropower scheduling problems, the state space is normally defined by the water volume in the reservoirs and the problem is solved for a set of discrete reservoir fillings. This means that (3.2) is solved for a set of defined start-reservoir fillings in stage t, and the state in the following stage (t+1) is given by the resulting end reservoir filling in stage t. The first term in (3.2) thereby considers the immediate cost of the hydropower production, while the second term considers the cost associated with the end reservoir filling or, in other words, *the value of storing water for later time periods.* The expected future value (or cost) curve is approximated by the expected value calculated for each discrete state in the following stage (t+1).

A major advantage of SDP, and a main reason why the method has been used in this work, is that the method permits non-convex characteristics to be included in the problem formulation, making it possible to consider nonlinear constraints or non-convex state-dependencies. A major drawback, on the other hand, is that the problem grows exponentially with the number of state variables, known as the curse of dimensionality [92]. This causes the method to be best suited for small systems, since the problem size increases with an additional state variable for each reservoir. Nevertheless, SDP may be used for larger systems by applying aggregation techniques like in [33] or different efficiency techniques, such as parallelisation techniques, efficient discretisation of the state space or Benders cuts like described in [94]. Alternatively, more computationally efficient methods like stochastic dual dynamic programming (SDDP) can be used to solve larger systems, however, such methods often require a convex model formulation. SDP can therefore be a preferred alternative for smaller systems with pronounced non-convexities.

The stochastic dual dynamic programming (SDDP) method overcomes the curse of dimensionality by utilising information from the dual solutions of the decision problems [95]. Instead of discretising the entire state space of the problem, the expected future cost curve is approximated step-wise by using a forwards-backwards sweeping algorithm. The forwards sweep finds the optimal solution for a sample of scenarios, whereas the backwards pass adds water value cuts based on the optimal state in the forwards iteration. Cuts are constraints that are added to the decision problem to restrict the solution space [89]. The method iterates back and forth until the upper and lower bounds of the objective function value converge within a statistically defined interval. The method is considered the state-of-the-art solution method for scheduling of large hydropower systems [96, 97] under uncertainty and allows for hundreds of state variables to be included in the problem [98].

As already mentioned, a disadvantage of SDDP is that the method requires a convex model formulation. One reason for this is that the method relies on cut-sharing between the states. For non-convex model formulations, some cuts may be valid only for certain states and therefore cut off parts of the feasible solution space (and potentially the optimal solution) if shared between all states. To obtain a convex model formulation, certain characteristics of the scheduling problem usually have to be simplified or omitted. In many situations, this is a reasonable trade-off to solve larger problems. Other alternatives are to use SDP or stochastic dual dynamic integer programming (SDDiP), a more recent advancement that overcomes some of the limitations of SDDP [83, 84]. However, SDDiP is still considered to be an immature solution method and induces considerable computational complexity compared to SDP.

3.1.2 Representation of the future value function

The representation of the future value of storing water is essential to obtain good solutions in hydropower scheduling. In DP, the expected future value function (also often referred to as the cost-to-go function) is approximated based on the optimal solutions for a set of system states. Different techniques can be used to represent the expected future value function in SDP. While a piecewise linear approximation based on water value cuts is used in SDDP, a classic approach in SDP is to interpolate between the calculated expected future value points. This approach is compared to a more advanced representation based on cubic splines in [99]. Furthermore, the expected future value function can be represented by applying the water values directly, either by interpolating in the water value tables like in [33] or to generate cuts like in [94]. A piecewise linear function can be obtained either by interpolation between the expected future value points or the use of water value cuts, as illustrated in Fig. 3.1.

Piecewise linear approximations based on interpolation between the future value points or water value cuts require that the expected future value function is concave (or convex) to guarantee an optimal solution, unless conditions are used to control which of the value points or cuts are used for different states. If the expected future value function is non-concave (or non-convex) the solution space may be inaccurately represented. Fig. 3.2 illustrates the implications it may have if a piecewise linear approximation is obtained based on an assumption of concavity for a non-concave function. Small non-convexities may not have large

(a) Interpolation (b) Cuts

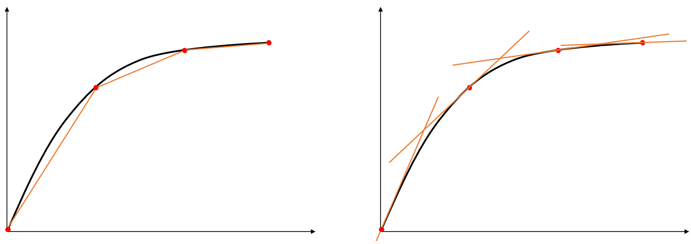


Figure 3.1: Illustrations of a piecewise linear approximation of a concave function obtained by interpolation between points (a) or water value cuts (b). A finer discretisation between the points will result in a more accurate approximation of the function.

implications on the optimal solution, but the severity of the inaccuracies may be difficult to measure without comparing it to an accurate solution.

(b) Cuts

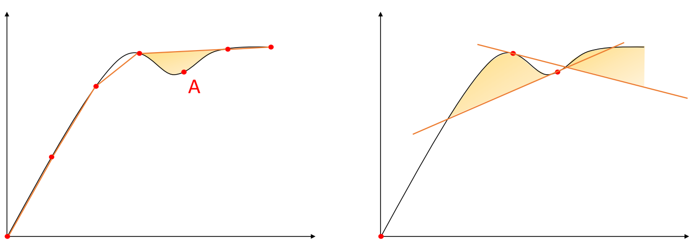


Figure 3.2: Illustrations of concave, piecewise linear approximations of a non-concave function using interpolation (a) and cuts (b). The interpolation procedure may overestimate the feasibility area by skipping unfavourable points (unless forced to use adjacent points), as illustrated by point A in (a). The cuts procedure may underestimate the feasibility area unless the cuts are limited in range, as shown in (b). The over- and underestimated areas are marked by the yellow-shaded areas.

Non-concave expected future value functions may occur frequently due to non-convexities in the problem formulation, such as non-convex environmental constraints. Different approaches based on binary variables or special ordered sets (SOS) may be used to represent non-concave (or non-convex) functions as a piecewise linear function (see e.g., [18, 100, 101]). In the scheduling models developed as part of this PhD, special ordered sets of type 2 (SOS-2) are used in the modelling of non-concave expected future value functions to enforce the use of neighbouring points, i.e., as illustrated in Fig. 3.3. SOS-2 are ordered sets of non-negative variables where only two adjacent variables are allowed to take on non-zero values. Special ordered sets are useful to control the behaviour of variables in optimisation models and are so frequently used in operational research that they are implemented in several commercial optimisation solvers, such as in CPLEX.

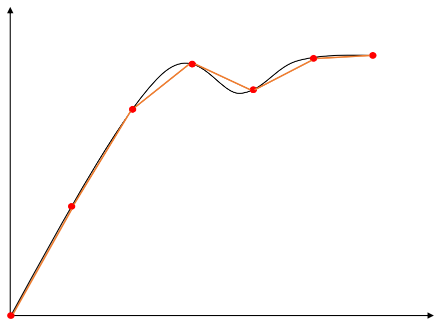


Figure 3.3: Illustration of a non-concave piecewise linear approximation of a non-concave function by the use of interpolation where adjacent points have to be used.

The method presented in [18] is used to formulate two-dimensional piecewise linear approximations of the expected future value functions in the scheduling models developed in this PhD. The method is an implementation of the triangle method through the use of SOS-2. Even though the use of SOS-2 is efficient, the method introduces binary variables, thereby turning the decision problem into a MILP. The implementation is described in **Paper II**.

3.2 Scenario generation

Stochastic optimisation methods require a realistic representation of uncertain parameters. As previously mentioned, uncertainty is normally represented in stochastic programming methods by a set of scenarios. For the optimisation methods to provide useful solutions, realistic scenarios that span the sample space of the uncertainty are required. This section describes two methods to represent uncertainty that are frequently used for hydropower scheduling.

3.2.1 Auto-regressive models

Auto-regressive (AR) models can be used to represent random processes. A general AR-model of order p (AR(p))is given in (3.4). As seen from (3.4), the predicted variable, Z_t, depends linearly on the previous variables, Z_{t-i}, and on a stochastic term (noise), ϵ_t. The auto-regressive coefficients, Φ_i, reflect the memory of the process backwards in time. The short-term memory of auto-regressive models allows for the representation of correlation in time.

$$Z_t = \sum_{i=1}^{p} \Phi_i Z_{t-i} + \epsilon_t \tag{3.4}$$

For multivariate time series, vector auto-regressive (VAR) models can be used to capture both correlations in time and between variables. A general VAR(p) model is given by (3.5), where $\boldsymbol{Z}_t$ are vectors of variables, $\boldsymbol{\Phi}_i$ are the coefficient matrices and $\boldsymbol{\epsilon}_t$ are noise vectors. The predicted variables $\boldsymbol{Z}_t$ are now given as a function of the previous values of all the variables involved, as well as the error term.

$$\boldsymbol{Z}_t = \sum_{i=1}^{p} \boldsymbol{\Phi}_i \boldsymbol{Z}_{t-i} + \boldsymbol{\epsilon}_t \tag{3.5}$$

Auto-regressive models are useful tools to represent stochastic processes as the models can capture correlations in time and between variables. Such models can be used to represent uncertainty directly in SDDP, while SDP requires a discrete representation of the uncertainty. In this work, auto-regressive models have been used to sample scenarios for the case studies. A VAR model was used for the case studies in **Papers IV** and **V**, since VAR models have been found to provide better descriptions of inflow in systems with correlations between inflow and wind than AR models [102].

3.2.2 Markov models

A Markov model is a discrete representation of uncertain variables, where the future states only depend on the current state. A Markov chain describes the probability of moving from each of the states (nodes) in one period to all possible states (nodes) in the next period, as illustrated in Fig. 3.4. Markov chains are often used to represent uncertainty in SDP-based models. The stochastic process in an SDP model can be stage-wise independent as in the formulation in (3.2), or correlation from one stage to the next can be represented by including a stochastic state

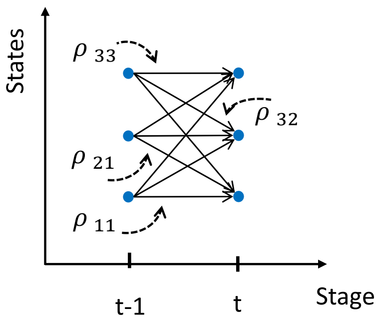


Figure 3.4: Illustration of a Markov chain where the transition probabilities, ρ_{lk}, give the probability of moving from a state (node) l in stage t-1 to a state (node) k in stage t.

Generating Markov models by using K-means clustering

Markov models are used to represent the stochastic parameters in the SDP models developed in this PhD. The Markov models are generated from a set of scenarios using K-means clustering [103, 104]. For each stage, the scenarios are clustered together into a set of representative nodes (i.e., a set of representative realisations of the stochastic variables), as illustrated in Fig. 3.5. The clustering algorithm considers the different types of stochastic variables simultaneously so that each node consists of one value for each of the stochastic variables. The result is a set of nodes (stochastic states) per stage connected together in a Markov chain (Fig. 3.5b). The transition probabilities are calculated by counting the number of scenarios that transition between two nodes (clusters) from one stage to the next.

An adequate representation of extreme realisations of uncertain variables, such as inflow and price, is essential in hydropower scheduling [105]. The most extreme outcomes may be under-represented in the Markov model when K-means clustering is used to determine the set of nodes, potentially leading to an underestimation of the consequences of extreme events. To counteract this, **Paper V** suggests extending the Markov model with additional “extreme nodes” that represent extreme outcomes of the stochastic variables, as illustrated by the red nodes in Fig. 3.5b. A similar approach was used in [105] to expand a Markov

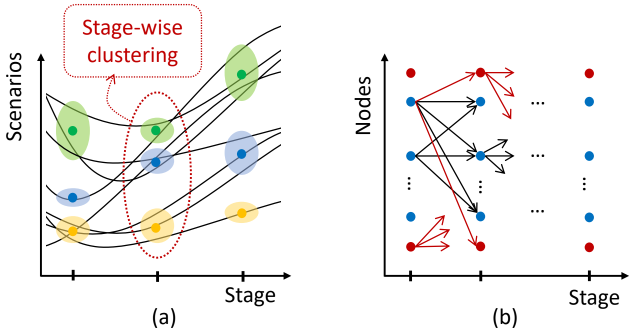


Figure 3.5: Illustration of the generation of a Markov model by clustering (from **Paper V**). The scenario trajectories are clustered together into three clusters per stage, marked by different colours in (a). The clusters in each stage are represented by the centre points of the clusters. The centre points are used as nodes (stochastic states) in the Markov model, as illustrated in (b). The probability of moving between different nodes (states) from one stage to the next is given by the transition probabilities, which are calculated by counting the number of scenario trajectories that moves between the clusters.

3.3 Hydropower modelling

This section briefly presents the mathematical formulation of the hydropower scheduling problem. Further discussion of the various modelling techniques, mathematical formulations and solution methods are provided in the research literature. The reader is referred to [90] for a basic description of the multi-reservoir optimisation problem and a review of solution methods, and to [35] for an overview of more detailed objectives and constraints that can be included in the modelling of the short-term scheduling problem.

Hydropower systems are complex physical installations with plenty of non-linear characteristics. As mentioned previously, the level of detail included in hydropower scheduling models depends on the scope and planning horizon of the problem. Stochastic scheduling models for multi-reservoir hydropower with long planning horizons usually consider the dispatch problem for a simplified representation of the systems, i.e., the production units, reservoirs and different waterways, for example as illustrated in Fig. 4.1. The problems are computationally difficult to solve due to the dynamic and stochastic characteristics, and non-convex characteristics are usually not considered or simplified. The formulations of the hydropower scheduling problem used in this PhD are based on linear and convex formulations, except for the representation of the environmental constraints. The developed models are based on SDP and can therefore handle non-convex problem formulations. Despite this, to limit the complexity, non-convex characteristics are only included (when necessary) in the modelling of the environmental constraints, as described in Section 3.4.

3.3.1 Objective functions

The objectives of the scheduling problem depends on the planning horizon of the scheduling problem and the system characteristics. This PhD considers two different objectives, namely that of a profit-maximising power producer operating in a competitive market and a cost-minimising system perspective. Other objectives can be to maximise the total power generation, minimise floods or even a combination of several targets (i.e., multi-objective).

Scheduling problems that consider long planning horizons are normally solved using methods based on decomposition techniques, such as SDP and SDDP, as discussed in Section 3.1. The objective functions of these problems usually consist of two terms, namely to maximise/minimise the value/cost in the current period (i.e., stage) and in the future. The expected future value or cost is approximated by a function, as previously discussed in Section 3.1.

Maximising total revenue

The objective of the medium-term scheduling model in this PhD is to maximise profit for the hydropower producer. Assuming that the operational costs of hydropower production are negligible, this turns into an objective of maximising revenues. Revenue maximisation is widely used in competitive power markets, such as the Nordic, where the power producers are assumed to be price-takers (i.e., the operational decisions of the producers are assumed to not impact the price). Maximum revenue is obtained by scheduling production (p) to achieve the highest possible price (λ) as given in (3.6), i.e., to maximise the expected revenue of producing in the current period ($\lambda_t p_t$) and the expected value of saving water in the reservoirs for later (α_{t+1}).

$$\max \left\{ \lambda_t p_t + \alpha_{t+1} \right\} \tag{3.6}$$

Minimising operational costs

From a system perspective, the aim is to optimise the use of available resources to meet certain obligations at the lowest possible cost. The objective functions minimises the operational costs of the system as given in (3.7). The cost in the current period (t) is given by a cost function ($C_t(\boldsymbol{x}_t)$) that describes the costs associated with a set of decision variables ($\boldsymbol{x}_t$) and the expected future cost (α_{t+1}).

$$\min \Big\{ C_t(\boldsymbol{x}_t) + \alpha_{t+1} \Big\} \tag{3.7}$$

A simplified version of the cost-minimising objective of the hydropower scheduling model used in **Paper V** is given in (3.8). Here, costs are associated with import of electricity and unmet system obligations such as curtailment of electricity demand and unmet reserve capacity requirements (described in section 3.3.8).

$$\min \Big\{ \lambda_t e_t + C^{ls} ls_t + C^r s_t + \alpha_{t+1} \Big\} \tag{3.8}$$

The operational system cost described in (3.8) is given by the cost in the current period (t) and the expected future cost (α_{t+1}). The operational costs comprise the cost/revenues of import/export (e_t) at an exogenously given power price (λ_t), the cost of curtailing electricity demand (ls_t) given the value of lost load (C^{ls}) and the cost of unmet reserve capacity requirements (s_t) given a high penalty cost (C^r). Operational costs of wind- and hydropower are assumed to be negligible, but there is a cost of using water rather than storing it for later (i.e., the expected future cost α_{t+1}).

3.3.2 Water balance of the reservoirs

The water balance describes the hydrologic balance in the reservoirs by keeping track of water that enters and exits each reservoir in each period (t) in the planning horizon (T), as given in (3.9).

$$v_{t+1} = v_t + \boldsymbol{q}_t^{UP} - \boldsymbol{q}_t - f_t + Z_t \qquad \forall t \in T \tag{3.9}$$

The reservoir volume in a period (v_{t+1}) is given by a initial reservoir volume (v_t) and the water that enters and exits the reservoir in the period. Water may enter the reservoir in the form of release from reservoirs higher up in the cascade ($\boldsymbol{q}_t^{UP}$) and inflow (Z_t), and exit the reservoir in the form of release ($\boldsymbol{q}_t$) and spillage (f_t). The release decisions are described by vectors ($\boldsymbol{q}^{UP}$ and $\boldsymbol{q}$) and may comprise different types of releases such as discharge through the turbines and bypass flows. Negative inflows (i.e. $Z_t < 0$) may occur if the system is exposed to evaporation.

3.3.3 Bounds on water storage in the reservoirs

The regulated volume of the reservoirs, i.e., the water volume that is available for hydropower production, is controlled by lower and upper bounds (V^{min} and V^{max}) as given in (3.10). Strategic boundaries may be imposed in certain periods as described further in Section (3.4.1).

$$V^{min} \leq v_t \leq V^{max} \qquad \forall t \in T \tag{3.10}$$

3.3.4 Bounds on release and power production

Upper and lower bounds on releases from the reservoirs (Q^{min} and Q^{max}) are defined in (3.11) and for power production (P^{min} and P^{max}) in (3.12). Release may be restricted due to physical limitations, or strategically to, for example, impose minimum flow obligations as described further in Section 3.4.2. The power-discharge relationship is described further in Section 3.3.6.

$$Q^{min} \leq q_t \leq Q^{max} \qquad \forall t \in T \tag{3.11}$$

$$P^{min} \leq p_t \leq P^{max} \qquad \forall t \in T \tag{3.12}$$

3.3.5 Operating status (commitment)

The operational status of a power station (or unit) describes if the station is running or not, also referred to as the commitment status of the unit. Unit commitment can be included to model the start and stop of units/stations and to avoid operation below the minimum production point. This can be imposed by defining binary "commitment" variables (also referred to as "running" variables), like given in (3.13), where $u_t = 1$ if the unit is running and $u_t = 0$ otherwise. However, this turns the problem into a mixed integer linear program (MILP) and unit commitment is therefore normally not considered in large, stochastic scheduling models. It is, on the other hand, more frequently included in short-term scheduling models.

$$u_t \in \{0, 1\} \tag{3.13}$$

Linearised unit commitment, as given in (3.14), is less precise, as partial start/stop and operation below the minimum production point may occur, but may be easier to include in stochastic scheduling models with long planning horizons.

$$u_t \in [0, 1] \tag{3.14}$$

3.3.6 The hydropower production function

The hydropower production function (HPF) is in reality a complex state-dependent, nonlinear and non-convex function. Modelling of the HPF is one of the core challenges in the short-term scheduling problem [35] and techniques to approximate the complex relationship between discharge, head and power output are, for example, discussed for MILP-based models in [101, 106]. Linear approximations or piecewise linear and concave approximations of HPF are often used in scheduling models with long-planning horizons because of the modelling complexity.

In the medium-term hydropower scheduling model used in **Papers II** and **III**, the HPF is described as a piecewise linear and concave approximation, as given by (3.15) and (3.16). The power-discharge relationship is described by several discharge segments ($d \in \mathcal{D}$), where the utilisation of each discharge segments ($q_{t,d}$) is restricted by a maximum limit (Q_d^{max}). The power output (p_t) is a function of the utilisation of each discharge segment and the efficiency (η_d) of each segment.

$$p_t = \sum_{d \in \mathcal{D}} \eta_d q_{t,d} \qquad \forall t \in T \tag{3.15}$$

$$q_{t,d} \leq Q_d^{max} \qquad \forall t \in T, d \in D \tag{3.16}$$

An important feature of hydropower is that the best operational point often is below the maximum operating point. This means that a hydropower plant operating at the best efficiency usually can increase (or decrease) production on demand. A piecewise linear and concave functional relationship can capture this characteristic but will overestimate the efficiency of operating at low output as illustrated in Fig.3.6a. To better represent the efficiency of operating at low output, a minimum discharge point can be incorporated like suggested in [28] and illustrated in Fig. 3.6b. The formulation assumes a concave and piecewise linear curve above the minimum output point, as illustrated in Fig. 3.6b. Operation below the minimum output point can be avoided by the use of binary commitment variables as given in (3.17)-(3.19). The binary commitment variable ($u_t \in \{0, 1\}$) controls if the station is running or not. If the station is running, the minimum production (P^{min}) and the minimum discharge (Q^{min}) define the minimum output point, while the total discharge (q_t) and the total power output (p_t) are given by the minimum output point and the piecewise linear and concave approximation of the power-discharge relationship as given by (3.17)-(3.19).

$$p_t = u_t P^{min} + \sum_{d \in \mathcal{D}} \eta_d q_{t,d} \qquad \forall t \in T \tag{3.17}$$

$$q_t \leq u_t Q^{min} + \sum_{d \in \mathcal{D}} q_{t,d} \qquad \forall t \in T \tag{3.18}$$

$$0 \leq q_{t,d} \leq u_t Q_d^{max} \qquad \forall t \in T, d \in D \tag{3.19}$$

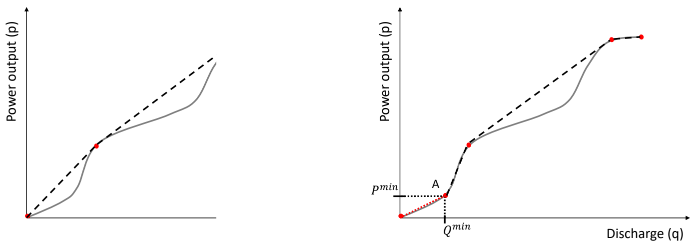


Figure 3.6: Illustration of a concave and piecewise linear approximation of the HPF (a) and a piecewise linear approximation of the HPF with a minimum output point A (b) for a station with several units (based on [28]). The approximation in (b) is extended with the red dotted line below point A if the commitment requirement is linearised.

An approximation of the HPF like the one illustrated in Fig. 3.6b was used together with linear unit commitment (i.e., $u_t \in [0, 1]$) in **Paper V**. Operation below the minimum output point may occur when the commitment requirement is linearised, as illustrated by the red dotted line between zero and point A in Fig. 3.6b. If this happens, i.e., u_t takes on a value between 0 and 1, the capacity of each discharge segment (Q_d^{max}) is reduced accordingly. The linear formulation is less accurate than using binary commitment variables. Nevertheless, the linear formulation provides some opportunities, such as to define a lower efficiency below the minimum output point or to limit available reserve capacity below the minimum output point (which is discussed in Section 3.3.7).

3.3.7 Provision of reserve capacity

Paper V addresses the interplay between environmental constraints and reserve capacity requirements in a region of a wind- and hydropower-dominated system. The reserve capacity that a hydropower plant can provide is limited by the scheduled production (p_t) and the minimum and maximum production capacity (P^{min} and P^{max}). To ensure a quick response time, provisions of upwards and downwards spinning reserves (r_t^{s+} and r_t^{s-}) require that the hydropower plant is running, as controlled by the commitment variable (u_t) in (3.20) and (3.21), respectively.

Provision of upwards non-spinning reserves is restricted by the total turbine capacity in (3.22) and the availability of water in the reservoirs in (3.23). Equation (3.23) ensures that there is enough water in the reservoir (v_t) to activate the reserve capacity (r_t^{ns+}). An optimistic estimate of the required water is calculated based on the maximum efficiency (η^{max}), where ϕ converts the units to a total amount of water for the period t.

$$p_t + r_t^{s+} \leq u_t P^{max} \qquad \forall t \in T \tag{3.20}$$

$$p_t - r_t^{s-} \geq u_t P^{min} \qquad \forall t \in T \tag{3.21}$$

$$r_t^{ns+} + r_t^{s+} + p_t \leq P^{max} \qquad \forall t \in T \tag{3.22}$$

$$\phi\Big(\frac{r_t^{ns+}}{\eta^{max}}\Big) \leq v_t \qquad \forall t \in T \tag{3.23}$$

If unit commitment is not modelled, or if a linearised unit commitment formulation is used (i.e., $u_t \in [0,1]$), operation between zero and the minimum production point may occur and the capability of the hydropower plants' to deliver spinning reserve capacity is likely to be overestimated [28]. However, if commitment between zero and one occurs in a linearised unit commitment formulation, the total available capacity in (3.20) and (3.21) will be partly reduced. Such a formulation may therefore provide better results than a dispatch formulation without unit commitment. Furthermore, the problem formulation can be tightened further to discourage operation below minimum output to occur for the purpose of delivering reserves, as suggested in [23]. The suggested approach was applied in **Paper V**.

3.3.8 System requirements

Papers IV and **Paper V** consider the operation of a wind- and hydropower dominated region of a power system, where the aim is to operate the system at the lowest possible cost while meeting the electricity demand and the requirements for reserve capacity (while also respecting other constraints). These obligations are defined as constraints in the problem. Slightly simplified formulations of the constraints are provided below.

Power balance

The power balance in (3.24) states that the total power production from the hydropower plants ($p_{h,t}$ for $h \in H$) and the wind power plants (w_t) must be larger than or equal the total electricity demand (D_t), or curtailment of demand (ls_t) will occur (and be penalised in the objective function).

$$\sum_{h \in H} p_{h,t} + w_t \geq D_t - ls_t \qquad \forall t \in T \tag{3.24}$$

Requirements for reserve capacity

Equation (3.25) ensures that the total provision of reserve capacity from all the hydropower plants is greater than the requirement for reserve capacity (R_t), where unmet reserve requirements (s_t) are penalised in the objective function. The formulation in (3.25) can be used to define requirements for different types of reserve capacity.

$$\sum_{h \in H} r_{h,t} \geq R_t - s_t \qquad \forall t \in T \tag{3.25}$$

3.4 Modelling of environmental constraints

This section presents the mathematical formulation of the environmental constraints considered in this work, and discusses some of the main modelling challenges. The four considered types of constraints are: 1) reservoir filling constraints (included in **Paper II-V**), 2) minimum release constraints (included in **Paper V**), 3) maximum flow ramping (included in **Paper V**) and 4) maximum reservoir ramping constraints (included in **Paper III**). An important goal of this thesis is to model soft reservoir filling constraints in medium-term scheduling and assess the implications of this type of constraint on the scheduling of Norwegian hydropower systems. Considerable attention is therefore devoted to this type of constraint.

3.4.1 Reservoir filling constraints

Reservoir filling constraints, or reservoir level constraints, limit the reservoir volume (v) to be in between the volume limits (V^{min} and V^{max}), as given in (3.10). Such constraints are used to define the regulation volume in the reservoir but can also be used to define strategic boundaries, e.g., to reduce the risk of flood or water shortage. In such cases, time-dependent reservoir limits that force the reservoir level to be above or below a strategic reservoir level in certain periods can be used. For example, equation (3.26) enforces the reservoir level to be above the filling target (V_t^{env}) for parts of the planning horizon ($\hat{T} \subset T$).

$$v_t \geq V_t^{env} \qquad \forall t \in \hat{T} \subset T \tag{3.26}$$

Hard reservoir filling constraints like (3.26) can in certain situations be difficult (or impossible) to respect because of the large uncertainty and variations in inflow. Alternative or relaxed formulations, such as probabilistic constraints [80] or soft reservoir filling constraints (state-dependent discharge limitations) [15], are therefore sometimes applied instead. In practice, soft reservoir filling constraints are limitations on discharge (q_t) where the maximum allowed discharge (Q_t^{max}) depends on the water level in the reservoir as given in (3.27).

$$q_t \leq Q_t^{max}(v_t) \qquad \forall t \in T' \subset T \tag{3.27}$$

In this thesis, the focus is on soft reservoir constraints used in the Nordic region. Several hydropower reservoirs in Norway have (high) target filling degrees for the summer season to facilitate recreational use and tourism, as discussed in Section 2.4.2. This is facilitated by the use of soft reservoir filling constraints that ensure that no discharge (other than to meet minimum flow obligations) is permitted when the water levels are below a target level for a certain period, as illustrated in Fig. 3.7.

The soft reservoir filling constraint is described mathematically by (3.28)-(3.29). First, (3.28) states that for a given period ($t \in T'$), discharge from the reservoir (q_t) is restricted to only allow environmental flow requirements (Q_t^{env}) if the water level in the reservoir is below a given threshold (V_t^{env}), as illustrated by phase 1 in Fig. 3.7. If the water level (within the given period) exceeds the threshold (V_t^{env}), (3.28) is replaced by a hard minimum reservoir level constraint enforcing the water level to stay above the threshold for the reminding period (illustrated by phase 2 in Fig. 3.7), as given in (3.29). The soft reservoir filling constraint can also be followed by a period, $\bar{T}$, where the reservoir level is not allowed to be reduced, as given in (3.30). This is illustrated by phase 3 in Fig. 3.7.

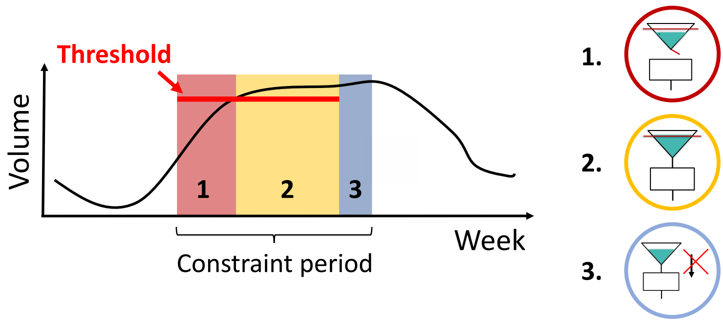


Figure 3.7: Illustration of the soft reservoir filling constraint (from **Paper III**). [1] The constraint period can be divided into three phases: (1) if the reservoir level is below the threshold, discharge from the reservoir is restricted, (2) if the reservoir level is above the threshold, the threshold becomes the minimum allowed reservoir level, and (3) the reservoir can not be drawn down, only filled up.

$$q_t \leq Q_t^{env} \quad | \quad v_{t-1} \leq V_t^{env} \qquad \forall t \in T' \subset T \tag{3.28}$$

$$v_t \geq V_t^{env} \quad | \quad v_{t-1} \geq V_t^{env} \qquad \forall t \in T' \subset T \tag{3.29}$$

$$v_t \geq v_{t-1} \qquad \forall t \in \bar{T} \subset T \tag{3.30}$$

Soft reservoir filling constraints are included in the models in **Papers II-V** to ensure high water levels in the summer. When used in this context, the discharge limitations (3.28) are normally activated when entering the constraint period (i.e., $t \in T'$), then changed to (3.29) when (if) the water level reaches the reservoir threshold (a high water level) and finally deactivated by the end of the constraint period. However, the discharge limitation can also be activated by high inflows (i.e., the start of the snow-melting period), as discussed in **Paper II**.

While hard reservoir filling constraints usually are straightforward to include in scheduling models, soft reservoir filling constraints comprise several complicating factors. First of all, the constraint includes reservoir dependencies and logical conditions, which make the problem non-convex. This complicates the use of methods that require a convex model formulation, such as SDDP. For the purpose of this PhD work, an SDP-based approach has been used to allow for non-convex model formulations. Furthermore, the state-dependent logical conditions can be handled in the SDP algorithm instead of in the decision problem, as shown in **Paper II**, reducing the number of binary variables in the optimisation problem. Consequently, the state-variables (i.e., the water levels) are only evaluated between the stages, implying that the discharge limitation (3.28) first will be replaced by a hard minimum reservoir level constraint (3.29) in the following stage. In practice, this means that (3.28) is active if $V_t^{start} \leq V_t^{env}$, where V_t^{start} is the reservoir filling at the beginning of a stage (which is the same as the end-reservoir filling in the previous stage). Furthermore, the non-convex characteristics of the constraint may result in a non-concave expected future value function. This is handled by the use of SOS-2 as described in Section 3.1.2, turning the decision problem into a MILP.

An alternative to using SDP is to use SDDiP, as demonstrated in [82]. However, the method is considered to be an immature solution method and introduces other modelling challenges and limitations, such as that the state variables have to be binary variables, the use of different types of cuts and convergence issues. Furthermore, tight linear approximations of the soft reservoir filling constraints have been found to provide good results in SDDP-based models for medium-term scheduling in a recently published study [85].

3.4.2 Minimum flow constraints

Minimum flow requirements can be attributed either to the bypass section or to the river section downstream of the outlet of the hydropower plant. Flow constraints restrict the release of water from the hydropower plant, i.e., bypass (q^b) and discharge (q) to be above a given minimum boundary (Q_t^{env}) in each period ($t \in T$). The constraint can be defined for total release, as in (3.31), or specifically for bypass or discharge. Advanced environmental regulations may include dynamic (time-dependent) release requirements such as low flows, seasonal variations and artificial flood releases. Seasonal minimum release requirements are included in **Paper V**.

$$q_t + q_t^b \geq Q_t^{env} \qquad \forall t \in T \tag{3.31}$$

Other more complex formulations can include dependencies on the water level in the reservoirs, dependencies on the flow at a certain point in the river or integral requirements. The latter may, for example, be if a hydropower plant is required to release a specified amount of water (Q^P) over a longer period ($\hat{T}$), as given in (3.32).

$$\sum_{t \in \hat{T}} (q_t + q_t^b) \geq Q^P \tag{3.32}$$

3.4.3 Flow ramping constraints

Flow ramping constraints mitigate rapid changes in the flow downstream hydropower plants by restricting the maximum change in discharge between two successive time steps. The constraint limits the up and down ramping in discharge (q_t) to stay below the maximum ramping rate (δ_t^{max}), as given in (3.33).

$$-\delta_t^{max} \leq q_{t+1} - q_t \leq \delta_t^{max} \qquad \forall t \in T \tag{3.33}$$

Ramping constraints introduce additional time couplings to the problem, which makes the constraints more challenging to represent accurately in DP-based models because of the decomposition into stage-wise subproblems. In **Paper V**, ramping constraints are included in each of the stage-wise subproblems (decision problem) in the SDP model but not between the stages in the backwards recursion. More sophisticated approaches can be applied to include flow ramping between the stages in SDP-based models. For example, discharge can be included as an additional state-variable [69], but this was not investigated further in this work as ramping between the stages was considered to be of small importance to the overall solution.

3.4.4 Reservoir ramping constraints

Reservoir ramping constraints can be imposed to limit rapid changes in the water levels in reservoirs, as given in (3.34). The change in reservoir volume (v) between two consecutive periods is restricted to be smaller than the maximum ramping rate (γ_t^{max}). The constraint depends on the reservoir level in the previous period and is thereby state-dependent. Furthermore, like flow ramping constraints, reservoir ramping constraints introduce a time coupling. However, this time coupling can be handled in SDP-based scheduling models without further adjustments since the reservoir level already is a state variable.

$$-\gamma_t^{max}(v_t) \leq v_{t+1} - v_t \leq \gamma_t^{max}(v_t) \qquad \forall t \in T \tag{3.34}$$

The maximum permitted ramping rate may be given as a maximum change in the water level in the regulation and be implemented as a maximum volumetric ramping rate in the modelling. The maximum permitted change in water volume depends on the shape of the reservoir and is a function of the water level in the reservoir (i.e., $\gamma_t^{max}(v_t)$). This introduces another state dependency, as well as a potential non-convexity due to the shape of the reservoir. A reservoir-dependent maximum ramping rate, which is represented by a step-wise function, is included in **Paper III**. The maximum ramping rate is determined by the reservoir level at the beginning of the stage and is constant within the stage. The non-convex characteristics of the ramping rate may result in a non-concave expected future value function, which is handled by the use of SOS-2 as described in Section 3.1.2.

The reservoir ramping constraint in **Paper III** restricts reservoir ramping between two consecutive periods, however, reservoir ramping restrictions may also be defined for periods of varying length, which may introduce more complex time couplings to the problem.

3.5 Overview solution framework

The results from the medium- and long-term hydropower scheduling models can be validated through simulations of the operational decision-making. This is a frequently used approach for SDP-based models, where the expected future values (FV_t) are calculated for a discrete set of system states in a backwards recursion. In the operational simulation, the decision problems are optimised in a forwards sequence for a set of scenarios using the calculated expected future value functions. Furthermore, the operational simulation may include a chosen level of detail in the stage-wise decision problem. The same model formulation as in the stochastic scheduling model can be applied directly, a refined problem formulation can be used as described in [33] or a more detailed short-term model can be implemented like in [107] and [71]. A detailed short-term model can be used to achieve a more realistic setup, while, for example, a simpler formulation may be preferred to isolate the impacts of the information given through the expected future value functions/water values.

Fig. 3.8 illustrates how an SDP-based modelling framework can be divided into two main parts: a strategy calculation (SDP model) and an operational forwards simulation. This modelling setup was used in **Paper II-V** for different problem formulations. First, the SDP model calculates an optimal strategy based on a discrete set of reservoir states and stochastic states in the strategy phase. The model is set up for a one-year planning horizon, but an infinite horizon effect is achieved by iterating until the water values in the first and last stages converge. The water values are calculated from the expected future value points at the end of each iteration and used to update the end-value at the start of the next iteration. The main results from the SDP model are the expected future value points and the water values. The expected future value points are used in the operational forwards simulation to represent the expected future value function, while the water values are useful to visualise and analyse the calculated strategy. The final simulation gives the optimal operation of the system for a range of simulated scenarios.

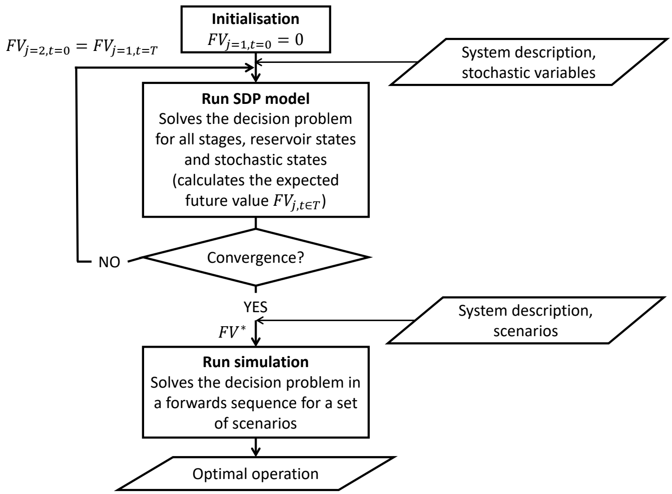


Figure 3.8: Flow chart of the strategy phase (SDP model) and final simulation.

The stage-wise decision problems can be formulated as MILPs to represent a non-concave expected future value function or to include other non-convex constraints. As mentioned previously, non-convex characteristics are only included in this work to model environmental constraints (if necessary). A higher computational time is to be expected to solve a MILP problem than a linear program (LP), and the computational time increases with the complexity of the problem. Furthermore, an LP formulation is required to obtain dual values from the optimal solutions. To obtain dual values from the MILP problems, a second simulation can be conducted with the binary variables fixed to the values from the first simulation. This approach is used in **Papers IV** and **V** to obtain dual values from the scheduling problems that include non-convex environmental constraints. It is worth mentioning that the dual values that are obtained by fixing variables may be inaccurate as the costs associated with the fixed variables are not considered.

4 Results and discussion

This section summarises and discusses the main results from the work conducted as part of this PhD. Firstly, Section 4.1 discusses the results from **Papers II** and **III**, which consider environmental reservoir constraints in medium-term hydropower scheduling from the hydropower producer perspective. Secondly, Section 4.2, presents the results from **Papers IV** and **V**. The focus of this work is on the implications of environmental constraints on hydropower plants in hydropower-dominated renewable power systems with an emphasis on operational flexibility.

4.1 Environmental reservoir constraints in medium-term hydropower scheduling

The optimal operation of hydropower systems considering environmental constraints on reservoir management is studied from the perspective of a profit-maximising power producer in **Papers II** and **III**. This work includes two types of environmental reservoir constraints: soft reservoir filling constraints and reservoir ramping constraints. Both constraints depend on the water level in the reservoir and are thereby state-dependent. Furthermore, both constraints introduce non-convexities to the problem. The soft reservoir constraint is studied in **Papers II** and **III**, while the reservoir ramping constraint is considered in **Paper III**.

Two hydropower systems are included in this part of the work (HPS 1 and HPS 2). HPS 1 is based on the two upper reservoirs and power stations of the Bergsdalen water course located in the west of Norway (used in **Papers II** and **III**). HPS 2 is based on the Driva water course located in Trøndelag in mid-Norway (used in **Paper III**). The technical specifications and topology of the two modelled systems are shown in Fig. 4.1, while Fig. 4.2 depicts the reservoir thresholds imposed on HPS 1 and HPS 2 together with the accumulated historic inflow to these reservoirs. The reservoir threshold imposed on HPS 2 (as part of the soft reservoir filling constraint) is more challenging to reach than the threshold imposed on HPS 1.

Paper III assesses the operational and economic impacts of the constraints under different power price assumptions. The assumed power price characteristics are illustrated in Fig. 4.3. Traditionally, the power price in the Nordic system is higher in the winter period and lower in the summer season (e.g., 2015 in Fig.

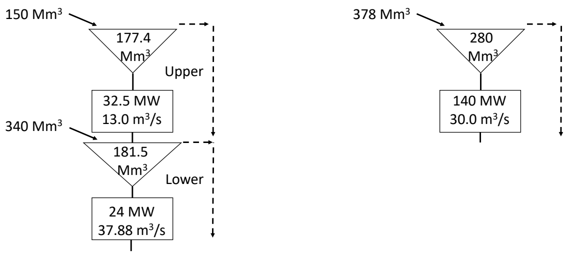


Figure 4.1: Topology of HPS 1 and 2 from **Paper III**. Reservoirs (triangles), plants (rectangles) and waterways for discharge (solid lines) and spillage (dashed lines) are shown, as well as maximum discharge (m^3/s), production (MW) and reservoir volumes (Mm^3) and average yearly inflow (Mm^3).

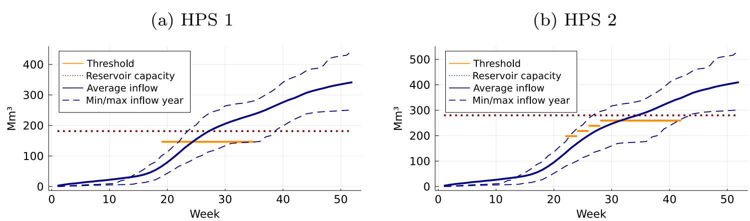
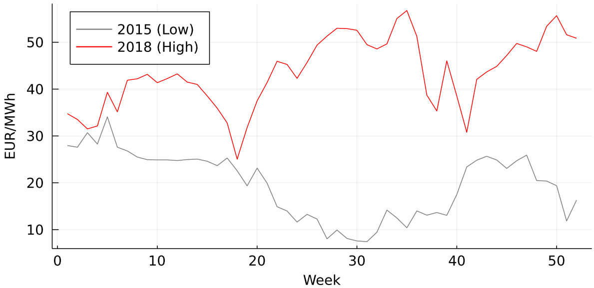


Figure 4.2: Illustration of the reservoir thresholds (orange lines) given in the soft reservoir filling constraints for HPS 1 (left) and HPS 2 (right) together with the historical accumulated inflow (blue lines) and the reservoir capacity (red dotted line).

4.3a). However, periods with high prices may occur in the summer if there is an abnormally dry spring/summer (e.g., 2018 in Fig. 4.3a) or as a result of higher short-term price variation in general (e.g., high price variation in Fig. 4.3b).

The rest of this section focuses on the operational implications of environmental reservoir constraints and the significance of including such constraints in medium-term hydropower scheduling. A short summary of the operational impacts of the constraints is given in Section 4.1.1. These results are based on simulations with the constraints, but without the constraints being considered in the water value calculation. The main purpose of medium-term hydropower scheduling models is to calculate water values for use in short-term operational decision-making.

(a) Seasonal profiles



(b) Intra-week price scaling

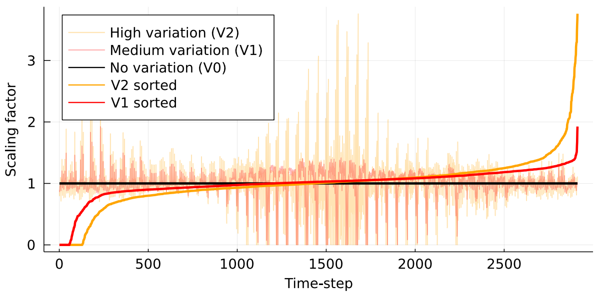


Figure 4.3: Power price characteristics used in **Paper V**. Historical weekly power prices (a) from Nordpool for price-zone NO5 and the assumed intra-week price variation (b) are plotted. The historical price series are chosen for their differences in seasonal profiles.

Section 4.1.2 therefore discusses the impacts of the two environmental reservoir constraints on the water value curves, while Section 4.1.3 discusses the economic implications to operational decision-making of using water values that consider these types of constraints.

4.1.1 Operational impacts of environmental reservoir constraints

This section summarises the economic and operational impacts of the environmental reservoir constraints. Operations of the hydropower systems are simulated with and without the environmental reservoir constraints.

Soft reservoir filling constraints

The soft reservoir filling constraint has a considerable impact on the operation of both hydropower systems. Even though the constraint is only active for a defined period, the reservoir management may change over the entire planning horizon. Considerably differences are seen in the spring/early summer, as the reservoir fills up more rapidly because of the strict discharge limitation given by the constraint (i.e., Eq. (3.28)). The results in **Paper III** show that the optimal reservoir management and the economic impact of the constraint are found to be strongly dependent on the expected power price and the characteristics of the hydropower system. As expected, the loss in profit for the power producer is larger if high power prices are expected in the constraint period (spring/summer) and the loss increases with the level of short-term price variability. The loss in profit varies from 0.04-4.35 M€ per year for the two hydropower systems under different price expectations (i.e., a reduction of less than 1% to almost 15% of the profit).

Reservoir ramping constraints

The reservoir ramping constraint has a milder impact on the operation of the considered hydropower systems than the soft reservoir filling constraint. Besides restricting down-ramping, the operational and economic impacts of this constraint strongly depend on the shape of the constrained hydropower reservoirs. This is because the volumetric maximum ramping rate, and thereby effectively the strictness of the constraint, is a function of the shape of the reservoir. This becomes apparent in **Paper III** where the same maximum ramping rate (in cm) results in a stricter limitation in discharge for certain reservoir fillings in HPS 1 than in HPS 2. Consequently, the reservoir ramping constraint is found to impact the reservoir management more for HPS 1 than HPS 2. In HPS 1, the water level in the reservoir is considerably higher in the reservoir throughout the year as the discharge is more restricted for lower reservoir fillings due to the constraint. In HPS 2, only small (but similar) changes are seen in the reservoir filling throughout the year, demonstrating that the magnitude of the impacts is site-specific. The case study in **Paper III** demonstrates a loss in profit due to the reservoir ramping constraint, however, the loss in profit is considerably smaller than for the soft reservoir filling constraint ranging from 0.07-0.34 M€ per year for the two hydropower systems (i.e., from less than 1% to 2.5%). The economic loss was found to increase with the level of price variation.

4.1.2 Water value characteristics

The main outputs from medium-term hydropower scheduling models are water value tables or water value cuts for use in the short-term operation of hydropower plants. An important focus of this PhD is therefore to analyse the impact of the environmental reservoir constraints on the water value curves.

The water values describe the marginal value of having one more unit of water within a week. In an unconstrained system, the water value would be set by the highest power price within the planning period, since this would give the value of having one more unit of water available for power production. In reality, all hydropower systems are constrained by physical, technical and regulatory conditions. Consequently, the water value will be higher for low reservoir fillings, because of the risk of running out of water, and lower for high reservoir fillings, because of the risk of spilling from the reservoir. Furthermore, the water values calculated by linear hydropower scheduling models will always be non-increasing for increasing water levels in the reservoir, given that the expected future value function is a concave function.

The environmental constraints discussed in this work reduce the operational flexibility of the power plants to varying degrees. In practice, both constraints limit the allowed discharge from the power plants in parts of the planning horizon. The soft reservoir filling constraint may strictly limit discharge in several weeks (if the reservoir filling is below a given threshold), while the reservoir ramping constraint may partly reduce the allowed discharge capacity depending on the reservoir filling and the hydrologic conditions. A reduced discharge capacity implies an increased duration time for the hydropower plant because the plant has to produce for a longer time to release the same amount of water over the year. For flexible hydropower plants, this normally means that part of the production is shifted from hours with higher power prices to hours with lower power prices, generally leading to lower water values. Furthermore, the environmental constraints may change the shape of the functional relation between the water value and reservoir volume, and the impacts of the constraints may vary between the weeks. Due to the non-convex characteristics of the constraints, the water values are not guaranteed to be non-increasing for increasing water levels in the reservoir.

Soft reservoir filling constraints

The impacts of the soft reservoir constraint on the water values from the medium-term hydropower scheduling model are studied in **Papers II** and **III**. The soft reservoir filling constraint is active for a limited number of weeks of the year and under certain conditions (i.e., the reservoir filling and inflow). The constraint impacts the water values in these weeks, but the effect may also propagate to weeks when the constraint is not active. Since the SDP algorithm iterates until the water values in the first and last week of the planning horizon converge, the effect of the constraint may spread to all weeks in the planning horizon. The case studies in **Papers II** and **III** indicate a considerable impact on the water values of the constraint. The changes are found to be sensitive to the power price assumptions, the strictness of the constraint and the characteristics of the hydropower system. Furthermore, the constraint is determined to give non-monotonic water value curves and a non-concave expected profit function.

The expected power prices within the constraint period will strongly influence the value of reaching the reservoir threshold and being allowed to produce. Suppose low power prices dominate the constraint period. In that case, a flexible hydropower plant may not want to produce in this period anyway, hence resulting in small changes in the water values due to the constraint. An example of this can be seen in Fig. 4.4 from **Paper III**, where the soft reservoir filling constraint only gives small changes in the water value curves. In this case, the constraint is active until week 42; this is therefore the first week where the constraint impacts the water value curves in the water value calculation (due to the backwards recursion in the SDP algorithm). Small differences can be seen in some of the weeks when the constraint is active, and as we move backwards in time, the constraint has no impact on the water values. There are no differences in the weeks before the constraint becomes active (as seen for week 20), implying that there is no value in changing the reservoir management in advance of the constraint for this case.

On the contrary, an expectation for high power prices within the constraint period may induce larger changes in the water value curves as the example in Fig. 4.5 from **Paper III** illustrates. Under a different power price assumption, but for the same hydropower system and case (as in Fig. 4.4), the changes in the water value curves induced by the constraint are considerably larger. In general, the water values close up to and around the threshold (from below) are higher when the constraint is considered. The same effect is spread out over a wider range of reservoir fillings (also lower reservoir fillings) in earlier weeks (as seen for week 28). The increase in the water values depends on the probability of reaching the threshold forwards in time (and thereby relaxing the discharge limitation) and the expected power prices in these weeks. The variations in expected inflow and power price result in an uneven impact on the marginal value, which is why the water value curves may be both increasing and decreasing from week to week. In week 22, the entire water value curve is lifted by the constraint, indicating an increased value of storing water for (almost) all reservoir fillings. Furthermore, this effect is carried down to the weeks before the constraint becomes active (as seen for week 20), implying that it can be optimal to change the reservoir management in advance of the constraint.

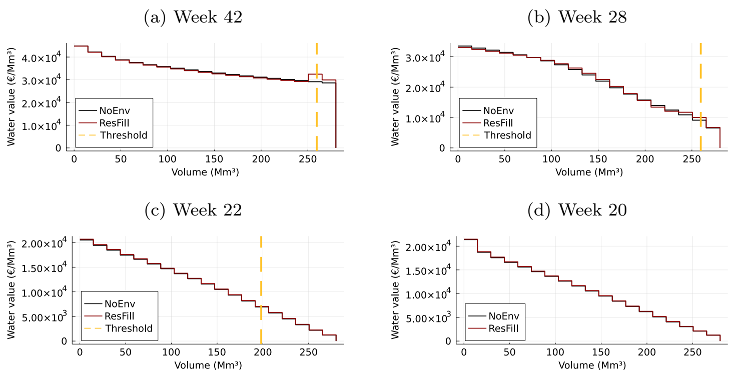


Figure 4.4: Water value curves without any environmental constraint (NoEnv case, black line) and with the soft reservoir constraint (ResFill case, red line) for HPS 2 assuming the Low-V0 price in **Paper III**, which is a traditional power price with low price variability (i.e., no or few high price periods in the summer). The reservoir threshold in the weeks when the constraint is active is given by the vertical line (orange, dashed line).

An example of a different situation is shown in Fig. 4.6 for HPS 1. Like in the previous example, there is a considerable difference in the water value curves when the constraint is considered and the effect propagates to the weeks before the threshold becomes active (see weeks 18 and 15). Compared to the water value curves calculated without considering the environmental constraint (NoEnv), the water values in these weeks are lower for low reservoir fillings and higher for reservoir fillings closer to the thresholds. Also, in this example, the changes in the water value curves indicate a value of changing the reservoir management before the constraint becomes active. However, for low reservoir fillings, lower water values indicate that it may be optimal to use more water rather than store more water, opposite from the situation for week 20 in Fig. 4.5. For higher reservoir fillings, the water values are higher when considering the constraint, indicating a higher value of storing water. In the last example, only a few high price periods are expected within the constraint period, resulting in a limited value of reaching the reservoir threshold earlier. The water value curves therefore represent a tipping point. For low reservoir fillings, it can be optimal to use more water before the constraint becomes active and accept a longer wait before the power production can be started up again (when the threshold is reached), while for higher reservoir fillings, it can be optimal to store water to reach the reservoir threshold earlier.

Finally, it is worth pointing out that the examples in Fig. 4.4 and Fig. 4.6 are

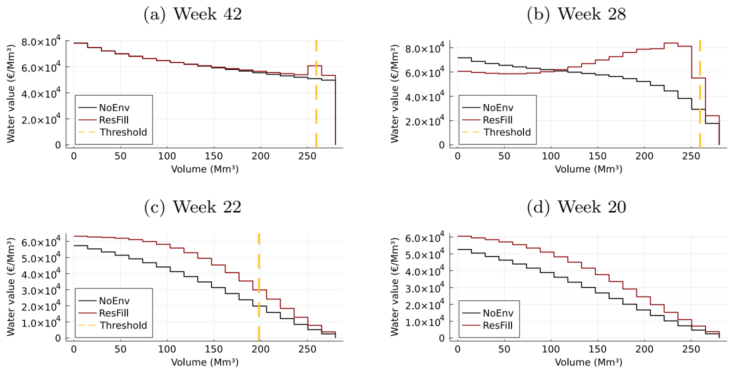


Figure 4.5: Water value curves without any environmental constraint (NoEnv case, black line) and with the soft reservoir constraint (ResFill case, red line) for HPS 2 assuming the High-V2 price in **Paper III**, which has higher power prices in the summer and high price variability (i.e., several high price periods in the summer). The reservoir threshold in the weeks when the constraint is active is given by the vertical line (orange, dashed line).

based on the same price assumptions, but for different systems and configurations of the soft reservoir filling constraint. Because of the different characteristics of the hydropower systems (i.e., the number of reservoirs, degree of regulation and capacity factors) and the soft reservoir filling constraints (e.g., the threshold levels and constraint periods), considerably larger changes are seen in the water value curves for HPS 1 than for HPS 2.

Reservoir ramping constraints

The impacts of the reservoir ramping constraint on the water values from the medium-term hydropower scheduling model are studied in **Paper III**. The reservoir ramping constraint is active throughout the entire planning horizon and the maximum ramping rate (volumetric) depends on the reservoir level. In practice, the constraint partly limits discharge in certain periods, depending on the reservoir filling, inflow and discharge from reservoirs higher up in the cascade. Because of this, the impact of the constraint on the water values may vary from week to week. The impact seen on the water values also varies between the hydropower systems and the price assumptions. The reservoir ramping constraint mainly impacts the water value curves in three ways. Firstly, the constraint limits rapid drawdown of the reservoir and may therefore induce an increased risk

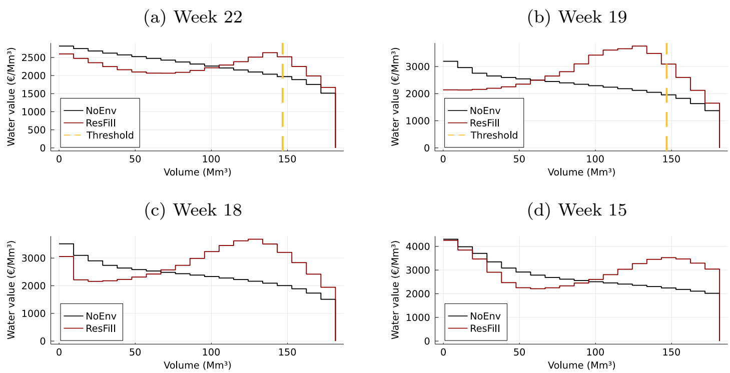


Figure 4.6: Water value curves without any environmental constraint (NoEnv case, black line) and with the soft reservoir constraint (ResFill case, red line) for HPS 1 assuming the Low-V0 price in **Paper III**, which is a traditional power price with low price variability (i.e., no or few high price periods in the summer). The reservoir threshold in the weeks when the constraint is active is given by the vertical line (orange, dashed line).

of spillage, resulting in lower water values for high reservoir fillings. Secondly, the constraint limits the operational flexibility of the plant, potentially increasing the duration time of the plant, which may reduce production in some high-price hours and thereby the value of storing water. And finally, the ramping constraint is stricter for lower reservoir levels (due to the maximum ramping rate being a function of the reservoir level), which may give a non-concave expected future value function and non-monotonic water value curves. In general, the changes in the water values due to the reservoir ramping constraint are much milder than for the soft reservoir filling constraint. This is reasonable, as the soft reservoir filling constraint is more intrusive than the reservoir ramping constraint.

Fig. 4.7 shows examples of calculated water value curves (presented in **Paper III**). For several weeks, the water values are slightly lower when considering the ramping constraint as seen for weeks 36 and 26. In some weeks, like weeks 6 and 16, more distinct changes can be seen in the shape of water value curves. The water values may increase with increasing reservoir fillings and, for some reservoir fillings, the water values may be higher with the constraint compared to without the constraint. These changes are a result of the state-dependent (i.e., reservoir level dependent) and non-convex characteristics of the ramping constraint.

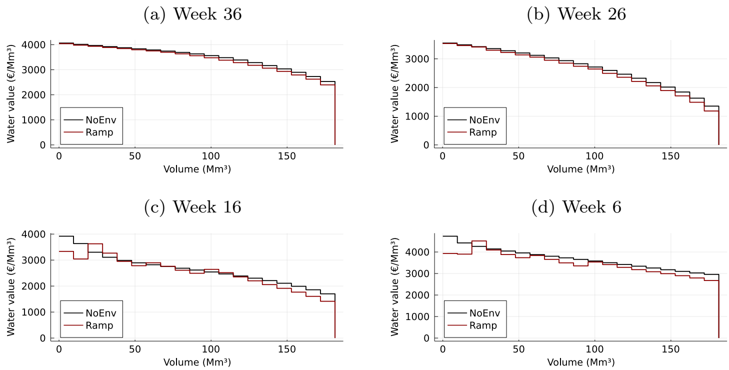


Figure 4.7: Water value curves without any environmental constraint (NoEnv case, black line) and with the reservoir ramping constraint (Ramp case, red line) for HPS 1 assuming the Low-V2 price in **Paper III**, which is a traditional seasonal power price with high price variability.

4.1.3 Operational and economic impacts of considering environmental reservoir constraints in the water value calculation

This section discusses the economic and operational impacts on operational decision-making of using water values that consider environmental reservoir constraints, or in other words, the economic and operational impacts of planning for the constraints, based on the work presented in **Paper III**. The influence of the water values is isolated by simulating the operation of the hydropower systems with the environmental reservoir constraints using water values that are calculated without the constraints and comparing it to simulated operation using water values that consider the constraints.

Water values are used in operational decision-making models to represent the value of storing water beyond the planning horizon. The water values make it possible to compare the value of producing electricity now (the power price) to the expected value of electricity production later (the water values). Higher water values are a signal to store water, while lower water values are a signal to produce (when seen against the power price). Several of the water value curves discussed in the previous section change considerably when environmental constraints are considered, which indicates that optimal reservoir management might change considerably when planning for the constraints in advance.

Soft reservoir filling constraints

The economic gain (reduction in loss) from including the soft reservoir filling constraint in the calculation of the water values is found to strongly depend on the power price assumptions. In the case study in **Paper III**, the economic improvements are found to be up to 1.4% (0.16 M€) for HPS 1 and 2.6% (0.66 M€) for HPS 2, reducing the cost of the constraint (i.e., loss in profit) by up to 50% and 15%, respectively. Nevertheless, improved planning is not found to give an improved economic performance under all power price assumptions. In general, improved planning is found to give substantial improvements in economic performance when relatively high power prices are expected within the constraint period. The economic gain is found to increase with the level of price variation.

The economic improvements are a result of changes in power production and reservoir management. The changes in the water value curves may impact power production and reservoir management in the weeks before the constraint becomes active and after the reservoir threshold is met. Since discharge from the hydropower plant is strictly restricted in the period when the constraint is active (until the reservoir level reaches the threshold), the water values are not influencing the power production from the constrained hydropower plants in these weeks. It is therefore interesting to see how the improved water value curves impact the reservoir filling before the soft reservoir filling constraint becomes active.

The producer can adjust the reservoir management to prepare for the constraint in advance. If high power prices are expected in the spring/summer, it may be optimal to keep the reservoir filling higher to more quickly reach the reservoir threshold, while, under the other price assumptions, it may instead be favourable to use more water before the constraint becomes active (in other words, have a lower reservoir filling). The results in **Paper III** show that higher water values in the weeks before the constraint becomes active (Fig. 4.5) lead to higher reservoir fillings and the reservoir threshold being met earlier, as shown in Fig. 4.8b. This is assuming the high expected price with high price variation. On the contrary, no or small changes in the water value curves (Fig. 4.4) give close to identical reservoir management, as seen in Fig. 4.8a for the low expected price with no price variation. Lower water values result in lower reservoir fillings and the reservoir threshold being met later. The largest changes in reservoir management, due to the constraint, are seen in the cases that have the highest loss in profit.

Fig. 4.9 shows the difference in the share of simulated scenarios that reach the reservoir threshold in different weeks when planning for the soft reservoir filling constraint in advance, compared to when not considering the constraint. If high power prices are expected within the constraint period, a higher share of the simulated scenarios reaches the threshold earlier. On the contrary, if low power prices are expected within the constraint period, the same amount or slightly fewer of the scenarios reach the threshold.

(a) HPS 2, Low-V0 (b) HPS 2, High-V2

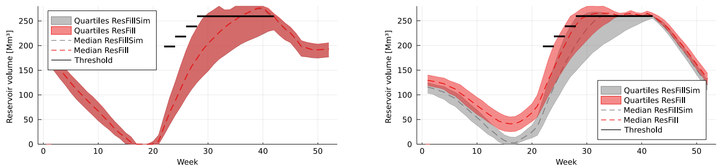


Figure 4.8: Simulated reservoir fillings based on water values calculated without considering the soft reservoir filling constraint (ResFillSim in grey) compared to simulated reservoir fillings based on water values calculated considering the constraint (ResFill in red). The results are from the case study in **Paper III**. A low price is expected in the constraint period for the cases in (a), while a higher price is expected for the cases in (b). The two cases in (a) give very similar results, and the grey area is therefore not visible.

(a) HPS 1 (b) HPS 2

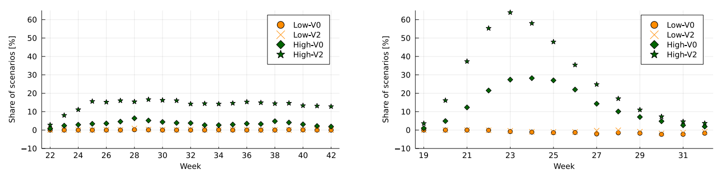


Figure 4.9: The difference in the share of scenarios for which the reservoir filling is above the threshold in each week within the constraint period when including the soft reservoir filling constraint in the water value calculation compared to when not considering the constraint. The plots are taken from **Paper III** and show the results under different power price assumptions.

Reservoir ramping constraints

Small or no economic improvements are found by including the reservoir ramping constraint in the calculation of the water values (**Paper III**). Under certain price assumptions, economic improvements of up to 0.22% (0.03 M€) are found for HPS 1. As a consequence of the reduction in the water values discussed in Section 4.1.2, the reservoir fillings are slightly reduced in some of the cases, but the seasonal curve is maintained. The fulfilment of the reservoir ramping constraint is not impacted by the water values, as the constraint is modelled as a hard constraint in the optimisation problem.

The considerably smaller impacts of planning for the reservoir ramping constraint compared to the soft reservoir filling constraint can be explained by several factors. Firstly, the constraint is not as intrusive as the soft reservoir filling constraint and has a lower associated cost. Secondly, the constraint is active during the entire planning horizon and seasonal differences in the power price and reservoir management may therefore be less influential on the consequences of the constraint. Furthermore, the influence of the reservoir level (state-dependency) on the strictness of the constraint is not as strong, meaning that actively changing the reservoir filling to relax the constraint may not be as effective as for the soft reservoir filling constraint.

4.2 Operational flexibility in hydropower-dominated renewable power systems with environmental constraints

Papers IV and **V** study the reduced flexibility in a wind- and hydropower-dominated region of a power system when different types of environmental constraints are imposed on parts of the hydropower fleet. The case study is relevant to the Norwegian power system, which comprises large hydropower plants spread across the country, power-intensive industries (often located close to large power plants) and scattered electricity demand from settlements. In [14], the Norwegian TSO (Statnett) underlines the importance of certain hydropower plants to ensure a secure power supply in particularly congested regions of the Norwegian power system. These regions typically comprise a few large hydropower plants or a hydropower cascade, some form of power-intensive industry, a (small) settlement and potentially also a more recently developed wind power park. In such regions, the operational flexibility of the hydropower plants may be imperative to ensure a secure power supply, which may lead to trade-off situations where ecological and recreational needs are weighted against the need for a flexible power supply.

Fig. 4.10 illustrates the test system used in **Paper V**. The system relies on power production from wind- and hydropower to meet the electricity demand and is connected to a larger system through a weak transmission link. The long- and short-term operational flexibility in the system is provided by the hydropower plants. The effect of the environmental constraints on the operational flexibility in the system is evaluated by assessing the curtailment of electricity demand, curtailment of demand for reserve capacity, provision of reserve capacity services, operational costs, and the marginal cost of meeting demand and reserve capacity requirements.

Three types of environmental constraints on hydropower are included in this part of the work: a soft reservoir filling constraint, a flow ramping constraint

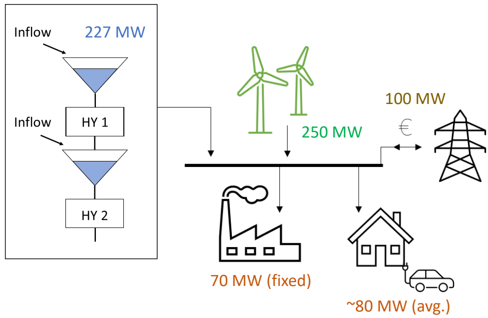


Figure 4.10: Illustration of the test system from **Paper V**.

and a minimum release constraint. The constraints restrict discharge from the hydropower plant in different ways: the soft reservoir filling constraint imposes a discharge reduction or stop in given periods, the minimum release constraint enforces the discharge to be above a minimum level at all times and the flow ramping constraint restricts the rate of change in discharge. The environmental constraints are imposed on the lower hydropower plant (HY2) in the cascade.

In addition, spinning and non-spinning reserve capacity requirements are considered. Table 4.1 lists the levels of reserve requirements used in the case study in **Paper V**. The spinning-reserve capacity levels are dimensioned to 10% of the household demand for electricity (Level 1) and 10% of the 90th percentile of the wind power generation (Level 2) for the winter and summer seasons. The non-spinning reserve capacity requirements are defined for the winter season (Level 1) or throughout the year (Level 2). The reserve capacity levels are dimensioned to cover approximately 25% of the average household demand (Level 1) and 30% of the average household demand (Level 2).

Table 4.1: Overview of the reserve capacity levels.

Case	**Spinning Reserve Req.**	**Non-spinning Reserve Req.**
Level 0	0 MW	0 MW
Level 1	5-10 MW	0-20 MW
Level 2	15.5-23.3 MW	25 MW

In general, the system becomes more constrained when environmental constraints and reserve capacity requirements are included, which leads to higher system costs. Furthermore, the reserve capacity requirements results in higher curtailment of wind power generation and lower net export of energy. Numeric results from the case study in **Paper V** are presented in Table 4.2 and a summary of the results is given below. The summary presents the main impacts of the environmental constraints on the operation of HY 2, followed by a short discussion of some of the system implications. Fig. 4.11 shows the resulting average provision of the different types of reserves by each of the hydropower plants without and with each of the environmental constraints.

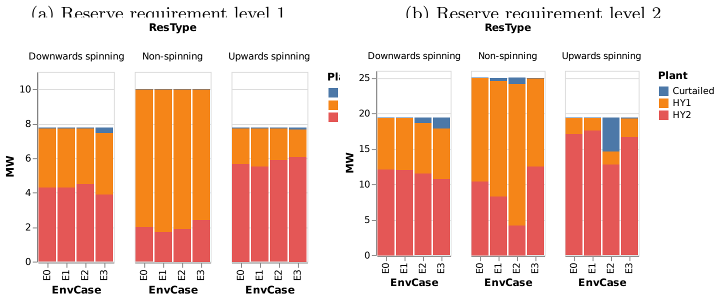


Figure 4.11: Average provision of reserve capacity services by the upper (HY1) and lower (HY2) hydropower plant for the level 1 and 2 reserve capacity requirements. The four cases are: no environmental constraint (E0), the soft reservoir filling constraint (E1), the flow ramping constraint (E2) and the minimum release constraint (E3). The environmental constraints are imposed on hydropower plant HY2. The results are from the case study in **Paper V**. A partly relaxed version of the soft reservoir constraint (E1) is used in (b).

4.2.1 Soft reservoir filling constraint

The soft reservoir filling constraint reduces the available power generation capacity in the system when the constraint is active. The hydropower plant subject to the constraint can not deliver electricity or reserve capacity services in this period because of the discharge limitation. The constraint also restricts the seasonal shifting of energy (i.e., storage of water), by enforcing a rapid filling in the spring/summer season under all conditions. Thereby, the constraint limits both the short-term operational flexibility in certain weeks, by reducing the capability to deliver reserve capacity and electricity, and the long-term flexibility in the system, by interfering in the seasonal reservoir management. However, the filling requirement of the constraint coincides with the natural filling season in the Nordic power system, i.e., in normal weather years inflows are high in this period. In that sense, the constraint may intensify the use of the reservoir for seasonal storage (following a traditional seasonal pattern).

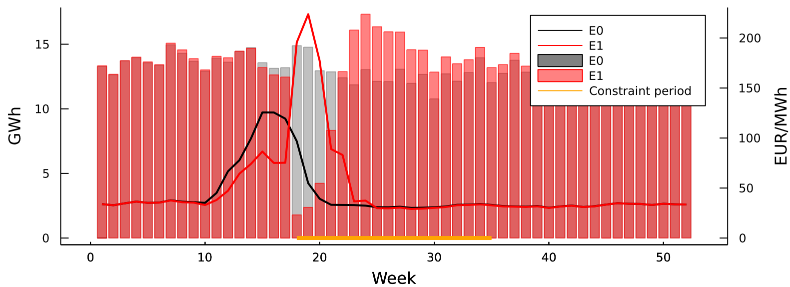


Figure 4.12: The average dual value of the power balance constraint (solid lines) and the average power production (bars) for the lower hydropower plant (HY2) with and without the state-dependent maximum discharge constraint (plotted in red and black respectively) for the Level 1 reserve capacity case. The dark red areas are where the grey and red bars overlap.

The change in power production from the constrained hydropower plant is illustrated in Fig. 4.12, together with the marginal cost of meeting the demand in the system, i.e., the dual value of the power balance (see equation (3.24)). The power production is reduced at the beginning of the constraint period but increases later in the summer. Overall, the constraint causes an increase in spillage and a slight reduction in hydropower generation. The constraint shifts the peak of the marginal cost by a few weeks, from the end of the dry winter season to the high-inflow spring season. The marginal cost is reduced in the late winter period because the reservoir filling is kept higher before the constraint becomes active, which reduces the risk of curtailment of electricity demand in these weeks. The new peak is caused by the reduction in power production in the constraint period, which increases the risk of curtailment of demand in this period. A similar pattern is seen for the supply of reserve capacity requirements in the period when the constraint is active. Overall, the constraint slightly reduces the average provision of upwards reserves (spinning and non-spinning) from the hydropower plant subject to the constraint (HY2), while the provision of downwards reserves is more or less unchanged (see Fig. 4.11).

4.2.2 Minimum release constraint

The minimum release constraint reduces the amount of water available for seasonal shifting as well as the plant's ability to provide downwards reserve capacity. Total hydropower production is reduced because the hydropower plant in periods operates at a lower efficiency to meet the minimum release requirement, while total spillage is reduced because the reservoir filling is lower. Curtailment of wind power production increases (see Table 4.2) due to the increased amount of unregulated power production (i.e., the hydropower production required to meet the minimum release constraint).

The reduced ability to store water for low-inflow periods increases the risk of curtailment of electricity demand in the winter season and thereby the marginal costs of meeting the electricity demand. The tight resource situation also increases the marginal cost of meeting the reserve capacity requirements. Particularly, the marginal costs of meeting the downwards reserve capacity requirements increase considerably (see Fig. 4.14b) due to the hydropower plant's reduced ability to ramp down production. Overall, the average provision of upwards reserves from the constrained hydropower plant (HY2) increases, while the provision of downwards spinning reserves is reduced (see Fig. 4.11).

4.2.3 Maximum flow ramping constraint

The maximum flow ramping constraint restricts how rapidly discharge, and thereby power production, can be increased or decreased. The constraint limits the hydropower plants' ability to respond to short-term fluctuations in electricity demand and to deliver reserve capacity services, but has no direct impact on the hydropower plants' ability to shift production between seasons.

The constraint is found to have small operational impacts but provides a slightly higher reservoir filling, which results in a small increase in total spillage and a slight reduction in curtailment of demand as can be seen in Table 4.2. Still, the constraint sets an upper limit to the amount of upwards and downwards reserves that can be provided by the hydropower plant, and thereby the amount of reserve capacity available in the system. The effect of this is clearly visible in Fig. 4.11b. If the reserve capacity requirements exceed the available amount of reserve capacity, curtailment of demand for reserve capacity becomes necessary and the marginal cost of meeting these requirements reaches the penalty for breaching these requirements. This can happen as a consequence of limited power capacity due to the ramping constraint and is independent of the energy situation in the system.

4.2.4 Additional remarks

The environmental constraints are found to affect the marginal costs of meeting the demand for electricity and reserves differently. The impacts of the environmental constraint on the marginal costs of meeting demand are illustrated in Fig. 4.13 and the impacts on the marginal costs of meeting the spinning reserve capacity requirements are shown in Fig. 4.14. The magnitude of the change and the numeric values are sensitive to the configuration of the system, the formulation of the environmental constraints and the assumed costs in the system (e.g., the value of lost load and other penalties). Nevertheless, some general remarks can be made based on the structural changes and the characteristics of the environmental constraints.

(a) Reserve requirement level 1

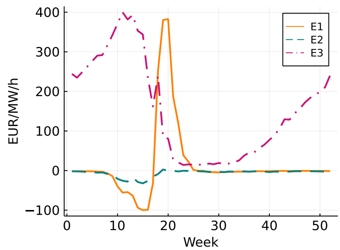


Figure 4.13: The change in the average marginal cost of meeting electricity demand when including the soft reservoir filling constraint (E1), the ramping constraint (E2) and the minimum release constraint (E3), compared to when no environmental constraints are considered (E0). The average marginal cost of E0 is plotted in Fig. 4.12.

(a) Level 1, upwards spinning reserves (b) Level 1, downwards spinning reserves

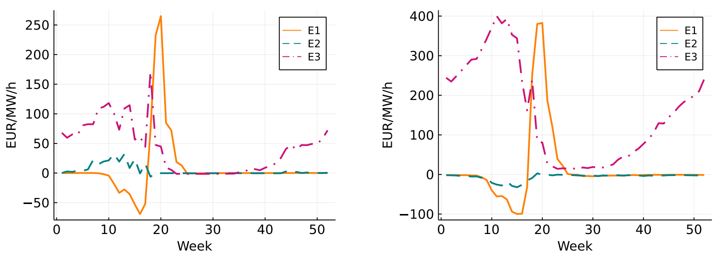


Figure 4.14: Change in the average marginal cost of meeting the requirements for spinning reserve capacities when including the soft reservoir filling constraint (E1), the ramping constraint (E2) and the minimum release constraint (E3), compared to when no environmental constraints are considered.

All the constraints impact the marginal costs in the most resource-constrained period of the year, namely the late winter. Furthermore, the soft reservoir filling constraint mainly impacts the marginal costs before and at the beginning of when the constraint is active, while the minimum release constraint impacts the marginal costs over a larger part of the planning horizon. The different behaviours are related to the scarcity of both energy and power. The soft reservoir filling constraint reduces the marginal cost in the late winter period because more water is available, which improves the energy situation and thereby also the power situation. Then, in the weeks after, the marginal costs increase as a result of reduced power capacity when the discharge limitation becomes active. The minimum release constraint reduces the availability of energy in the system, especially in the winter, which leads to higher costs of meeting demand and providing upwards reserve capacity. At the same time, the available power capacity for providing downwards reserves is reduced, which significantly increases the costs of meeting the requirements for downward reserve capacities. Finally, the ramping constraint tightens the power situation in the system, but for moderate reserve capacity requirements (such as Level 1 in the case study), this only results in small changes in the marginal cost. Still, the ramping constraint significantly reduces the amount of reserve capacity available and may make it impossible to meet high requirements for reserve capacity (such as Level 2 in the case study). In such cases, the ramping constraint has a large impact on the marginal costs of meeting the requirements for reserve capacity, depending on the penalties for breaching the constraints.

It is not always possible to meet all the requirements in a heavily constrained system. In such situations, the model is forced to accept penalties that may have large impacts on the water values and the price formation in the system. A special feature of the soft reservoir filling constraint is that the limitations associated with the constraints can be counteracted by reaching the reservoir threshold. The penalties may therefore strongly impact the reservoir management, to the extent that the reservoir management no longer follows a seasonal pattern. This was, for example, seen in some of the cases in **Paper IV**. This signifies a system under high pressure, where extreme measures are taken (by the model) to unlock flexibility, but where the optimal solution is not realistic as the environmental constraint has unwanted consequences for the reservoir management. To overcome this, a partly relaxed version of the soft reservoir filling constraint was used in combination with high requirements for reserve capacity in **Paper V**. In the relaxed version of the constraint, operation at the minimum output was allowed even though the threshold was not met. By using a less strict (but still restrictive) version of the constraint, the impacts on the marginal costs of meeting electricity demand and spinning reserve capacity requirements were considerably reduced, as these services could partly be supplied by the constrained power plant within the constraint period. The result demonstrates how alternative formulations of environmental constraints may unlock valuable flexibility in renewable power systems and should be investigated further.

Table 4.2: Average yearly results from all the case runs in **Paper V**.

Case		Operational costs $[M€/yr]$	Hydropower $[GWh/yr]$	Wind power $[GWh/yr]$	Net export $[GWh/yr]$	Curtailment of demand $[GWh/yr]$	Spillage $[GWh/yr]$[1]	Curtailment of wind $[GWh/yr]$	Curtailed demand for reserves[2] $[MW/h]$
L0	**E0**	-12.68	844.61	726.10	254.90	0.12	2.08	1.77	na
L0	**E1**	-11.79	841.15	725.88	251.36	0.27	3.88	1.99	na
L0	**E2**	-12.37	845.51	725.95	255.64	0.12	2.30	1.92	na
L0	**E3**	-9.84	818.41	726.12	228.77	0.18	0.95	1.75	na
L1	**E0**	-8.43	846.15	708.12	238.77	0.43	1.85	19.75	0.08
L1	**E1**	-8.09	842.32	707.84	234.64	0.42	3.78	20.03	0.09
L1	**E2**	-8.37	846.83	707.57	238.82	0.35	1.91	20.29	0.09
L1	**E3**	1.66	813.40	704.62	202.76	0.67	0.83	23.24	0.43
L2	**E0**	-7.87	844.78	692.38	221.39	0.17	2.32	35.49	0.10
L2	**E1**	-0.93	842.64	691.85	218.69	0.14	3.54	36.02	0.50
L2	**E2**	101.01	844.77	694.19	223.06	0.03	2.48	33.68	6.37
L2	**E3**	24.76	800.58	684.75	169.87	0.48	1.10	43.11	1.69

[1]The energy loss from spillage is estimated assuming operation at best point
[2]Average curtailed demand for reserve capacity over all time steps

4.3 Further discussion

4.3.1 Implications for hydropower producers

The results from **Papers II** and **III** reveal that the value of planning for the state-dependent (i.e., reservoir-level dependent) constraints depends on the expected power price, the characteristics of the hydropower system and the strictness and design of the constraints. The findings indicate that there can be a decent economic value in incorporating the soft reservoir filling constraint in the medium-term hydropower scheduling for the power producers, especially if the model improvements can be obtained at a reasonable cost. Furthermore, the value is higher for price characteristics that are expected to become more frequent in the future, such as higher price variability and (potentially) shifted seasonal price profiles.

Notably, the attainment of the reservoir threshold is also found to be sensitive to the power price and this is intensified when the power producers plan for the constraint. The attainment of the reservoir threshold increases with higher expected power prices within the constraint period, and in such situations, the higher value of planning for the constraint coincides with improved effectiveness of the constraint. On the other hand, low expected power prices in the constraint period may trigger a more rapid down-drawing of the reservoir before the constraint period, which again may result in the threshold being met at a later point in time.

In addition to being price sensitive, the impacts of the constraints depend on the characteristics of the constraints, such as how intrusive or strict the constraints are and time- and state-dependencies. The results indicate that there is value in planning for intrusive state-dependent constraints, perhaps especially if the constraints are only active for a limited period. However, if the constraint is very strictly formulated (e.g., a reservoir threshold that is very difficult to reach), the operational leeway may be limited and thereby also the value of planning for the constraint.

4.3.2 Implications for regulators and system operators

Even though every system and hydropower plant is unique, and requires individual assessments, some general observations may be taken from this work concerning the implications for the power system.

For regulators (that impose environmental constraints), the results from **Papers II** and **III** illustrate a couple of interesting effects. The loss in profit for the producers varies considerably depending on the power price assumptions and system characteristics, but several of the cases give low costs for the producers. The reservoir ramping constraint was, for example, mainly found to have small "unintended" operational and economic impacts. However, the impacts of this constraint also depend strongly on the characteristics of the hydropower system.

Furthermore, the soft reservoir filling constraint is interesting since the aim of the constraint concerns the reservoir level, but discharge is the variable that is directly restricted. The goal of this constraint is to obtain a high reservoir filling in the summer season but instead of defining a hard reservoir limit, the constraint limits discharge from the reservoir until the threshold is met or for a given period. The constraint effectively facilitates high reservoir fillings in the summer, without imposing (unreasonable) system costs in low-inflow years. Nevertheless, in a competitive market setting like the Nordic power market, this causes the effectiveness of the constraint to depend on the power prices in addition to the inflow. The constraint may therefore trigger different operational behaviour depending on the price characteristics, which should be considered when designing environmental constraints for future system conditions.

More research is required on the interplay between environmental constraints and the need for flexible power supply in power systems with high shares of variable energy sources, but there are some takeaways from the work in **Papers IV** and **V**. The results from these papers illustrate how some types of constraints, with different characteristics, reduce the flexibility in the system. The constraints may introduce both power- and energy-related challenges. The minimum release constraint has an energy impact and changes the use of seasonal storage by reducing the amount of water that can be used for regulated power generation. This leads to a tighter energy situation in the low inflow period and higher marginal costs of meeting electricity demand and reserve capacity requirements. The minimum release constraint also reduces the availability of capacity for down-regulation. The soft reservoir filling constraint and the flow ramping constraint reduce the available capacity for up- and down-regulation. An important difference is that the soft reservoir filling constraint only limits the available capacity for a given period but also limits energy production in this period (energy and power impact). Furthermore, the state-dependency of the constraint (in combination with the limit on generation) restricts how the seasonal storage in the reservoir can be used.

Additionally, the configuration of the constraints should not be underestimated. Partly relaxing certain requirements may unlock valuable flexibility and reduce system costs. Parts of this work considered a less strict version of the soft reservoir filling constraint, where production at the minimum output was allowed before the threshold was met. The results demonstrated that such relaxations may have a positive effect on the operational impacts but should be more thoroughly assessed to evaluate the consequences for the effectiveness of the constraint. Also, research from other fields has indicated that environmental constraints can be made more efficient from an ecological perspective by making the constraint more specialised. This could, for example, be achieved by relaxing and tightening constraints depending on the season, inflow and the state of the system. However, this may make the constraints more challenging to incorporate into scheduling tools and thereby lead to less efficient resource allocation.

4.3.3 Main limitations

There are several limitations to the work conducted as a part of this thesis. Some of the most important are discussed here.

Firstly, the choice of solution method, stochastic dynamic programming (SDP), restricts the scalability of the developed models and thereby the size of the systems that have been considered in the case studies. The method was chosen to allow for the modelling of non-convex characteristics in stochastic scheduling models that consider long planning horizons, but more research is needed on methods that can incorporate complex environmental constraints in models for larger hydropower systems, e.g., building on the SDDiP approach like in [82] or linear approximations like in [85]. Alternatively, systems with more reservoirs could potentially be considered by applying different efficiency techniques in the SDP algorithm, as discussed in [94].

Secondly, the conducted work focuses on the stochastic scheduling of hydropower operations for long planning horizons and assumes several simplifications in the detailed modelling of the hydropower operations. At the same time, there is a particular interest in understanding the implications of environmental constraints for operational flexibility on different time scales. The simplified representation of the hydropower functions, such as linearising the hydropower production function and unit commitment, results in an overestimation of the short-term flexibility of the power plants, and may, for example, lead to an underestimation of the impacts on the provision of ancillary services.

Finally, the necessity to prioritise between a higher level of detail and a larger scope is another challenge when evaluating the implications of environmental constraints. This thesis considers a limited geographical scope, taking either the perspective of a single hydropower producer operating in a competitive market or the perspective to minimise system cost for a region of the power system. Environmental constraints may have large impacts on a single hydropower plant or cascade but only small implications for the system if there are enough flexible assets available. However, in a different region, the situation may be completely different and a specific plant may be essential to security of supply. Furthermore, in a hydropower-dominated system like the Norwegian one, environmental constraints on several hydropower plants may coincide and induce a larger total impact on the power system. The implications of environmental constraints should therefore be investigated from different scopes, considering both more detailed, local implications and aggregated system effects.

5 Conclusions and further work

This PhD has investigated the implications of environmental constraints in stochastic hydropower scheduling problems for long planning horizons. The work has made new contributions with respect to the modelling of state-dependent (i.e., reservoir-level dependent) environmental constraints, given new insights into how different types of state-dependent environmental constraints impact the strategy for reservoir operation (i.e., the water values) and assessed the implications of this to operational decision making. Furthermore, the impacts of different types of environmental constraints on the operation of hydropower plants have been explored from the perspective of a profit-maximising hydropower producer and from a cost-minimising perspective in the context of a wind- and hydropower-dominated region of a power system.

The work conducted in this PhD aimed to answer the four research questions given in Section 1.2. To conclude this thesis, the main findings of the work are highlighted in response to these questions in Section 5.1, while suggestions for further work are provided in Section 5.2.

5.1 Concluding remarks

In this thesis, particular attention has been devoted to the modelling and assessment of certain state-dependent environmental constraints, namely, a soft reservoir filling constraint and a reservoir ramping constraint. State-dependent (i.e., reservoir-level dependent) constraints can be challenging to model in medium-term scheduling models based on linear programming as they introduce non-convex characteristics to the scheduling problem. An SDP-based modelling approach has been used in this work to allow for an accurate representation of environmental constraints in the scheduling problem. SDP was used because of the method's ability to handle non-convex relationships and because it is a well-established method for solving stochastic hydropower scheduling problems.

Two SDP-based hydropower scheduling models have been developed; a producer-centric, profit-maximising medium-term hydropower scheduling model and a cost-minimising optimisation model for long-term scheduling of a wind- and hydropower-dominated region of a power system. The models are presented in detail in **Papers III** and **V**, respectively. Both models have been used to assess the implications of state-dependent environmental constraints on the operation of hydropower plants. The work demonstrated the usefulness of adopting SDP-based models to investigate the implications of state-dependent environmental constraints on hydropower systems with one to two reservoirs, but the models are not well-suited to analyse large multi-reservoir systems because of limited scalability. However, the models developed here provide a fundament for the implementation of environmental constraints in more computationally efficient scheduling models suited for larger hydropower systems.

The case studies in **Papers II** and **III** show that the modelled environmental reservoir constraints have a considerable impact on the operation of the hydropower plants. Particularly, the soft reservoir filling constraint changes the reservoir management throughout the year significantly. The operational and economic implications of this constraint were shown to be sensitive to the seasonal profile of the expected power price and the level of price variations. More periods with high power prices in the period when the constraint is active (spring/summer) were found to result in higher costs (loss in profit) of the constraint. Furthermore, the water value curves clearly demonstrate the impacts of including state-dependent environmental reservoir constraints in medium-term hydropower scheduling. Again the largest impacts were found for the soft reservoir filling constraint, where significant changes in the shape of the water value curves were detected under certain price assumptions. The non-convex characteristics of the constraints were found to result in a non-concave expected future value function.

The consequences to operational decision-making of including environmental reservoir constraints in the strategy calculation (i.e., the medium-term scheduling) were investigated in **Paper III**. Small to no economic improvements were determined for the reservoir ramping constraint, while improvements of up to 2.6% (i.e., reductions in the economic loss) were found for the soft reservoir filling constraint. The economic improvements may seem modest, but hydropower producers often aspire to such marginal improvements when operating in competitive markets. Furthermore, both the economic improvements and the fulfilment of the constraint were found to be sensitive to the power price assumptions. Higher expected power prices in the constraint period gave higher water levels in the reservoirs and a higher economic gain from planning for the constraint. Improved planning for this type of constraint may therefore have larger operational and economic consequences in the future, as the ongoing transition of the power system may lead to more frequent occurrences of high prices throughout the year, underlining the importance of considering different price characteristics in these types of studies.

The last research question of this thesis concerns the implications of environmental constraints on system flexibility and security of supply in hydropower-dominated power systems. This is a broad question, and has by no means been fully answered by the work herein, but was addressed in **Papers IV** and **V**. Three types of environmental constraints were considered in **Paper V**: a soft reservoir filling constraint, a flow ramping constraint and a minimum release constraint. The constraints have fundamentally different impacts on the operation of hydropower plants. The first imposes a time- and state-dependent discharge stop, the second restricts the rate of change in discharge and the last sets a lower bound for release. The interplay between the environmental constraints and requirements for spinning and non-spinning reserve capacity was discussed in the study. The constraints change the operation of the hydropower plants and may thereby reduce or increase the provision of reserves from the constrained hydropower plant. Reduced provision of reserve capacity from the constrained hydropower plant was compensated by increasing the provision of reserves from the other hydropower plant. Nevertheless, for high reserve capacity requirements, the amount of unmet reserve capacity increased considerably for some of the cases. Furthermore, the impacts on the marginal costs of meeting the energy demand and the reserve capacity requirements were found to vary considerably between the constraints, both in magnitude and structure.

In the Norwegian power system, a large share of the hydropower fleet is in the process of receiving revised licences whereby new or updated environmental constraints on the operation of the plants may be imposed. In this process, the regulator (NVE) has to consider the requests of different stakeholders to restrict the plants' operation, while simultaneously preserving electricity generation and flexibility resources so that the TSO (Statnett) can ensure security of supply. This thesis considered several environmental constraints that are relevant to the Norwegian system. Particularly, the soft reservoir filling constraint has been thoroughly assessed, contributing to a deeper understanding of the implications of this type of constraint under different conditions from the perspective of the hydropower producer and the power system. Furthermore, the results in **Paper V** may provide useful insights into how different environmental constraints impact the availability of energy and power in a hydropower-dominated system. Finally, the configuration of the constraints is important. Efficient environmental constraints may be achieved by tailored or more intricate formulations, but may also be challenging to incorporate into the hydropower scheduling.

5.2 Suggestions for further work

Further work should consider complex environmental constraints in stochastic scheduling models for larger hydropower systems. The use of SDDiP such as in [82] or the use of tight linear approximations for linear programming-based models (such as SDDP in [85]) could be further investigated. An interesting topic could be to formulate and investigate the use of tight linear approximations for different types of complex, non-convex environmental constraints.

Furthermore, advanced environmental constraints may be imposed more frequently in the future as tailored formulations (e.g., which include dependencies on time, flow or water levels) can increase the ecological benefits and/or reduce the negative impacts on the power system. However, a major drawback is that more complex constraints are often difficult to consider in the scheduling models. In general, the modelling of advanced environmental constraints in stochastic scheduling models, such as temperature- or inflow-dependent minimum flow requirements and flow-dependent ramping limits, remains a key topic for further research.

Another topic that needs further investigation is the interplay between different types of requirements in hydropower-dominated power systems. To capture short-term flexibility impacts better, an improved simulator combining stochastic scheduling models that consider complex environmental constraints with more detailed short-term models could be used in future studies. Alternatively, methods to incorporate more details into the stochastic hydropower scheduling problem could be investigated. Additionally, for hydropower-dominated systems, the implications to the power systems of coincident environmental constraints should be considered for larger regions with several hydropower plants.

Finally, future research should strive to achieve more generalised results as some similarities can be expected between hydro-dominated systems globally. An interesting topic could be to work conceptually with how different types of constraints impact the operational flexibility of hydropower plants in different regions of the world, and, based on this, develop a standardised categorisation.

Bibliography

[1] UNFCCC, "The Paris Agreement," accessed: 2023-03-25. [Online]. Available: https://unfccc.int/documents/184656

[2] IEA, "Net Zero by 2050," IEA, Paris, Tech. Rep., 2021. [Online]. Available: https://www.iea.org/reports/net-zero-by-2050

[3] IRENA, "World Energy Transitions Outlook 2022: 1.5°C Pathway," International Renewable Energy Agency, Abu Dhabi, Tech. Rep., 2022. [Online]. Available: https://www.irena.org/Publications/2022/Mar/World-Energy-Transitions-Outlook-2022

[4] United Nations Environment Programme (UNEP), "Emissions Gap Report 2022: The Closing Window - Climate Crisis Calls for Rapid Transformation of Societies," UNEP, Nairobi, Tech. Rep., 2022. [Online]. Available: https://wedocs.unep.org/20.500.11822/40874.

[5] IEA, "World Energy Outlook 2022," IEA, Paris, Tech. Rep., 2022. [Online]. Available: https://www.iea.org/reports/world-energy-outlook-2022

[6] IEA, "Hydropower Special Market Report," IEA, Paris, Tech. Rep., 2021. [Online]. Available: https://www.iea.org/reports/hydropower-special-market-report

[7] O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, and C. von Stechow, "IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation," IPCC, Cambridge, UK and New York, NY, USA., Tech. Rep., 2011.

[8] M. Mattmann, I. Logar, and R. Brouwer, "Hydropower externalities: A meta-analysis," *Energy Economics*, vol. 57, pp. 66–77, 2016.

[9] IPBES, *Summary for policymakers of the global assessment report on biodiversity and ecosystem services*, S. Díaz, J. Settele, E. S. Brondízio, H. T. Ngo, M. Guèze, J. Agard, A. Arneth, P. Balvanera, K. A. Brauman, S. H. M. Butchart, K. M. A. Chan, L. A. Garibaldi, K. Ichii, J. Liu, S. M. Subramanian, G. F. Midgley, P. Miloslavich, Z. Molnár, D. Obura, A. Pfaff, S. Polasky, A. Purvis, J. Razzaque, B. Reyers, R. Roy Chowdhury, Y. J. Shin, I. J. Visseren-Hamakers, K. J. Willis, and C. N. Zayas, Eds. Bonn, Germany: IPBES Secreteriat, 2019. [Online]. Available: https://zenodo.org/record/3553579

[10] "European Water Framework Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy," 2000. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32000L0060

[11] B. Köhler, A. Ruud, Ø. Aas, and D. N. Barton, "Decision making for sustainable natural resource management under political constraints – the case of revising hydropower licenses in Norwegian watercourses," *Civil Engineering and Environmental Systems*, vol. 36, no. 1, pp. 17–31, 2019.

[12] J. Sørensen, E. Brodtkorb, I. Haug, and J. Fjellanger, "Vannkraftkonsesjoner som kan revideres innen 2022 (in Norwegian)," NVE, Tech. Rep., 2013. [Online]. Available: https://www.miljodirektoratet.no/globalassets/publikasjoner/M49/M49.pdf

[13] J. H. Halleraker, M. S. Kenawi, J. H. L'Abée-Lund, T. H. Bakken, and K. Alfredsen, "Assessment of flow ramping in water bodies impacted by hydropower operation in Norway – Is hydropower with environmental restrictions more sustainable?" *Science of The Total Environment*, vol. 832, p. 154776, 2022.

[14] Statnett, "Verdien av regulerbar vannkraft - Betydning for kraftsystemet i dag og i fremtiden (in Norwegian)," Statnett, Oslo, Tech. Rep., 2021. [Online]. Available: https://www.statnett.no/contentassets/b82dcf206acc4762b2abcc3182e5bc52/verdien-av-regulerbar-vannkraft-statnett-mars-2021.pdf

[15] A. Helseth, "Environmental Constraints in Seasonal Hydropower Scheduling - Survey and Feasibility," HydroCen, Trondheim, Tech. Rep., 2019. [Online]. Available: https://www.ntnu.no/hydrocen/hydrocen-rapport

[16] C. A. Veie, M. Sidelnikova, S. Skau, V. J. Koestler, N. Y. Aksnes, J. Hole, F. Arnesen, and C. Birkeland, "Kraftproduksjon i Norden til 2040 (in Norwegian)," NVE, Tech. Rep., 2019. [Online]. Available: https://publikasjoner.nve.no/rapport/2019/rapport2019_43.pdf

[17] "NVE Norsk kraftproduksjon (Norwegian power production)," https://www.nve.no/energi/energisystem/kraftproduksjon/, accessed: 2023-03-13.

[18] R. Misener and C. A. Floudas, "Piecewise-Linear Approximations of Multidimensional Functions," *J Optim Theory Appl*, vol. 145, pp. 120–147, 2010.

[19] B. Sørensen, "A combined wind and hydro power system," *Energy Policy*, vol. 9, no. 1, pp. 51–55, 1981.

[20] J. O. Tande, M. Korpås, and K. Uhlen, "Planning and Operation of Large Offshore Wind Farms in Areas with Limited Power Transfer Capacity," *Wind Engineering*, vol. 36, no. 1, pp. 2012–69, 2012. [Online]. Available: https://www.researchgate.net/publication/273080951

[21] J. Matevosyan, M. Olsson, and L. Söder, "Hydropower planning coordinated with wind power in areas with congestion problems for trading on the spot and the regulating market," *Electric Power Systems Research*, vol. 79, no. 1, pp. 39–48, 1 2009.

[22] A. Khodadadi, L. Herre, P. Shinde, R. Eriksson, L. Soder, and M. Amelin, "Nordic Balancing Markets: Overview of Market Rules," *International Conference on the European Energy Market, EEM*, vol. 2020-September, 2020.

[23] A. Helseth, M. Fodstad, and B. Mo, "Optimal Medium-Term Hydropower Scheduling Considering Energy and Reserve Capacity Markets," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 3, pp. 934–942, 2016.

[24] J. I. Pérez-Díaz, I. Guisández, M. Chazarra, and A. Helseth, "Medium-term scheduling of a hydropower plant participating as a price-maker in the automatic frequency restoration reserve market," *Electric Power Systems Research*, vol. 185, p. 106399, 2020.

[25] M. N. Hjelmeland, A. Helseth, and M. Korpås, "A Case Study on Medium-Term Hydropower Scheduling with Sales of Capacity," *Energy Procedia*, vol. 87, pp. 124–131, 2016.

[26] M. N. Hjelmeland, C. T. Larsen, M. Korpas, and A. Helseth, "Provision of rotating reserves from wind power in a hydro-dominated power system," *2016 International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2016 - Proceedings*, 2016.

[27] M. Chazarra, J. García-González, J. I. Pérez-Díaz, and M. Arteseros, "Stochastic optimization model for the weekly scheduling of a hydropower system in day-ahead and secondary regulation reserve markets," *Electric Power Systems Research*, vol. 130, pp. 67–77, 2016.

[28] A. Helseth, M. Haugen, H. Farahmand, B. Mo, S. Jaehnert, and I. Stenkløv, "Assessing the benefits of exchanging spinning reserve capacity within the hydro-dominated Nordic market," *Electric Power Systems Research*, vol. 199, p. 107393, 2021.

[29] A. Helseth and A. C. G. de Melo, "Scheduling Toolchains in Hydro- Dominated Systems - Evolution, Current Status and Future Challenges," SINTEF, Trondheim, Tech. Rep., 2020. [Online]. Available: https://sintef.brage.unit.no/sintef-xmlui/handle/11250/2672581

[30] C. Ahlfors and M. Amelin, "Weekly planning of hydropower in systems with large volumes and varying power generation: A literature review," *2021 IEEE Madrid PowerTech, PowerTech 2021 - Conference Proceedings*, 2021.

[31] M. Maceira, L. A. Terry, F. S. Costa, J. M. Damázio, and A. C. G. Melo, "Chain of Optimization Models for Setting the Energy Dispatch and Spot Price in the Brazilian System," in *15th Power Systems Computation Conference, PSCC 2002*, no. 1, 2002.

[32] O. B. Fosso, A. Gjelsvik, A. Haugstad, B. Mo, and I. Wangensteen, "Generation scheduling in a deregulated system - the Norwegian case," *IEEE Transactions on Power Systems*, vol. 14, no. 1, pp. 75–80, 1999.

[33] O. Wolfgang, A. Haugstad, B. Mo, A. Gjelsvik, I. Wangensteen, and G. Doorman, "Hydro reservoir handling in Norway before and after deregulation," *Energy*, vol. 34, no. 10, pp. 1642–1651, 2009.

[34] A. L. Diniz, F. D. S. Costa, M. E. Maceira, T. N. Dos Santos, L. C. B. Dos Santos, and R. N. Cabral, "Short/Mid-term hydrothermal dispatch and spot pricing for large-scale systems - The case of Brazil," *20th Power Systems Computation Conference, PSCC 2018*, 2018.

[35] J. Kong, H. I. Skjelbred, and O. B. Fosso, "An overview on formulations and optimization methods for the unit-based short-term hydro scheduling problem," *Electric Power Systems Research*, vol. 178, p. Article 106027, 2020.

[36] D. M. Carlisle, D. M. Wolock, and M. R. Meador, "Alteration of streamflow magnitudes and potential ecological consequences: a multiregional assessment," *Frontiers in Ecology and the Environment*, vol. 9, no. 5, pp. 264–270, 2011.

[37] N. L. Poff and J. K. Zimmerman, "Ecological responses to altered flow regimes: A literature review to inform the science and management of environmental flows," *Freshwater Biology*, vol. 55, no. 1, pp. 194–205, 2010.

[38] T. H. Bakken, A. Harby, T. Forseth, O. Ugedal, J. F. Sauterleute, J. H. Halleraker, and K. Alfredsen, "Classification of hydropeaking impacts on Atlantic salmon populations in regulated rivers," *River Research and Applications*, 2021. [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.1002/rra.3917https://onlinelibrary.wiley.com/doi/abs/10.1002/rra.3917https://onlinelibrary.wiley.com/doi/10.1002/rra.3917

[39] P. E. Hirsch, A. P. Eloranta, P. A. Amundsen, Å. Brabrand, J. Charmasson, I. P. Helland, M. Power, J. Sánchez-Hernández, O. T. Sandlund, J. F. Sauterleute, S. Skoglund, O. Ugedal, and

H. Yang, “Effects of water level regulation in alpine hydropower reservoirs: an ecosystem perspective with a special emphasis on fish,” *Hydrobiologia*, vol. 794, no. 1, pp. 287–301, 2017. [Online]. Available: https://link.springer.com/article/10.1007/s10750-017-3105-7

[40] A. P. Eloranta, A. G. Finstad, I. P. Helland, O. Ugedal, and M. Power, “Hydropower impacts on reservoir fish populations are modified by environmental variation,” *Science of The Total Environment*, vol. 618, pp. 313–322, 2018.

[41] J. Heggenes, M. Stickler, K. Alfredsen, J. E. Brittain, A. Adeva-Bustos, and A. Huusko, “Hydropower-driven thermal changes, biological responses and mitigating measures in northern river systems,” *River Research and Applications*, vol. 37, no. 5, pp. 743–765, 6 2021. [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.1002/rra.3788https://onlinelibrary.wiley.com/doi/abs/10.1002/rra.3788https://onlinelibrary.wiley.com/doi/10.1002/rra.3788

[42] R. Scott Winton, E. Calamita, and B. Wehrli, “Reviews and syntheses: Dams, water quality and tropical reservoir stratification,” *Biogeosciences*, vol. 16, no. 8, pp. 1657–1671, 2019.

[43] U. Pulg, K. W. Vollset, G. Velle, and S. Stranzl, “First observations of saturopeaking: Characteristics and implications,” *Science of The Total Environment*, vol. 573, pp. 1615–1621, 2016.

[44] Y. T. Prairie, J. Alm, J. Beaulieu, N. Barros, T. Battin, J. Cole, P. del Giorgio, T. DelSontro, F. Guérin, A. Harby, J. Harrison, S. Mercier-Blais, D. Serça, S. Sobek, and D. Vachon, “Greenhouse Gas Emissions from Freshwater Reservoirs: What Does the Atmosphere See?” *Ecosystems*, vol. 21, no. 5, pp. 1058–1071, 8 2018. [Online]. Available: https://link.springer.com/article/10.1007/s10021-017-0198-9

[45] K. Alfredsen, P. A. Amundsen, L. Hahn, P. M. Harrison, I. P. Helland, E. G. Martins, W. M. Twardek, and M. Power, “A synoptic history of the development, production and environmental oversight of hydropower in Brazil, Canada, and Norway,” *Hydrobiologia*, vol. 849, no. 2, pp. 269–280, 2022. [Online]. Available: https://link.springer.com/article/10.1007/s10750-021-04709-4

[46] B. M. Pracheil, A. L. Levine, T. L. Curtis, M. S. Aldrovandi, R. Uría-Martínez, M. M. Johnson, and T. Welch, “Influence of project characteristics, regulatory pathways, and environmental complexity on hydropower licensing timelines in the US,” *Energy Policy*, vol. 162, p. 112801, 2022.

[47] N. L. Poff, R. E. Tharme, and A. H. Arthington, “Evolution of Environmental Flows Assessment Science, Principles, and Methodologies,” in *Water for the Environment: From Policy and Science to Implementation and Management*. Elsevier Inc., 2017, pp. 203–236.

[48] M. Bussettini, M. Linsen, T. Petitguyot, G. Schmidt, M. Arqued, N. Smolar-Žvanut, M. Alves, T. Christos, N. Skoulikidis, E. H. Herrero, R. Navarro, K. Tanner, and J. Maeso, “Ecological flows in the implementation of the Water Framework Directive,” European Commission, Tech. Rep., 2015. [Online]. Available: http://ec.europa.eu

[49] N. L. Poff, J. D. Allan, M. B. Bain, J. R. Karr, K. L. Prestegaard, B. D. Richter, R. E. Sparks, and J. C. Stromberg, “The Natural Flow Regime,” *BioScience*, vol. 47, no. 11, pp. 769–784, 1997.

[50] M. Acreman and M. J. Dunbar, “Defining environmental river flow requirements – a review,” *Hydrology and Earth System Sciences*, vol. 8, no. 5, pp. 861–876, 2004.

[51] T. Linnansaari, W. Monk, D. Baird, and R. Curry, “Review of approaches and methods to assess Environmental Flows across Canada and internationally,” DFO Canadian Science Advisory Secretary Research Document 2012/039, Canada, Tech. Rep., 2012. [Online]. Available: www.dfo-mpo.gc.ca/csas-sccs/

[52] T. Bakken, P. Zinke, A. Melcher, H. Sundt, T. Vehanen, K. Jorde, and M. Acreman, “Setting environmental flows in regulated rivers,” SINTEF, Trondheim, Tech. Rep., 2012. [Online]. Available: https://www.sintef.no/en/publications/publication/995812/

[53] N. L. Poff, “Beyond the natural flow regime? Broadening the hydro-ecological foundation to meet environmental flows challenges in a non-stationary world,” in *Freshwater Biology*, vol. 63, no. 8. Blackwell Publishing Ltd, 2018, pp. 1011–1021.

[54] K. Alfredsen, A. Harby, T. Linnansaari, and O. Ugedal, “Development of an inflow-controlled environmental flow regime for a Norwegian river,” *River Research and Applications*, no. 6, pp. 731–739, 2012.

[55] L. Kosnik, “Balancing Environmental Protection and Energy Production in the Federal Hydropower Licensing Process,” *Land Economics*, vol. 86, no. 3, pp. 444–466, 2010. [Online]. Available: https://www.jstor.org/stable/27821437

[56] T. H. Bakken, T. Forseth, and A. Harby, *Miljøvirkninger av effektkjøring: Kunnskapsstatus og råd til forvaltning og industri (in Norwegian)*. Trondheim: NINA Temahefte 62, 2016.

[57] M. Moreira, D. S. Hayes, I. Boavida, M. Schletterer, S. Schmutz, and A. Pinheiro, “Ecologically-based criteria for hydropeaking mitigation: A review,” pp. 1508–1522, 2019.

[58] F. B. Ashraf, A. T. Haghighi, J. Riml, K. Alfredsen, J. J. Koskela, B. Kløve, and H. Marttila, "Changes in short term river flow regulation and hydropeaking in Nordic rivers," *Scientific Reports*, vol. 8, no. 1, pp. 1–12, 2018.

[59] E. Solvang, J. Charmasson, J. Sauterlaute, A. Harby, Å. Killingtveit, H. Egeland, O. Andersen, Ø. Ruud, and Ø. Aas, "Norwegian hydropower for large scale electricity balancing needs - Pilot study of technical, environmental and social challenges," SINTEF, Tech. Rep., 2015.

[60] O. Wolfgang, A. L. Henden, M. M. Belsnes, C. Baumann, A. Maaz, A. Schäfer, A. Moser, M. Harasta, and T. Døble, "Scheduling when Reservoirs are Batteries for Wind- and Solar-power," in *Energy Procedia*, vol. 87. Elsevier Ltd, 2016, pp. 173–180.

[61] T. H. Bakken, V. Beck, L. H. Schönfelder, J. Charmasson, J.-E. Thrane, M. Lindholm, and A. Brabrand, "Testing and evaluation of a HYMO classification system for lakes and reservoirs - Proposed new and modified hydromorphological (HYMO) classification system," SINTEF-report: 01365, Trondheim, Norway, Tech. Rep., 2019. [Online]. Available: https://ntnuopen.ntnu.no/ntnu-xmlui/handle/11250/2642179

[62] M. A. Olivares, "Optimal hydropower reservoir operation with environmental requirements," Ph.D. dissertation, The University of California, Davis, USA, 2008.

[63] A. C. Valle, M. A. Aguiar, and G. Cruz, "The impact of water quality as an environmental constraint on operation planning of a hydro-thermal power system," *Renewable Energy*, vol. 34, no. 3, pp. 655–659, 2009.

[64] A. R. Shaw, H. Smith Sawyer, E. J. LeBoeuf, M. P. McDonald, and B. Hadjerioua, "Hydropower Optimization Using Artificial Neural Network Surrogate Models of a High-Fidelity Hydrodynamics and Water Quality Model," *Water Resources Research*, vol. 53, no. 11, pp. 9444–9461, 2017.

[65] D. N. Barton, H. Sundt, A. A. Bustos, H. P. Fjeldstad, R. Hedger, T. Forseth, Berit Köhler, Ø. Aas, K. Alfredsen, and A. L. Madsen, "Multi-criteria decision analysis in Bayesian networks - Diagnosing ecosystem service trade-offs in a hydropower regulated river," *Environmental Modelling and Software*, vol. 124, 2020.

[66] M. J. Kotchen, M. R. Moore, F. Lupi, and E. S. Rutherford, "Environmental constraints on hydropower: An ex post benefit-cost analysis of dam relicensing in Michigan," *Land Economics*, vol. 82, no. 3, pp. 384–403, 2006.

[67] S. Niu and M. Insley, "On the economics of ramping rate restrictions at hydro power plants: Balancing profitability and environmental costs," *Energy Economics*, vol. 39, pp. 39–52, 2013.

[68] J. I. Pérez-Díaz and J. R. Wilhelmi, "Assessment of the economic impact of environmental constraints on short-term hydropower plant operation," *Energy Policy*, vol. 38, no. 12, pp. 7960–7970, 2010.

[69] I. Guisández González, "Long-term Optimal Hydropower Reservoir Operation with Minimum Flows and Maximum Ramping Rates," Ph.D. dissertation, Technical University of Madrid, 2016.

[70] I. Guisández, J. I. Pérez-Díaz, and J. R. Wilhelmi, "Assessment of the economic impact of environmental constraints on annual hydropower plant operation," *Energy Policy*, pp. 1332–1343, 2013.

[71] I. Guisández, J. I. Pérez-Díaz, W. Nowak, and J. Haas, "Should environmental constraints be considered in linear programming based water value calculators?" *International Journal of Electrical Power and Energy Systems*, vol. 117, 2020.

[72] S. Niu and M. Insley, "An options pricing approach to ramping rate restrictions at hydro power plants," *Journal of Economic Dynamics and Control*, vol. 63, pp. 25–52, 2016.

[73] H. Huuki, S. Karhinen, F. B. Ashraf, A. T. Haghighi, and H. Marttila, "The economic cost of hydropower environmental constraints under decreasing price volatility," *River Research and Applications*, vol. 38, no. 10, pp. 1815–1828, 2022. [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.1002/rra.4049https://onlinelibrary.wiley.com/doi/abs/10.1002/rra.4049https://onlinelibrary.wiley.com/doi/10.1002/rra.4049

[74] I. Guisández, J. I. Pérez-Díaz, and J. R. Wilhelmi, "Influence of the Maximum Flow Ramping Rates on the Water Value," in *Energy Procedia*, vol. 87. Elsevier Ltd, 2016, pp. 100–107.

[75] I. Guisández, J. I. Pérez-Díaz, and J. R. Wilhelmi, "The influence of environmental constraints on the water value," *Energies*, vol. 9, no. 6, 2016.

[76] M. A. Olivares, J. Haas, R. Palma-Behnke, and C. Benavides, "A framework to identify Pareto-efficient subdaily environmental flow constraints on hydropower reservoirs using a grid-wide power dispatch model," *Water Resources Research*, vol. 51, no. 5, pp. 3664–3680, 2015.

[77] B. K. Edwards, S. J. Flaim, and R. E. Howitt, "Optimal provision of hydroelectric power under environmental and regulatory constraints," *Land Economics*, vol. 75, no. 2, pp. 267–283, 1999.

[78] J. Rand, "Overlooked trade-offs of environmentally protective hydropower operation: Impacts to ancillary services and greenhouse gas emissions," *River Research and Applications*, vol. 34, no. 9, pp. 1123–1131, 2018.

[79] E. Ibanez, T. Magee, M. Clement, G. Brinkman, M. Milligan, and E. Zagona, "Enhancing hydropower modeling in variable generation integration studies," *Energy*, vol. 74, no. C, pp. 518–528, 9 2014.

[80] B. Clair, A. Leefsma, S. Balaguer, and A. Lavergne, "Multi-objective optimization for water management," Presentation at the 7th International Conference on Hydropower Scheduling in Competitive Electricity Markets, 2022. [Online]. Available: https://publikasjoner.nve.no/rapport/2019/rapport2019_43.pdf

[81] J. C. Alais, P. Carpentier, and M. De Lara, "Multi-usage hydropower single dam management: chance-constrained optimization and stochastic viability," *Energy Systems*, vol. 8, no. 1, pp. 7–30, 2017. [Online]. Available: https://link.springer.com/article/10.1007/s12667-015-0174-4

[82] A. Helseth, B. Mo, and H. O. Hagenvik, "Nonconvex Environmental Constraints in Hydropower Scheduling," *2020 International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2020 - Proceedings*, 2020.

[83] J. Zou, S. Ahmed, and X. A. Sun, "Stochastic dual dynamic integer programming," *Mathematical Programming*, vol. 175, no. 1-2, pp. 461–502, 2019.

[84] M. N. Hjelmeland, J. Zou, A. Helseth, and S. Ahmed, "Nonconvex Medium-Term Hydropower Scheduling by Stochastic Dual Dynamic Integer Programming," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 1, pp. 481–490, 2019.

[85] A. Helseth, B. Mo, H. O. Hågenvik, and L. E. Schäffer, "Hydropower Scheduling with State-Dependent Discharge Constraints: An SDDP Approach," *Journal of Water Resources Planning and Management*, vol. 148, no. 11, p. 04022061, 2022. [Online]. Available: https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29WR.1943-5452.0001609https://ascelibrary.org/doi/10.1061/%28ASCE%29WR.1943-5452.0001609

[86] S. A. Borresen and L. E. Schaffer, "Evaluating Modelling Approaches for State-Dependent Environmental Constraints in Medium-Term Hydropower Scheduling," *2022 18th International Conference on the European Energy Market (EEM)*, pp. 1–6, 9 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9921089/

[87] S. A. Børresen, "Evaluating Modeling Approaches for State-Dependent Environmental Constraints in Medium-Term Hydropower Scheduling," Master's thesis, Norwegian University of Science and Technology (NTNU), Trondheim, 2022. [Online]. Available: https://ntnuopen.ntnu.no/ntnu-xmlui/handle/11250/3016978

[88] E. Pereira-Bonvallet, S. Püschel-Løvengreen, M. Matus, and R. Moreno, "Optimizing Hydrothermal Scheduling with Non-Convex Irrigation Constraints: Case on the Chilean Electricity System," in *Energy Procedia*, vol. 87. Elsevier Ltd, 2016, pp. 132–140. [Online]. Available: https://doi.org/10.1016/j.egypro.2015.12.342

[89] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*, ser. Springer Series in Operations Research and Financial Engineering. New York, NY: Springer New York, 2011. [Online]. Available: https://link.springer.com/10.1007/978-1-4614-0237-4

[90] J. W. Labadie, "Optimal Operation of Multireservoir Systems: State-of-the-Art Review," *Journal of Water Resources Planning and Management*, vol. 130, no. 2, pp. 93–111, 2004.

[91] V. K. Singh and S. K. Singal, "Operation of hydro power plants-a review," *Renewable and Sustainable Energy Reviews*, vol. 69, pp. 610–619, 2017.

[92] R. Bellman, "Dynamic programming and stochastic control processes," *Information and Control*, vol. 1, no. 3, pp. 228–239, 1958.

[93] J. A. Tejada-Guibert, S. A. Johnson, and J. R. Stedinger, "The Value of Hydrologic Information in Stochastic Dynamic Programming Models of a Multireservoir System," *Water Resources Research*, vol. 31, no. 10, pp. 2571–2579, 1995. [Online]. Available: https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/95WR02172

[94] P. Côté and R. Arsenault, "Efficient Implementation of Sampling Stochastic Dynamic Programming Algorithm for Multireservoir Management in the Hydropower Sector," *Journal of Water Resources Planning and Management*, vol. 145, no. 4, p. 05019005, 2019. [Online]. Available: http://ascelibrary.org/doi/10.1061/%28ASCE%29WR.1943-5452.0001050

[95] M. V. Pereira and L. M. Pinto, "Multi-stage stochastic optimization applied to energy planning," *Mathematical Programming*, vol. 52, no. 1-3, pp. 359–375, 1991.

[96] M. E. Maceiral, D. D. Penna, A. L. Diniz, R. J. Pinto, A. C. Melo, C. V. Vasconcellos, and C. B. Cruz, "Twenty years of application of stochastic dual dynamic programming in official and agent studies in Brazil-main features and improvements on the NEWAVE model," *20th Power Systems Computation Conference, PSCC 2018*, 2018.

[97] A. Gjelsvik, B. Mo, and A. Haugstad, "Long- and Medium-term Operations Planning and Stochastic Modelling in Hydro-dominated Power Systems Based on Stochastic Dual Dynamic Programming," in *Handbook of Power Systems I. Energy Systems.*, P. Pardalos, S. Rebennack, M. Pereira, and N. Iliadis, Eds. Springer, Berlin, Heidelberg, 2010, pp. 33–55.

[Online]. Available: https://link.springer.com/chapter/10.1007/978-3-642-02493-1_2

[98] K. S. Gjerden, A. Helseth, B. Mo, and G. Warland, "Hydrothermal scheduling in Norway using stochastic dual dynamic programming; A large-scale case study," *2015 IEEE Eindhoven PowerTech, PowerTech 2015*, 2015.

[99] J. A. Tejada-Guibert, S. A. Johnson, and J. R. Stedinger, "Comparison of two approaches for implementing multireservoir operating policies derived using stochastic dynamic programming," *Water Resources Research*, vol. 29, no. 12, pp. 3969–3980, 1993. [Online]. Available: http://doi.wiley.com/10.1029/93WR02277

[100] C. D'Ambrosio, A. Lodi, and S. Martello, "Piecewise linear approximation of functions of two variables in MILP models," *Operations Research Letters*, vol. 38, no. 1, pp. 39–46, 2010.

[101] I. Guisández and J. I. Pérez-Díaz, "Mixed integer linear programming formulations for the hydro production function in a unit-based short-term scheduling problem," *International Journal of Electrical Power and Energy Systems*, vol. 128, p. 106747, 2021.

[102] C. T. Larsen, G. Doorman, and B. Mo, "Joint Modelling of Wind Power and Hydro Inflow for Power System Scheduling," *Energy Procedia*, vol. 87, pp. 189–196, 2016.

[103] S. P. Lloyd, "Least Squares Quantization in PCM," *IEEE Transactions on Information Theory*, vol. 28, no. 2, pp. 129–137, 1982.

[104] D. Arthur and S. Vassilvitskii, "k-means++: The Advantages of Careful Seeding," in *SODA '07: Proceedings of the eighteenth annual ACM-SIAM symposium on Discrete algorithms*, New Orleans, 2007, pp. 1027–1035. [Online]. Available: https://theory.stanford.edu/~sergei/papers/kMeansPP-soda.pdf

[105] B. Mo, A. Gjelsvik, A. Grundt, and K. Kåresen, "Optimisation of hydropower operation in a liberalised market with focus on price modelling," *2001 IEEE Porto Power Tech Proceedings*, vol. 1, pp. 228–233, 2001.

[106] H. I. Skjelbred, J. Kong, and O. B. Fosso, "Dynamic incorporation of nonlinearity into MILP formulation for short-term hydro scheduling," *International Journal of Electrical Power & Energy Systems*, vol. 116, p. 105530, 2020.

[107] H. O. Hagenvik, S. Mathisen, A. Helseth, and B. Mo, "A Comprehensive Simulator for Hydropower Investment Decisions," *2022 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2022.

Publications

Paper I

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Modelling of Environmental Constraints for Hydropower Optimization Problems – a Review

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***Abstract*—Hydropower plants and reservoirs can have negative impacts on their surrounding ecosystems. To limit such impacts, environmental regulations may be imposed. This paper provides a review of literature on the most commonly used environmental constrains in scheduling of hydro-dominated systems and proposed constraints for future market conditions. Furthermore, we review literature on how environmental constraints are included in hydropower scheduling methods and discuss the main modelling challenges. We find an increasing interest in modelling of environmental constraints in recent literature, and conclude by highlighting challenges to improving the representation of environmental regulations in hydropower scheduling models.**

I. Introduction

The European power system is going through rapid changes as a consequence of technological developments and political targets to limit climate change. Among the changes are integration of large capacities of variable renewable energy generation into the power system, increased cross-border transmission capacity and the decommissioning of traditional power generation technologies in several countries. The ongoing changes in the European power system are expected to give increased short-term variability in power generation and increase the need for balancing resources. Technologies that can respond to rapid fluctuations in intermittent renewable generation and load, such as hydropower, can play an important role as flexibility providers to the system [1]. Reservoir hydropower plant operators can adapt their operational profiles to the needs of the system by rapidly adjusting production. This flexibility benefits system operation and provides added value for hydropower plant operators in liberalized markets [2].

On the other hand, hydropower modify the surrounding ecosystems [3]. Hydropower projects may alter the flow regime downstream the hydropower outlet, leave bypassed river sections dry in longer periods, create barriers for fish migration due to the establishment of dams and impose impacts to the terrestrial ecosystem [4]. Flow alterations and associated ecological consequences are major environmental concerns which have been assessed in several studies. An evaluation of streams and rivers in the US found that 86% of the assessed cases had modified flow magnitude because of hydropower or other water use [5], while [6] found that 92% of in total 165 reviewed papers reported lower values for recorded ecological metrics as a result of flow alteration. The flow regime is central to sustaining the ecological state of rivers and can influence important factors such as water quality, nutrition, physical habitat and biotic interactions [7].

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To limit the burden of hydropower on the local fluvial ecosystems, many countries impose regulations on the operation of hydropower plants. In the hydropower scheduling such regulations are normally represented as constraints on operations. In addition to an environmental benefit, environmental regulations normally also have an economic impact on the operation of the power system and the specific hydropower plant. The economic impact depends on the definition of the imposed constraint, the characteristics of the power plant and the system and market which the plant operate in. Accurate modelling of environmental regulation in the scheduling problem is therefore important to correctly assess the reduced flexibility associated with such constraints.

This paper provides a review of literature on current and future environmental constraints (ECs) in the scheduling of hydro-dominated systems from an environmental and modelling perspective. ECs are here defined as legislative conditions on operation of hydropower plants with the origin from ecological or social considerations. In section II we present the development of environmental regulations, the most commonly used mitigation measures and expected developments considering future market conditions. In section III, the representation of environmental regulations as operational constraints in the planning of hydropower and modelling challenges are discussed. Finally, we discuss the findings in section IV and highlight challenges to improve the representation of environmental regulations in hydropower scheduling models.

II. Environmental Regulations on Hydropower

In most parts of the world, the rights to operate hydropower plants are regulated through some form of licensing process controlled at different governmental levels [8], [9], [10], [11]. The level of environmental regulation and how it is controlled vary depending on how the power sector is regulated (e.g. centrally coordinated or deregulated market), the national or regional water resource management [12] and the priority of environmental considerations in general. We here discuss regulation framework and mitigation measures mostly based on the Nordic region and the US. However, there are clear similarities to how hydropower is managed in other European countries and Canada.

In some parts of the world, such as Europe and the US, hydropower is normally regulated through the licensing terms of the plant, where environmental regulations might be defined. However, many hydropower plants have licences that were granted up to a century ago that are currently under revision or will be revised [9], [13], [14], [10]. More than 400 licences can come up for revision only in Norway before 2022 [15]. In these processes, many plants can be imposed environmental regulation and measures to improve ecological conditions. It has been widely recognized that modifications of flow regimes is associated with ecological change and can have cascading impacts on the fluvial ecosystems [5], [6]. When revising environmental regulation of regulated water courses, environmental or societal gains have to be weighed against loss in hydropower production and security of electricity supply and at the same time fulfil environmental policy and regulations. Knowledge about the operational regime of hydropower plants is an important factor for understanding ecological responses to dam regulation and support development of mitigation measures for today and future market conditions [16].

The future of hydropower is closely linked to sustainable energy policies, as well as electricity market design and dynamics [1]. It is argued that the ongoing development of wind power in the Nordic region may give more frequent and rapid fluctuations in the operation of hydropower (hydropeaking) as a result of increase in balancing services provided from hydropower [17]. Such operations can have large additional environmental impacts downstream the outlet of the power plants compared to rivers exposed to traditional, base-load production [17]. Examination of data from 150 sites in Nordic rivers have shown that hydropeaking occur at a considerably high level, with an increasing trend over the last decade [18]. On the another hand, the magnitude of the hydropeaking operations in Norwegian rivers has been found to be moderate compared to selected rivers in Austria, Switzerland and Canada [17].

A. Mitigation Measures Today and in the Future System

There was a rapid progress in the 1970's in Europe and the US regarding the implementation of mitigation measures, such as minimum flow. This was a result of new environmental and freshwater legislation coupled with the needs of quantitative assessment of flows to protect aquatic species impacted by dam construction [19]. For example, in Norway before the 70's, all water was diverted from the bypassed rivers to the hydropower plant and no minimum flow requirements were defined in the majority of the licences. As the environmental movement was advancing the introduction of minimum flows was standardised as a small constant flow, sometimes diversified as seasonal flows [20]. From the late 1980's, we see cases where the environmental terms develop towards more dynamic release to better meet the ecological needs, e.g. including low flows, seasonal variations and artificial flood releases [21]. Environmental flows, also referred to as ecological flows and e-flows, have a firm place in many intergovernmental agreements and are integrated into water policy and legislation in several countries and regions around the world [19], such as the implementation the Water Framework Directive (WFD) [22] in Europe.

Traditionally, ECs focus on preserving certain flow or reservoir levels, or avoiding too rapid changes in water levels in rivers and reservoirs. It naturally follows that minimum flows and maximum ramping rates are commonly applied environmental regulations on operation of hydropower plants [23]. A table of representative environmental requirements issued in the US is provided in [10]. The list includes familiar requirements that impact operation, such as minimum release constraints (discharge or bypass) and constraints on ramping rates for flow and reservoir, as well as more extreme measures such as mandatory run-of-river operation. The lack of consistent data and strong local variations have made it difficult to develop quantitative guidelines to support regional environmental flow standards [6]. Hence, local assessments are necessary to evaluate to what extent environmental regulations can mitigate local environmental impacts [24].

When considering mitigation measures for hydropower operations under future system conditions, market optimisation and simulations of hydropower operations are recommended [25]. It has been demonstrated that environmental considerations can be united with power production [26]. The impacts on environmental conditions in reservoirs induced by hydropower under future market conditions have been analysed in [27], and it has been demonstrated that increasing supply of flexibility services from hydropower can result in more frequent and rapid hydropower induced water-fluctuations in the future [28]. Such types of operational regimes might not have been considered in the original licensing process, and the revision of licences are expected to give more advanced and sophisticated restriction to improve or sustain ecological qualities [15]. The terms in the revised licences may be more dynamic, based on the needs of the ecosystem and the hydrological state of the basin, e.g. environmental flow releases defined for finer temporal resolution [1] [29], [30] or flow regimes based on expected inflow [31].

B. External Impacts of Environmental Regulations

In addition to the intended ecological benefits, ECs often have other consequences, depending on the system where the plant operate and the formulation of the constraint. Normally, these are economic consequences, but can also be impacts on greenhouse gas emissions from the power system or other water use. ECs should ideally be determined based on marginal value. To estimate the marginal value, environmental and other contextual impacts are considered. It can be more challenging to quantify the environmental benefits than the economic costs of mitigation measures [32], but for some cases the benefits

[1] for example hour to hour or day to day basis rather than seasonal

of environmental mitigation measures has been quantified to exceed the economic cost of the measures [33]. In general, an interdisciplinary approach should be used when assessing impacts from renewable energy sources on ecosystems [34], and some research indicate that such an approach facilitate solutions where both environmental improvements and economic advantages can be achieved [25].

Studies of economic impacts are case specific and sensitive to the available flexibility in the power system. Also, it is important to distinguish between system costs and the revenues of an operator when assessing economic impacts. If sufficient flexibility is available in the system, ramping rates may not have a significant impact on system costs [35], but the constrained power plant may see a loss of revenue. Furthermore, participation in several markets, such as provision of ancillary services, has been shown to impact the cost of environmental regulations [36]. Restrictions on minimum release, ramping rates and total water release have been found to have a significant effect on hydropower generation in off-peak and peak hours [37]. Several studies find an increase in cost when minimum flow and ramping constraints become more restrictive, [38], [39], [40], and for several cases the cost has been shown to increase linearly and quadratic with minimum flow and maximum ramping respectively [23]. In addition, the economic impact has been found to be larger in systems with higher price volatility for certain cases [41].

The reduced operational flexibility caused by ECs can also result in increased overall CO_2-emissions [42], [36]. By reducing the available flexibility from hydropower, other sources of flexibility have to be unlocked that potentially have higher CO_2-emissions. Similarly, it can become beneficial to reduce the flexibility contribution from hydropower in order to reduce the ecological costs if new sustainable sources of flexibility, e.g. demand response, is added to the system [43].

III. Environmental Constraints on Hydropower Operations

As discussed, environmental regulations can have large impacts on operation of hydropower plants and are therefore important to include in the operational planning models. Operational planning of hydro-dominated power systems applies models and methods that have matured over several decades [44]. The key task in systems with reservoir storage is to balance the optimal use of water in the short-term with the volumes stored for later use to minimize the expected operational cost of the system. The problem formulation should consider the characteristics of the system and the deployed constraints, planning horizon and temporal resolution. Some factors that typically increase the complexity of hydropower scheduling are: storage which make the problem dynamic in time, topology with dependencies between several reservoirs and power stations, physical characteristics that introduce nonlinearities (e.g. head dependencies), and uncertainty in inflow and power prices. The problem is typically divided into a long-term model and a short-term model because of the complexity and quickly growing size of the problem. The short-term model includes more operational details, while the long-term model has a longer planning horizon, includes uncertainty and sometimes also covers a wider geographical scope. The models are often linked together by a strategy for use of water which is calculated in the long-term model and used as a boundary condition to the short-term model. Sometimes a medium-term model is used to obtain a more detailed strategy calculation, i.e. refining water values from aggregated to individual reservoirs.

Environmental regulations can be considered in the modelling either through the objective function or through constraints which is the focus in this paper. An example of the former is multi-objective formulations and objectives based purely on ecological metrics [45], [46], [47]. ECs can be included in both long-, medium- and short-term modelling, but the formulation of the constraint have to be adjusted depending on the type of model and solution method, e.g. linear programming (LP), mixed integer LP (MILP) and nonlinear programming (NLP) models.

A. Environmental Constraints

This section present the most common ECs used to regulate hydropower operations, as well as some more complex formulations. Other specific ECs also exist, such as constraints based on temperature limits [40] and water quality [48], [49]. The presented constraints are defined for each time step t in the planning horizon, T, if not otherwise specified.

1) Reservoir level constraints: restrict the reservoir level to be between defined boundaries by limiting the reservoir volume v_t to be in between the volume limits V^{min} and V^{max} [50], as given in (1). The reservoir limits can be defined for certain periods, i.e. time dependent boundaries.

$$V^{min} \leq v_t \leq V^{max} \tag{1}$$

2) Release constraints: limit the release from the power plant, i.e. discharge q^D and bypass q^B, to be in between certain boundaries, Q^{min} and Q^{max}, per time period [38]. The constraint can be on the total release as in (2), or defined specifically for bypass or discharge.

$$Q^{min} \leq q_t^D + q_t^B \leq Q^{max} \tag{2}$$

These constraints are typically defined as a constant minimum/maximum level, sometimes with seasonal variations (time dependent) [50]. More complex formulations of the constraint can be dependent on the water level in the reservoir or the inflow (see state-dependent constraints (9)) and/or on logical conditions (see constraints (7)- (8)). A slightly different definition of the release constraint occur when hydropower plants are required to release a specified amount of water Q^P over a given period (e.g. a month) [37], such as given in (3):

$$\sum_{t=\tau,..,\tau+N} (q_t^D + q_t^B) \geq Q^P \tag{3}$$

In the more extreme cases, release can be regulated as *mandatory run-of-river operation* [38], where the release is forced to equal the inflow Z_t as in (4). Run-of-river operation can be mandatory for parts of the planning horizon (e.g. certain weeks/moths), T', or the entire planning horizon, $T' = T$.

$$(q_t^D + q_t^B) = Z_t \tag{4}$$

3) River flow constraints: are often given as conditions on flow at a certain point in the river downstream of the power plant. For practical reasons flow constraints are normally implemented as a constraint on release. To account for the transportation time of flowing water, constant time delay between the reservoirs in the system is sometimes included. However, often a more accurate modelling of the physical flow in the river could be beneficial. To achieve an improved description, an alternative is to use a river routing approach based on streamflow routing curves [51]. The curves describe how different amounts of the water released from an upstream reservoir reach the downstream reservoir in different times based on empirical streamflow data. The improved flow modelling makes it possible to include constraints in specific river points, such as constraints on river level and hourly and daily variation in river level.

4) Ramping constraints: restrict the maximum change of plant release and reservoir volume between two successive time intervals. Rapid changes in flow downstream of the plant is avoided by constraining release or discharge [52], as given in (5). The maximum rate of change per time step is given by δ^{max}.

$$-\delta^{max} \leq q_t^D - q_{t-1}^D \leq \delta^{max} \tag{5}$$

Another objective of ramping constraints can be to limit how quickly the water level in the reservoir is permitted to be changed. The water level is a function of the water volume in the reservoir. Hence, the restriction can be enforced by constraining the decrease in reservoir volume v between two consecutive periods [53], as given in (6), or by applying a maximum discharge limit as given in (2). The maximum change in reservoir volume between two consecutive periods is given by γ^{max}.

$$-\gamma^{max} \leq v_t - v_{t-1} \leq \gamma^{max} \tag{6}$$

5) Logical constraints: refer to a set of constraints governed by logical conditions [54]. Given specific conditions constraints can be activated or deactivated, or the constraint formulation can be modified. An example can be that the maximum discharge level is lower *if* the reservoir level is below a certain threshold. Such conditions can normally be modeled by using binary variables. An example is given in (7)-(8), where the binary variable u_t is true ($= 1$) if the reservoir level v_t is above the reservoir level threshold $\frac{V^{max}}{2}$ and false (zero) if not [55].

$$q_t^D - (1 + u_t)\frac{Q^{max}}{2} \leq 0 \tag{7}$$

$$u_t\frac{V^{max}}{2} \leq v_{t-1} < (1 + u_t)\frac{V^{max}}{2} \tag{8}$$

6) State-dependent constraints: are constraints that depend on the value of one or more state variables in the problem formulation [56], e.g. reservoir volume and inflow [31]. Often such constraints also depend on logical conditions [55]. The previous discharge constraints (7)-(8) are state dependent as the discharge levels depend on the reservoir volume, i.e. the upper discharge level Q^{max} is a function of the reservoir volume v [54]. This can be expressed as:

$$q_t^D \leq Q^{max}(v) \tag{9}$$

7) Constraints dependent on the origin of the water: are constraints that become valid depending on when the water was accumulated in a reservoir or where the water originally came from. In such cases it can be necessary to keep track of the water present in the reservoir *before* a constraint became active, to keep track of the water accumulated *during* a constraint interval, or to keep track of water accumulated through a specific intake. Since the water may have different constraints dependent on *time* or *path*, the water within the same reservoir can be used differently and therefore also have different value. A possible approach to handle such constraints is to include virtual reservoirs in addition to the physical reservoirs in the modelling and calculate separate water values for the virtual reservoirs [57].

B. Modelling Challenges

More detailed operational constraints, such as ECs, are most commonly included in the modelling of the short-term problem. However, in hydropower dominated systems (e.g. the Nordic, the Brazilian and the Canadian), ECs may have an important impact on the overall flexibility in the system and should also be considered in the long-term planning. Even if the effect of a constraint on the system is limited, the impact on the long-term use of water in a reservoir could be significant and should be considered in the strategy. A main conclusion from the review in [23] was that minimum flow and maximum ramping rate constraints seldom were included in the water value calculation and the effect of such constraints on long-term operations was not estimated. The author demonstrated that such constraints have a significant impact on water values in some regions [50] and should be included in the calculation of medium to long-term strategies for water use [58]. If a constraint not significantly affects the medium- to long-term use of water, it may be sufficient to include it in the short-term models. In general, cautiousness of adding extra constraints to the problem is important to limit the problem size.

The long and medium-term hydropower scheduling problems are traditionally solved using LP and formal optimisation methods such as stochastic dynamic programming (SDP) [59] or stochastic dual dynamic programming (SDDP) [60]. A drawback of the SDDP method is that a convex problem formulation is required. Most ECs can be included in convex model formulations without considerable difficulty, such as constraints (1)-(6). However, state-dependent constraints (9) and logically conditioned constraints (7)-(8), introduce non-convexities into the problem. For an exact modelling of the non-convex medium term hydropower scheduling (MTHS) problem the SDDiP method [61] can be used [62]. The method is very time consuming, but has been used to solve the MTHS problem with non-convex ECs of type (9) in [56]. A more time efficient approach can be to represent complicating constraints with linear approximations [54]. In [63], an SDDP model is used to investigate trade-offs between multiple use of water by including irrigation withdrawals in the water balance. Furthermore, non-convex irrigation constraints included in a SDDP based approach has been found to give feasible solutions close to the optimal solutions determined by a MILP model [55]. The short-term models, including nonlinear and non-convex constraints, can normally be modelled exact [64], [65] or by using a wide range of heuristics and meta-heuristics [66] . In [58], a MILP short-term model is used together with a medium term, SDP based model to test the solution of the medium-term model and estimate the impact of including ECs in the water value calculation.

In methods based on dynamic programming (DP), preservation of constraints with bindings in time, such as constraint (5), (6), (8), or integral requirements like in constraint (3) can be a challenge between consecutive stages. In DP the problem is decomposed into several stages (e.g. weeks) with time steps on a finer resolution (e.g. hours) within each stage. As each stage normally is solved as a separate (sub)problem, flow constraints are not preserved from the last time step in one stage to the first time step in the following stage. This can give unwanted results, such as rapid ramping between stages. To ensure continuity across the stages for constraints of type (5), flow can be included as a state variable [23], or an heuristic approach can be used. For example can a simple rule-based method be used to set the flow in the first period of a stage equal the flow in the last period in the previous stage [67]. Reservoir volume is normally used as a state variable and constraints of type (6) will therefore change the calculation of cut coefficients in cut based methods such as SDDP. Some of the same challenges considering time couplings appears at the end of the planning horizon where the value of the affected variables can be set to be free or forced to take specified values.

The river flow is a crucial driver for ecological processes [7], still the water flow in the river between reservoirs are normally not modelled in hydropower scheduling models since accurate flow modelling is very complex. To improve the representation of flow in planning models for hydropower [68] suggest a non-linear function for water delay in cascaded hydro systems, while a river routing approach is used in [51] and [69]. The river routing approach has been demonstrated to yield a high accuracy in maximum daily and hourly river-level variations [51], as well as cost reductions as a result of improved coordination of hydropower generation [69]. In [70], a coupled reservoir operation and water diversion model is developed to consider the interaction of reservoir operation and downstream water diversions. The model is demonstrated to provide improved decision support to balance the ecological needs with other needs for water use.

IV. Concluding Remarks

Trade-offs between environmental benefits, economic costs and other consequences have to be considered when developing environmental regulations, as discussed in section II. For hydropower producers, expected higher price volatility will give increased value of flexibility compared to today and hence also higher costs of being imposed restrictions on own operation. This implies that accurate modelling becomes more important as the cost of model simplifications or inaccuracies can increase. Neglected or simplified model representations of ECs should therefore be revisited. In the long-term models, omitting or simplifying ECs can result in an overestimation of the flexibility of hydropower. In hydropower-dominated systems this could lead to problems for security of supply and potential high system costs. We find that there has been modest emphasis on accurate representation of ECs in long-term models in the technical literature, while such constraints more often are accurately handled in short-term models. Thus, there is a time-inconsistency [71] between long- and short-term models in the treatment of such constraints. As shown in section III, most of the ECs in use can be included in both long- and short-term operational models, but time couplings and non-convexities can be more demanding to model.

Based on the ecological considerations discussed in section I and II, it is clear that future operational conditions may be ecological demanding and environmental regulations are required. Improved knowledge over the last decades has made more exact formulation of the ECs to fit the primary ecological needs achievable, such as more dynamic constraints. Furthermore, in certain cases local knowledge can be used to achieve wanted ecological benefits, while also preserving most of the operational flexibility of the plants. In this context we find another trade-off. On one side, tailored constraints can minimize the impact on flexibility and associated cost while realising the wanted ecological benefit. But on the other side, tailored constraints make standardization difficult which again could make accurate modelling more resource demanding.

To conclude, we see that modelling of ECs in hydropower planning models has seen increased interest in the literature in the last decade. This can be a result of improved modelling methods and computational performance, which makes it possible to implement more complex constraints in operational models. Furthermore, the literature shows that improved modelling of ECs can be beneficial both from an environmental and economic perspective. Still, exact modelling of ECs can become hard or even impossible in operationally used models if modelling complexity is not considered in the formulation of the ECs. Model implementations can in turn provide poor ecological performance if not considering the underlying purpose of the ECs. Hence, cross-disciplinary knowledge is necessary to achieve environmental regulations that perform well both considering ecology and economy. When succeeded, previous projects have shown that it is possible to realise win-win situations.

References

[1] L. Gaudard and F. Romerio, "The future of hydropower in Europe: Interconnecting climate, markets and policies," *Environmental Science and Policy*, vol. 37, pp. 172–181, 2014.

[2] L. E. Schäffer, B. Mo, and I. Graabak, "Electricity Prices and Value of Flexible Generation in Northern Europe in 2030," in *International Conference on the European Energy Market, EEM*, 2019.

[3] M. Mattmann, I. Logar, and R. Brouwer, "Hydropower externalities: A meta-analysis," *Energy Economics*, vol. 57, pp. 66–77, 2016.

[4] O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, and C. von Stechow, "IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation," IPCC, Cambridge, UK and New York, NY, USA., Tech. Rep., 2011.

[5] D. M. Carlisle, D. M. Wolock, and M. R. Meador, "Alteration of streamflow magnitudes and potential ecological consequences: a multiregional assessment," *Frontiers in Ecology and the Environment*, vol. 9, no. 5, pp. 264–270, 2011.

[6] N. L. Poff and J. K. Zimmerman, "Ecological responses to altered flow regimes: A literature review to inform the science and management of environmental flows," pp. 194–205, 2010.

[7] N. L. Poff, J. D. Allan, M. B. Bain, J. R. Karr, K. L. Prestegaard, B. D. Richter, R. E. Sparks, and J. C. Stromberg, "The Natural Flow Regime," *BioScience*, vol. 47, no. 11, pp. 769–784, 1997.

[8] "A Contribution to the Debate A Contribution to the Debate Environmental Licensing for Hydroelectric Projects in Brazil," The World Bank, Tech. Rep., 2008.

[9] J.-M. Glachant, M. Saguan, V. Rious, S. Douguet, and E. Gentzoglanis, "Regimes for granting rights to use hydropower in Europe," European University Institute, Tech. Rep., 2014.

[10] L.-R. D. Kosnik, "Balancing Environmental Protection and Energy Production in the Federal Hydropower Licensing Process," *SSRN Electronic Journal*, 2011.

[11] P.-O. Pineau, L. Tranchecoste, and Y. Vega-Cárdenas, "Hydropower Royalties: A Comparative Analysis of Major Producing Countries (China, Brazil, Canada and the United States)," *Water*, vol. 9, no. 4, p. 287, 2017.

[12] S. M. A. Salman and D. D. Bradlow, "Regulatory frameworks for for water resource management," The World Bank, Washington, D. C., Tech. Rep., 2006.

[13] B. M. Renöfält, R. Jansson, and C. Nilsson, "Effects of hydropower generation and opportunities for environmental flow management in Swedish riverine ecosystems," *Freshwater Biology*, vol. 55, no. 1, pp. 49–67, 2010.

[14] B. Köhler, A. Ruud, Ø. Aas, and D. N. Barton, "Decision making for sustainable natural resource management under political constraints – the case of revising hydropower licenses in Norwegian watercourses," *Civil Engineering and Environmental Systems*, vol. 36, no. 1, pp. 17–31, 2019.

[15] J. Sørensen, E. Brodtkorb, I. Haug, and J. Fjellanger, "Vannkraftkonsesjoner som kan revideres innen 2022. Nasjonal gjennomgang og forslag til prioriteringer (in Norwegian)." NVE, Tech. Rep., 2013.

[16] R. A. McManamay, C. O. Oigbokie, S. C. Kao, and M. S. Bevelhimer, "Classification of US Hydropower Dams by their Modes of Operation," *River Research and Applications*, vol. 32, no. 7, pp. 1450–1468, 2016.

[17] T. H. Bakken, T. Forseth, and A. Harby, *Miljøvirkninger av effektkjøring: Kunnskapsstatus og råd til forvaltning og industri (in Norwegian).* Trondheim: NINA Temahefte 62, 2016.

[18] F. B. Ashraf, A. T. Haghighi, J. Riml, K. Alfredsen, J. J. Koskela, B. Kløve, and H. Marttila, "Changes in short term river flow regulation and hydropeaking in Nordic rivers," *Scientific Reports*, vol. 8, no. 1, pp. 1–12, 2018.

[19] N. L. Poff, R. E. Tharme, and A. H. Arthington, "Evolution of Environmental Flows Assessment Science, Principles, and Methodologies," in *Water for the Environment: From Policy and Science to Implementation and Management*. Elsevier Inc., 2017, pp. 203–236.

[20] R. E. Tharme, "A global perspective on environmental flow assessment: Emerging trends in the development and application of environmental flow methodologies for rivers," *River Research and Applications*, vol. 19, no. 5-6, pp. 397–441, 2003.

[21] T. H. Bakken, P. Zinke, A. Melcher, H. Sundt, T. Vehanen, K. Jorde, and M. Acreman, "Setting environmental flows in regulated rivers," SINTEF TRA 4276, Trondheim, Tech. Rep., 2012.

[22] "European Water Framework Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy," *Official Journal of the European Communities (OJEC)*, 2000.

[23] I. Guisández González, "Long-term Optimal Hydropower Reservoir Operation with Minimum Flows and Maximum Ramping Rates," Ph.D. dissertation, Technical University of Madrid, 2016.

[24] R. Hastik, S. Basso, C. Geitner, C. Haida, A. Poljanec, A. Portaccio, B. Vrščaj, and C. Walzer, "Renewable energies and ecosystem service impacts," pp. 608–623, 2015.

[25] J. Charmasson, M. Belsnes, O. Andersen, A. Eloranta, I. Graabak, M. Korpås, I. P. Helland, H. Sundt, and O. Wolfgang, "Roadmap for large-scale balancing and energy storage from Norwegian hydropower," CEDREN, SINTEF, NINA, NTNU, Trondheim, Tech. Rep., 2017.

[26] O. Ugedal, U. Pulg, H.-P. Fjeldstad, G. Robertsen, B. Barlaup, K. Alfredsen, H. Sundt, S. Jakob Saltveit, H. Skoglund, E. Kvingedal, L. Elisabeth Sundt-Hansen, A. Gravbrøt Finstad, S. Einum, and J. V. Arnekleiv, *Handbook for environmental design in regulated salmon rivers*, T. Forseth and A. Harby, Eds. Trondheim: Norsk institutt for naturforskning, 2014.

[27] E. Solvang, J. Charmasson, J. Sauterlaute, A. Harby, Å. Killingtveit, H. Egeland, O. Andersen, Ø. Ruud, and Ø. Aas, "Norwegian hydropower for large scale electricity balancing needs - Pilot study of technical, environmental and social challenges," SINTEF, Tech. Rep., 2015.

[28] O. Wolfgang, A. L. Henden, M. M. Belsnes, C. Baumann, A. Maaz, A. Schäfer, A. Moser, M. Harasta, and T. Døble, "Scheduling when Reservoirs are Batteries for Wind- and Solar-power," in *Energy Procedia*, vol. 87. Elsevier Ltd, 2016, pp. 173–180.

[29] N. L. Poff, "Beyond the natural flow regime? Broadening the hydro-ecological foundation to meet environmental flows challenges in a non-stationary world," in *Freshwater Biology*, vol. 63, no. 8. Blackwell Publishing Ltd, 2018, pp. 1011–1021.

[30] M. D. Bejarano, A. Sordo-Ward, C. Alonso, and C. Nilsson, "Characterizing effects of hydropower plants on sub-daily flow regimes," *Journal of Hydrology*, vol. 550, pp. 186–200, 2017.

[31] K. Alfredsen, A. Harby, T. Linnansaari, and O. Ugedal, "Development of an inflow-controlled environmental flow regime for a norwegian river," *River Research and Applications*, no. 6, pp. 731–739, 2012.

[32] D. N. Barton, H. Sundt, A. A. Bustos, H. P. Fjeldstad, R. Hedger, T. Forseth, Berit Köhler, Ø. Aas, K. Alfredsen, and A. L. Madsen, "Multi-criteria decision analysis in Bayesian networks - Diagnosing ecosystem service trade-offs in a hydropower regulated river," *Environmental Modelling and Software*, vol. 124, 2020.

[33] M. J. Kotchen, M. R. Moore, F. Lupi, and E. S. Rutherford, "Environmental constraints on hydropower: An ex post benefit-cost analysis of dam relicensing in Michigan," *Land Economics*, vol. 82, no. 3, pp. 384–403, 2006.

[34] G. Grilli, J. Balest, I. De Meo, G. Garegnani, and A. Paletto, "Experts' opinions on the effects of renewable energy development on ecosystem services in the Alpine region," *Journal of Renewable and Sustainable Energy*, vol. 8, no. 1, p. 013115, 2016.

[35] M. A. Olivares, J. Haas, R. Palma-Behnke, and C. Benavides, "A framework to identify Pareto-efficient subdaily environmental flow constraints on hydropower reservoirs using a grid-wide power dispatch model," *Water Resources Research*, vol. 51, no. 5, pp. 3664–3680, 2015.

[36] J. Rand, "Overlooked trade-offs of environmentally protective hydropower operation: Impacts to ancillary services and greenhouse gas emissions," *River Research and Applications*, vol. 34, no. 9, pp. 1123–1131, 2018.

[37] B. K. Edwards, S. J. Flaim, and R. E. Howitt, "Optimal provision of hydroelectric power under environmental and regulatory constraints," *Land Economics*, vol. 75, no. 2, pp. 267–283, 1999.

[38] J. I. Pérez-Díaz and J. R. Wilhelmi, "Assessment of the economic impact of environmental constraints on short-term hydropower plant operation," *Energy Policy*, vol. 38, no. 12, pp. 7960–7970, 2010.

[39] S. Niu and M. Insley, "On the economics of ramping rate restrictions at hydro power plants: Balancing profitability and environmental costs," *Energy Economics*, vol. 39, pp. 39–52, 2013.

[40] M. A. Olivares, "Optimal hydropower reservoir operation with environmental requirements," Ph.D. dissertation, The University of California, Davis, USA, 2008.

[41] S. Niu and M. Insley, "An options pricing approach to ramping rate restrictions at hydro power plants," *Journal of Economic Dynamics and Control*, vol. 63, pp. 25–52, 2016.

[42] I. Guisández, J. I. Pérez-Díaz, and J. R. Wilhelmi, "Approximate formulae for the assessment of the long-term economic impact of environmental constraints on hydropeaking," *Energy*, vol. 112, pp. 629–641, 2016.

[43] H. Huuki, S. Karhinen, F. Ashraf, A. Torabi Haghighi, and H. Marttila, "The Economic Cost of Hydropower Environmental Constraints Under Decreasing Price Volatility," *SSRN Electronic Journal*, 2020.

[44] J. W. Labadie, "Optimal operation of multireservoir systems: State-of-the-art review," *Journal of Water Resources Planning and Management*, vol. 130, no. 2, pp. 93–111, 2004.

[45] N. Yang, Y. Mei, and C. Zhou, "An Optimal Reservoir Operation Model Based on Ecological Requirement and Its Effect on Electricity Generation," *Water Resources Management*, vol. 26, no. 14, pp. 4019–4028, 2012.

[46] H. I. Jager and B. T. Smith, "Sustainable reservoir operation: Can we generate hydropower and preserve ecosystem values?" pp. 340–352, 2008.

[47] Z. k. Feng, W. j. Niu, and C. t. Cheng, "Optimization of hydropower reservoirs operation balancing generation benefit and ecological requirement with parallel multi-objective genetic algorithm," *Energy*, vol. 153, pp. 706–718, 2018.

[48] A. C. Valle, M. A. Aguiar, and G. Cruz, "The impact of water quality as an environmental constraint on operation planning of a hydro-thermal power system," *Renewable Energy*, vol. 34, no. 3, pp. 655–659, 2009.

[49] A. R. Shaw, H. Smith Sawyer, E. J. LeBoeuf, M. P. McDonald, and B. Hadjerioua, "Hydropower Optimization Using Artificial Neural Network Surrogate Models of a High-Fidelity Hydrodynamics and Water Quality Model," *Water Resources Research*, vol. 53, no. 11, pp. 9444–9461, 2017.

[50] I. Guisández, J. I. Pérez-Díaz, and J. R. Wilhelmi, "The influence of environmental constraints on the water value," *Energies*, vol. 9, no. 6, 2016.

[51] A. L. Diniz and T. M. Souza, "Short-term hydrothermal dispatch with river-level and routing constraints," *IEEE Transactions on Power Systems*, vol. 29, no. 5, pp. 2427–2435, 2014.

[52] A. Borghetti, C. D'Ambrosio, A. Lodi, and S. Martello, "An MILP approach for short-term hydro scheduling and unit commitment with head-dependent reservoir," *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 1115–1124, 2008.

[53] G. Chang, M. Aganagic, J. Waight, J. Medina, T. Burton, S. Reeves, and M. Christoforidis, "Experiences with Mixed Integer Linear Programming-Based Approaches in Short-Term Hydro Scheduling," *IEEE Transactions on Power Systems*, vol. 16, no. 4, 2001.

[54] A. Helseth, "Environmental Constraints in Seasonal Hydropower Scheduling - Survey and Feasibility," HydroCen, Trondheim, Tech. Rep., 2019.

[55] E. Pereira-Bonvallet, S. Püschel-Løvengreen, M. Matus, and R. Moreno, "Optimizing Hydrothermal Scheduling with Non-Convex Irrigation Constraints: Case on the Chilean Electricity System," in *Energy Procedia*, vol. 87. Elsevier Ltd, 2016, pp. 132–140.

[56] A. Helseth, B. Mo, and H. O. Hågenvik, "Nonconvex Environmental Constraints in Hydropower Scheduling," in *International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2020.

[57] L. A. Barroso, S. Granville, P. R. Jackson, M. V. F. Pereira, and E. G. Read, "Overview of Virtual Models for Reservoir Management in Competitive Markets," Bergen, Norway, 2012.

[58] I. Guisández, J. I. Pérez-Díaz, W. Nowak, and J. Haas, "Should environmental constraints be considered in linear programming based water value calculators?" *International Journal of Electrical Power and Energy Systems*, vol. 117, 2020.

[59] J. R. Birge, "Decomposition and Partitioning Methods for Multistage Stochastic Linear Programming." *Operations Research*, vol. 33, no. 5, pp. 989–1007, 10 1985.

[60] M. V. Pereira and L. M. Pinto, "Multi-stage stochastic optimization applied to energy planning," *Mathematical Programming*, vol. 52, no. 1-3, pp. 359–375, 5 1991.

[61] J. Zou, S. Ahmed, and X. A. Sun, "Stochastic dual dynamic integer programming," *Mathematical Programming*, vol. 175, no. 1-2, pp. 461–502, 2019.

[62] M. N. Hjelmeland, J. Zou, A. Helseth, and S. Ahmed, "Nonconvex Medium-Term Hydropower Scheduling by Stochastic Dual Dynamic Integer Programming," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 1, pp. 481–490, 2019.

[63] A. Tilmant and R. Kelman, "A stochastic approach to analyze trade-offs and risks associated with large-scale water resources systems," *Water Resources Research*, vol. 43, no. 6, 2007.

[64] J. Kong, H. I. Skjelbred, and O. B. Fosso, "An overview on formulations and optimization methods for the unit-based short-term hydro scheduling problem," 2020.

[65] R. Taktak and C. D'Ambrosio, "An overview on mathematical programming approaches for the deterministic unit commitment problem in hydro valleys," *Energy Systems*, vol. 8, no. 1, pp. 57–79, 2017.

[66] M. Nazari-Heris, B. Mohammadi-Ivatloo, and G. B. Gharehpetian, "Short-term scheduling of hydro-based power plants considering application of heuristic algorithms: A comprehensive review," pp. 116–129, 2017.

[67] I. Guisández, J. I. Pérez-Díaz, and J. R. Wilhelmi, "Assessment of the economic impact of environmental constraints on annual hydropower plant operation," *Energy Policy*, pp. 1332–1343, 2013.

[68] X. Ge, S. Xia, W. J. Lee, and C. Y. Chung, "A successive approximation approach for short-term cascaded hydro scheduling with variable water flow delay," *Electric Power Systems Research*, vol. 154, pp. 213–222, 2018.

[69] E. A. Martínez Ceseña, M. Panteli, J. Mutale, P. Mancarella, J. Tomlinson, and J. J. Harou, "Integrated energy-water model for interdependent storage, run-of-river and pump hydropower," in *2019 IEEE Milan PowerTech, PowerTech 2019*. Institute of Electrical and Electronics Engineers Inc., 2019.

[70] X. A. Yin and Z. F. Yang, "Development of a coupled reservoir operation and water diversion model: Balancing human and environmental flow requirements," *Ecological Modelling*, vol. 222, no. 2, pp. 224–231, 2011.

[71] A. Brigatto, A. Street, and D. M. Valladão, "Assessing the cost of time-inconsistent operation policies in hydrothermal power systems," *IEEE Transactions on Power Systems*, vol. 32, no. 6, pp. 4541–4550, 2016.

Paper II

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A stochastic dynamic programming model for hydropower scheduling with state-dependent maximum discharge constraints

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ABSTRACT

We present a medium-term hydropower scheduling model that includes inflow- and volume-dependent environmental constraints on maximum discharge. A stochastic dynamic programming algorithm (SDP) is formulated to enable an accurate representation of nonconvex relationships in the problem formulation of smaller hydropower systems. The model is used to assess the impact of including state-dependent constraints in the medium-term hydropower scheduling on the calculated water values. The model is applied in a case study of a Norwegian hydropower system with multiple reservoirs. We find that the maximum discharge constraint significantly impacts the water values and simulated operation of the hydropower system. A main finding is that the nonconvex characteristics of the environmental constraint are reflected in the water values, implying a nonconvex objective function. Operation according to the computed water values is simulated for cases with and without the environmental constraint. Even though operation of the system changes considerably when the environmental constraint is included, the total electricity generation over the year is kept constant, and the total loss in expected profit is limited to less than 0.8%.

1. Introduction

Through the European Green Deal, the EU has set ambitious targets for both climate change mitigation and broader environmental sustainability [1]. To align capital flows with these policy goals, the EU is in the process of defining requirements for environmentally sustainable activities. Hence, power producers have strong incentives to operate in an environmentally sustainable way.

Like all power plants, hydropower operations may modify the surrounding ecosystems [2]. The environmental concerns of hydropower operations are often related to alteration of the flow regime downstream the plant [3], but can also be related to the changes in water temperatures or changed water volumes in the reservoirs. To protect ecological and recreational interests, regulation often imposes mitigation measures and limitations on operation, see e.g., Refs. [4,5].

Environmental regulation should be incorporated as constraints in optimisation-based hydropower scheduling models. Omitting such constraints can result in misestimation of hydropower electricity generation, revenues, and the amount of flexibility hydropower can provide to the electricity system [6]. The need for flexible resources is expected to increase as the transition of the European power system moves forwards. In the transition towards a low-carbon system, hydropower can play an important role as a flexibility provider by responding to rapid fluctuations in intermittent renewable generation and load [7]. Additional constraints on operation may reduce this flexibility potential. To correctly represent hydropower operation requires properly accounting for environmental constraints imposed on hydropower production.

In this research we are concerned with operational hydropower scheduling, i.e., the sequence of decisions that are made leading up to the actual operation of the system. Due to the computational complexity, the scheduling problem is normally solved for different planning horizons and technical details. Medium-term hydropower scheduling considers reservoir management under uncertainty over a planning horizon of several months up to a few years. In contrast, short-term scheduling usually concerns operational decisions over a period of days to weeks, and typically accounts for more technical details. In the decentralised Nordic system, medium-term scheduling models are used to compute water values, which are an essential input to the operational short-term models [8]. The purpose of water values is to reflect the long-term value of short-term operational decisions.

State-of-the-art methods to solve the medium-term scheduling of hydropower systems use stochastic dual dynamic programming

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Nomenclature

Index Sets

$\mathcal{D}_h$	Set of discharge segments per hydropower plant h
$\mathcal{G}$	Set of subsets used in the triangle method
$\mathcal{H}$	Set of hydropower plants
$\mathcal{H}_h^{up}$	Set of hydropower plants with outlet to plant h
$\mathcal{J}$	Set of iterations in SDP algorithm
$\mathcal{K}$	Set of time steps within each stage
$\mathcal{N}$	Set of reservoir segments per reservoir
$\mathcal{N}_{l,h}^{Comb}$	Set of combinations of discrete reservoir storage segments that includes segment l for reservoir h
$\mathcal{N}_g^{Diag}$	Set of γ for each diagonal g used in the triangle method
$\mathcal{S}^p$	Set of endogenous states
$\mathcal{S}^u$	Set of stochastic states
$\mathcal{T}$	Set of stages

Decision Variables

α_{t+1}	Expected future profit in stage t, in $\frac{€}{MWh}$
$\beta_{h,n}$	Auxiliary variable for segment n in reservoir h
χ_g	Auxiliary variable for set g
$\gamma_{n,m}$	Weighting variable for reservoir segments n, m
$f_{k,h}$	Spillage in time step k from reservoir h, in m^3/s
$p_{k,h}$	Generated electricity in time step k from hydropower station h, in MW
$q_{k,h,d}$	Discharge in time step k per segment d from reservoir h, in m^3/s
$u_{k,h}$	Slack variable used to penalise low storage volumes in time step k in the reservoir h, in Mm^3
$v_{k,h}$	Storage volume in reservoir h, time step k, Mm^3

Parameters

Δ	Change in water value matrix
$\eta_{h,d}$	Efficiency per hydropower plant h and discharge segment d, $\frac{MW}{m^3/s}$
$\hat{H}$	Hydropower plant restricted by the state-dependent maximum discharge constraint
$\hat{Z}_t$	Sum inflow per stage t, in Mm^3
λ_t	Power price in stage t, in $\frac{€}{MWh}$
ω_h	Scaling factor, distributing the weekly sum inflow $\hat{Z}_t$ to each reservoir h
φ_k	Distribution factor of inflow to each time step k
$\Phi_{j,t}(\ldots)$	Expected future profit matrix, in stage t,iteration j
$\Psi_{j,t}^h(\ldots)$	Water value matrix for reservoir h, stage t, iteration j
θ_k	Scaling factor for price variability in time stage k
ξ_t	Environmental state in stage t
C^R	Penalty cost for low reservoir filling, in $\frac{€}{Mm^3}$
C^S	Penalty cost for spillage, in $\frac{€}{m^3/s}$
F_k^H	Conversion factor, number of hours in time step k
F^C	Conversion factor, flow to volume, $\frac{Mm^3}{m^3/s}$
$FV_{n,m}$	Expected future profit for reservoir segments n and m, in €
J	Maximum number of iterations in SDP algorithm
K	Number of time steps in each stage
$Pr(\ldots)$	Transition probability matrix
Q_h^{lim}	Regulatory maximum discharge limit of hydropower plant h, in m^3/s
Q_h^{min}	Minimum discharge limit of hydropower plant h, in m^3/s
$Q_{h,d}^{max}$	Maximum discharge per reservoir h and discharge segment d, in m^3/s
s^p	Endogenous state
s_t^u	Stochastic state in stage t
T	Number of stages in the planning horizon
t_A	First stage when the inflow is above a given threshold
t_B	Time-dependent activation stage of the environmental constraint (16)
t_C	First stage when the reservoir level is above a given threshold
t_D	Stage from when "no decrease in storage volume is allowed"
t_E	Stage when the environmental regulation is deactivated
V_h^{lim}	Environmental threshold for reservoir h, in Mm^3
$V_{n,h}^{seg}$	Volume of each segment n in reservoir h, in Mm^3
V_h	Initial storage volume in reservoir h, in Mm^3
V_h^{max}	Maximum storage volume in reservoir h, in Mm^3
V_h^{min}	Minimum storage volume in reservoir h, in Mm^3
Z_h	Inflow to reservoir h, in Mm^3

(SDDP) [9] algorithms. These algorithms decompose the problem without discretising the state variables (such as reservoir volume and inflow), making it computationally tractable for systems with multiple reservoirs. For medium-term scheduling in the Nordic market, the combined SDP/SDDP method described in Ref. [10] is widely used. It combines SDDP with an outer layer based on stochastic dynamic programming (SDP) [11] to treat uncertainty in market prices. Still, a major drawback of the method is that non-convexities cannot be easily treated in the modelling.

Nonconvex problem formulations are typically needed to represent the complex interaction between power output and water [12], and unit commitment of generators [13]. The challenge of representing nonconvex relationships in the SDDP algorithm has frequently been addressed in the literature by the use of approximations, e.g., Refs. [14–17]. A few studies also consider accurate modelling of non-convexities by the use of SDP [18] or stochastic dual dynamic integer programming (SDDiP), such as in Refs. [19,20].

SDP was used early on in hydropower planning, as it allows for explicit representation of uncertainty, e.g., in inflow and price [21–23]. The method has the advantage that it can represent nonconvex and nonlinear relationships. The main drawback of the method is that the state variables have to be discretised, causing the problem to grow exponentially in size with the number of state variables (e.g., reservoirs). The method is therefore best suited to solve systems with a small number of reservoirs, unless an aggregation technique is used like in Refs. [24–26]. Despite of this weakness, the SDP method is very well suited for accurate scheduling of hydropower systems with pronounced nonconvexities.

Regulators have imposed a wide range of environmental constraints on hydropower systems. Ecological flow requirements and maximum ramping rates are often applied, and may have significant impact on the flexibility of the hydro system. These constraints have been extensively studied in the technical literature, see e.g., Refs. [27–29], and can be included in hydropower scheduling models without compromising the convexity requirement of the SDDP algorithm. However, fewer research studies consider environmental constraints that involve state-dependencies or logical conditions, which can not easily be treated in a convex model formulation [30]. Furthermore, only a very limited number of studies discuss the impact of environmental constraints on water values. To the best of our knowledge, the impact of environmental constraints on water values has only been discussed in Refs. [31,32]. In Ref. [32], an SDP-based model is used to evaluate the sensitivity of the water values to environmental flows and ramping restrictions. The authors of [31] find that incorporating the same environmental constraints into a linear programming based water value model has significant impacts on the profitability of hydropower plants with one or at most two turbines.

This research considers the representation of a particular type of state-dependent environmental constraint in the medium-term scheduling of hydropower operation. Several European countries consider lake water alterations to be relevant mitigation measure to reduce impacts from water regulations [33], one example being state-dependent maximum discharge regulations. In the Nordic region, such constraints are imposed on several reservoirs, and are likely to be implemented in other hydropower reservoirs in the future. The purpose of the regulation is to retain inflow during spring, to meet the ecological and recreational needs for high water levels in the reservoir through summer. In other regions, volume-dependent maximum discharge constraints are also used to allocate available water between irrigation purposes and electricity production [17].

Volume-dependent maximum discharge regulation in long- and medium-term hydropower scheduling has previously been studied by the use of SDDiP in Ref. [20] and approximated using SDDP in Ref. [17]. We accurately represent state-dependent maximum discharge constraints in a medium-term hydropower scheduling model based on SDP. Compared to Ref. [17], a different type of maximum-discharge regulation is considered. Furthermore, we use a different methodology (based on SDP) allowing an accurate formulation of state-dependent constraints. Compared to Ref. [20], we use a more mature methodology (SDP) and take a broader view of state-dependencies, studying a formulation of the maximum discharge constraint with a dynamically defined constraint period dependent on inflow. SDP-based models have previously been used to study environmental constraints in Refs. [31,32], but not for environmental constraints that include state-dependencies such as those discussed here.

The developed model is tested on a two-reservoir case study of a Norwegian hydro system. We discuss how the state-dependent environmental constraint modifies the resulting water value curves from the SDP algorithm, further distinguishing our research from Refs. [17,20], and use the water values to simulate operation of the system. The simulation results show the impact of the constraint on reservoir operation and economics. The novel contribution of this research is twofold in that we:

- Formulate a medium-term hydropower scheduling model based on SDP that accurately treats state-dependencies in the maximum allowed discharge from hydropower stations. Maximum discharge depends on the state variables reservoir volume, weekly inflow and a variable indicating if the low-inflow period has ended.
- Assess the impact of including such state-dependent maximum discharge constraints on the water value curves and shed light on the potential impacts that system operation guided by such curves may have. The assessment is carried out for a hydropower cascade in Norway.

The remainder of this paper is structured as follows: Section 2 describes the developed hydropower scheduling model; a case study is presented in Section 3; and concluding remarks are found in Section 4. Section 2 comprises subsections describing the weekly decision problem (Section 2.1), the state-dependent environmental constraint on maximum discharge (Section 2.2), the stochastic variables (Section 2.3) and the solution strategy (Section 2.4). The case study in Section 3 presents calculated water values (Section 3.2) and results from the simulations (Section 3.3).

2. Hydropower scheduling model

In the following we present a medium-term hydropower scheduling model that is formulated for a hydropower cascade operated by a single hydropower producer assumed to be a risk-neutral price taker. The model maximises profit from operating the hydropower system for a presumed stationary future system state. The operation of the system is optimised for weekly decision stages over a horizon of one year.

The hydropower scheduling problem is a multi-stage stochastic optimisation problem. To solve the problem, we decompose the overall problem into several smaller subproblems, using the principles of SDP [11]. By decomposing the problem, we obtain one separate decision problem for each stage and state of the system. The SDP algorithm solves the decision problem, described in Section 2.1, for all stages and system states until convergence, as described in Section 2.4. The scope of potential system states is divided into a set of discrete states. The discrete states include all the information that is passed between the decision stages, from $t-1$ to t. The set of states comprise subsets of endogenous states $\mathcal{S}^p$ and exogenous stochastic state variables $\mathcal{S}^u$. The storage volume in the reservoirs is the endogenous state variable. The stochastic state variables are: the weekly average energy price λ, the weekly total inflow into the system $\hat{Z}$ and the environmental state variable ξ. The stochastic variables are represented by a discrete Markov chain, as described in Section 2.3. The environmental state variable indicates if the so-called "low-inflow period" has ended. In practice, the variable indicates whether the inflow level has exceeded a certain threshold over a shorter period of time. The extension of the discrete Markov chain to include an environmental state variable is explained further in Section 2.3, while the environmental constraint is described thoroughly in Section 2.2. The implementation of the environmental constraint in the SDP algorithm is described in Section 2.4.

2.1. The weekly decision problem

The decision problem is solved for all system states, i.e., combinations of discrete reservoir volumes and stochastic nodes in the Markov chain. Since the stochastic variables are known at the beginning of the stage, each single decision problem is solved as a deterministic problem. The stochastic nature of the problem is managed in the SDP algorithm. Uncertainty is represented through the price and inflow states, and the uncertainty of future realisations of the stochastic variables are reflected in the expected water values. Each stage is divided into K number of time steps.

The objective function (1) maximises the immediate profit of the decisions and the impact on the expected future profit given by α_{t+1}. The expected future profit is a function of the stochastic state of the system and the resulting storage volume in the reservoirs at the end of the stage. Spillage of water is penalised according to a low cost C^S. Furthermore, operation of the reservoirs below a filling degree of 10% is penalised to represent risk-aversion of the producer.

$$\begin{aligned}\alpha_t(s^p, s^u_t) \quad &= \max\Bigg\{\lambda_t \sum_{k\in\mathcal{K}} F^H_k \theta_k \sum_{h\in\mathcal{H}} p_{k,h} - C^S \sum_{k\in\mathcal{K}} \sum_{h\in\mathcal{H}} f_{k,h} \\ &\quad - C^R \sum_{k\in\mathcal{K}} \sum_{h\in\mathcal{H}} u_{k,h} + \alpha_{t+1}(v_{h\in H,k=K}, s^u_{t+1})\Bigg\}\end{aligned} \tag{1}$$

The energy production is a function of the discharge, $q_{k,h,d}$, from each of the reservoirs, as given in (2). The maximum and minimum discharge is limited by (3) and (4). Furthermore, the discharge is bounded by the availability of water in the reservoirs. The reservoir balance (5), keeps track of the change in water volume in each reservoir, where the volumes, $v_{k,h}$, are bounded by (6). To calibrate the reservoir management, a soft-constraint on minimum reservoir volume is used to reflect the risk-aversion of the producer.

$$p_{k,h} - \sum_{d \in \mathcal{D}_h} \eta_{h,d} q_{k,h,d} = 0 \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{2}$$

$$q_{k,h,d} \leq Q^{max}_{h,d} \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H}, d \in \mathcal{D}_h \tag{3}$$

$$\sum_{d \in \mathcal{D}_h} q_{k,h,d} \geq Q^{min}_h \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{4}$$

$$\begin{aligned} &v_{k,h} - v_{k-1,h} + F^C \left(\sum_{d \in \mathcal{D}_h} q_{k,h,d} + f_{k,h} \right) \\ &\quad -F^C \sum_{j \in \mathcal{H}^{up}_h} \left(\sum_{d \in \mathcal{D}_j} q_{k,j,d} + f_{k,j} \right) = \varphi_k Z_h \\ &\qquad \forall \quad k \in \mathcal{K} \backslash 1, h \in \mathcal{H} \end{aligned} \tag{5}$$

$$\begin{aligned} &V^{min}_h + 0.1 * (V^{max}_h - V^{min}_h) \\ &\quad \leq v_{k,h} + u_{k,h} \leq V^{max}_h \\ &\quad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \end{aligned} \tag{6}$$

While (1)–(6) describes the general decision problem, the following equations present the interpolation in the expected future profit function for a system with two reservoirs. The expected future profit α_{t+1} is a function of the storage volume in the reservoirs at the end of the stage, and is bounded by (7)-(12). A two-dimensional, piecewise-linear approximation obtained by the triangle method is used to represent α_{t+1}. The triangle method approximates multidimensional functions by the use of linear triangles, see e.g., Refs. [34,35]. The method was chosen for its ability to approximate nonconvex functions and its simplicity [36]. The formulation can be adapted to larger hydropower systems by expanding the dimensions of the expected future profit approximation.

The optimal expected future profit is obtained by convex combination of the expected future profit points $FV_{n,m}$ using the weighting variables $\gamma_{n,m}$, as given by (7)-(9). The points are calculated for each of the discrete reservoir states in the previous stage, and given as input to the optimisation problem. The sum of the weighting variables in each dimension are used to find the total weight of the discrete volume segments for each reservoir in (10)-(11), binding the expected future profit to the storage volumes in the reservoirs at the end of the stage.

$$\alpha_{t+1} - \sum_{n \in \mathcal{N}} \sum_{m \in \mathcal{N}} \gamma_{n,m} FV_{n,m} = 0 \tag{7}$$

$$\sum\nolimits_{n=1}^{N} \sum\nolimits_{m=1}^{N} \gamma_{n,m} = 1 \tag{8}$$

$$\gamma_{n,m} \leq 1, \qquad \forall \quad n \in \mathcal{N}, m \in \mathcal{N} \tag{9}$$

$$\beta_{l,h} = \sum_{\{n,m\} \in \mathcal{N}^{comb}_{l,h}} \gamma_{n,m} \qquad \forall \quad l \in \mathcal{N}, h \in \mathcal{H} \tag{10}$$

$$v_{k,h} - \sum_{n \in \mathcal{N}} \beta_{h,n} V^{seg}_{h,n} = 0 \qquad \forall \quad k = K, h \in \mathcal{H} \tag{11}$$

$$\chi_g = \sum_{\{n,m\} \in \mathcal{N}^{Diag}_g} \gamma_{n,m} \qquad \forall \quad g \in \mathcal{G} \tag{12}$$

$$p, v, q, f, \gamma, u \in \mathbb{R}^+, \quad \alpha_{t+1} \in \mathbb{R} \tag{13}$$

Nonconvex characteristics in the expected future profit function are dealt with by restricting the weighing variables (γ). In the optimal solution, a maximum of two adjacent weights (γ) in each dimension can have non-zero values, thereby forming a square of adjacent weighting variables that can be active. Such behaviour can be enforced by special ordered sets of type 2 (SOS2) [37]. In SOS2, only two adjacent variables in the set can be non-zero. SOS2 are included in most commercial solvers, such as CPLEX, which is used in this research. In (14), β_h is defined as one SOS2 for each dimension h (i.e., for each reservoir). By using four weights to describe a point in two dimensions, the model is given the freedom to decide which points to use. To ensure one unique solution, we force the model to use a predefined set of weights (3 out of 4) by defining the set χ to be a SOS2 in (15) [37]. The set χ comprises the sum of the weights γ in the diagonal direction, hence forming a triangle of adjacent weighting variables. Piecewise-linear formulations of functions in two and three dimensions are thoroughly discussed in Ref. [35]. The SOS2 defined in (14) and (15) can be removed if the future profit function is concave, changing the formulation from an MILP to an LP.

$$\beta_h \ \ \text{SOS}-2 \quad \forall \quad h \in \mathcal{H} \tag{14}$$

$$\chi \ \ \text{SOS}-2 \tag{15}$$

2.2. Activation of the environmental regulation

The purpose of the considered state-dependent maximum discharge regulation is to meet the needs of ecological habitat and recreational use for high water levels in the hydropower reservoir in summer. Due to high seasonal and yearly variations in inflow, time-dependent minimum reservoir level constraints may lead to inefficient reservoir management during the low-inflow, winter period and increased system costs. To avoid this, the regulation is rather formulated as a state-dependent restriction on discharge from the reservoir. As discussed in section 1, formulations that include state-dependencies can present modelling challenges. We here present a general formulation of the regulation where a selection of different requirements can be included:

- Other than to honour minimum flow obligations, no discharge is allowed within a given period of time, unless the storage volume in the reservoir reaches a given threshold. If the required threshold is reached, discharge is permitted as long as the storage volume is kept above the threshold.
- The constraint can be activated by a given date or by the-end of the "low-inflow period", i.e., inflow levels above a given threshold over a short period. This is normally the beginning of the snow-melting in spring.
- From a given date and until the end of the restriction period, discharge from the reservoir is permitted as long as the storage volume in the reservoir does not decrease.

The above regulation can be expressed mathematically by a set of constraints. The activation and/or deactivation criteria defined in the regulation are often formulated as logical conditions dependent on the state variables, i.e., storage volume in the reservoirs and inflow. The state-dependent conditions are illustrated in Fig. 1. The dependencies on both inflow and storage volume in the reservoir are handled in the SDP algorithm, as described in section 2.4.

The different types of constraints imposed by the maximum discharge regulation are described by (16)-(19). Depending on the current state of the system, the constraints are added to the formulation before the decision problem is solved. The first part of the environmental regulation is a regulatory maximum discharge capacity constraint. When the constraint period is initiated, (16) replaces (3) to restrict release from the reservoir only to serve downstream requirements for minimum river flows. The constraint is activated by inflow above a certain threshold (in t_A) or by a given date, t_B.

$$\sum_{d\in\mathcal{D}_h} q_{k,h,d} \le Q_h^{lim} \qquad \forall \quad k\in\mathcal{K}, h=\hat{H} \tag{16}$$

When (and if) the storage volume in the reservoir reaches the predefined threshold V_h^{lim}, constraint (16) is relaxed and replaced with a minimum reservoir level regulation, (17)—(18). (17) is active for the first week the storage volume in the reservoir reaches the wanted threshold (in t_C), while (18) becomes active from the following week. When (17) or (18) are active, discharge is permitted but the storage volume in the reservoir must be kept above the threshold.

$$v_{k=K,h} \ge V_h^{lim} \qquad \forall \quad h=\hat{H} \tag{17}$$

$$v_{k,h} \ge V_h^{lim} \qquad \forall \quad k\in\mathcal{K}, h=\hat{H} \tag{18}$$

Finally, for a given period, t_D-t_E, the storage volume in the reservoir is not permitted to decrease. This constraint is shown in (19). The formulation ensures that the storage level in the reservoir at the end of a stage is equal or higher than the storage level at the beginning of the stage. The storage level could also be bounded over each time step k.

$$v_{k,h} \ge V_h \qquad \forall \quad k=K, h=\hat{H} \tag{19}$$

The formulation assumes that the reservoir level can be maintained once above the threshold. This can be challenging in some hydropower systems due to minimum flow requirements or negative inflow (e.g., evaporation). While we did not encounter feasibility issues, these can be avoided by including a slack-variable that is penalised in the objective function in (18) and (19).

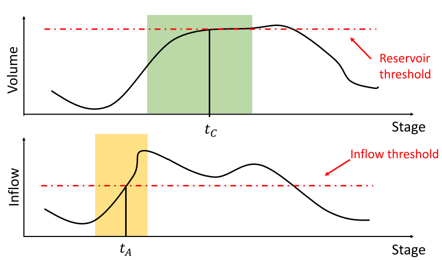


Fig. 1. Illustration of the state-dependent conditions in the environmental regulation. Within the orange shaded period, the constraint can be activated by inflow above a defined threshold, illustrated by point t_A. Similarly, the no discharge restriction can be deactivated within the green shaded area by storage volume above the reservoir threshold, as illustrated by point t_C.

2.3. Stochastic variables

We consider three exogenous stochastic variables in this research; the total weekly inflow into the system, the weekly average energy price and the environmental state, i.e., if the inflow has been above a certain threshold. Inflow normally has a strong weekly correlation, while inflow and price tend to be negatively correlated in hydro-dominated systems. The environmental state variable is an extension of the inflow state. For computational simplicity, we assume that the stochastic variables can be described by discrete nodes using a Markov decision process. The following procedure is used to generate the Markov chain:

- Inflow and price data is given as input to the model, e.g., historical or forecasted data.
- An auto-regressive model is fitted to the input data. Serial correlation in inflow and cross-correlation between inflow and price is considered.
- 10 000 scenarios are sampled from the auto-regressive model.
- A given number of discrete nodes per week are generated from the scenarios, using K-means clustering. Each node represents one inflow value and one price value.
- The transition probabilities are determined by counting the share of scenarios transitioning between the different nodes from one week to the next.

In addition, information on the environmental state is required. The environmental state represents a binary variable, indicating whether the inflow has been above a certain threshold. For the weeks when this is applicable, the Markov chain is expanded with an additional environmental state (activated and not activated) in each of the nodes, as illustrated in Fig. 2. The transition probabilities are updated by multiplying with the probability of inflow above (or below) the threshold in each node, presuming that the inflow level has not previously been above the threshold. Once the environmental state is activated, it can only be deactivated by the reservoir storage level reaching above the given threshold or by a given date.

2.4. Solution strategy

The hydropower scheduling problem is solved using the SDP algorithm described in Algorithm 1. The algorithm is based on backwards recursion and solves the decision problem for each stage and state of the system for a planning horizon of one year. To account for end-of horizon effects, an iterative approach is used until the water values in the last and first stage converge. The algorithm

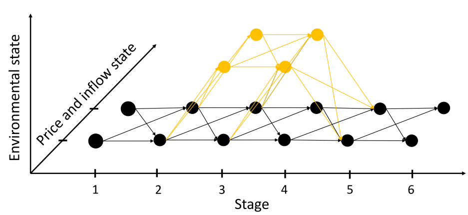


Fig. 2. Illustration of a Markov chain with two nodes per stage representing unique price and inflow values, and an additional environmental state in t = 3 to 4. The additional nodes are illustrated in yellow.

iterates over all stages ($\mathcal{T}$), all reservoir states ($\mathcal{S}^p$) and all stochastic states ($\mathcal{S}^u$) in lines 4–6. $\mathcal{S}^p$ comprises all combinations of discrete storage volumes for the reservoirs in the system. The stochastic variables are updated in line 7, while reservoir specific data is updated for each hydropower plant in lines 8–11. The expected future profits for all end reservoir states are updated in line 12.

The decision problem is solved in line 13 following the

Algorithm 1: SDP Algorithm

1 $j \leftarrow 0, \Delta \leftarrow \infty, \alpha_{t=T}(...) \leftarrow 0$
2 **while** $\Delta > \epsilon$ *or* $j < J$ **do**
3   $j \leftarrow j + 1$
4   **for** t = *T:-1:1* **do**
5   **for** $s^p \in \mathcal{S}^p$ **do**
6   **for** $s_t^u \in \mathcal{S}^u$ **do**
7         $\{\lambda_t, \hat{Z}_t, \xi_t\} \leftarrow stochVar(s_t^u)$
8   **for** $h \in \mathcal{H}$ **do**
9           $V_h \leftarrow resVolume(s^p, h)$
10           $Z_h \leftarrow \omega_h \times \hat{Z}_{t,s_t^u}$
11   **end**
12         $FV \leftarrow \Phi_{j,t}(\{1, ..., P\}, s_t^u)$
13         $\alpha_t(s^p, s_t^u) \leftarrow solveProblem(t, \xi_t, V_{h=\hat{H}}, Z_{h=\hat{H}})$
14   **end**
15   **for** $s_{t-1}^u \in \mathcal{S}^u$ **do**
16         $\Phi_{j,t-1}(s^p, s_{t-1}^u) \leftarrow \sum_{s_t^u=1}^{|\mathcal{S}^u|} Pr(s_t^u|s_{t-1}^u)\alpha_t(s^p, s_t^u)$
17   **if** $s^p > 1$ **then**
18           $\Psi_{j,t-1}^{h\in\mathcal{H}}(s^p - 1, s_{t-1}^u) \leftarrow$ $getWV(\Phi_{j,t-1}(\{1, ..., s^p\}, s_{t-1}^u))$
19   **end**
20   **end**
21   **end**
22   **end**
23   $\Delta \leftarrow |\Psi_{j,t=T}^h(s^p, s_t^u) - \Psi_{j,t=0}^h(s^p, s_t^u)|, \quad s^p \in \mathcal{S}^p, s_t^u \in \mathcal{S}^p, h \in \mathcal{H}$
24   **if** $\Delta > \epsilon$ **then**
25     $\Psi_{j+1,t=T}^h(s^p, s_t^u) \leftarrow \Psi_{j,t=0}^h(s^p, s_t^u), \quad s^p \in \mathcal{S}^p, \; s_t^u \in \mathcal{S}, h \in \mathcal{H}$
26     $\Phi_{j+1,t=T}(s^p, s_t^u) \leftarrow \Phi_{j,t=0}(s^p, s_t^u), \quad s^p \in \mathcal{S}^p, \; s_t^u \in \mathcal{S}^u$
27   **end**
28 **end**

procedure described in algorithm 2. The algorithm checks if any of the environmental conditions described in Section 2.2 are met, and solves the associated decision problem with the corresponding constraints included, i.e., (16), (17), (18) or (19). The inflow dependent early activation of the constraint is included as a stochastic state ξ in the discrete Markov chain. The environmental constraints are only included in a selection of the subproblems, but the non-concave characteristics of the expected future profit function may carry down to earlier stages before fading out. For efficiency, the expected future profit approximation is checked for concavity before each subproblem is solved. If the function is concave, (14) and (15) are relaxed and the problem is solved as an LP. If the problem is solved for a system without the environmental regulation, the decision problem is an LP described by (1)-(13).

The solution of the optimisation problem for all stochastic states s_t^u is used to calculate the expected future profit, in line 16. The expected future profit is stored to matrix Φ. The water values are calculated and stored to the water value matrix Ψ in line 18, following a similar approach as in Ref. [18]. When an iteration is completed, convergence is determined in line 23, by comparing the calculated water values in the last and first stage. If the algorithm has not converged in iteration j, the water value matrix and the expected future profit matrix for the last stage T is updated with the values from the first stage in iteration j, in lines 25 and 26, before the next iteration.

Algorithm 2: Function solveProblem(...)

Input: $t, V_{h=\hat{H}}, Z_{h=\hat{H}}, \xi_t$

if $(t_B \le t < t_D) \wedge (V_{\hat{h}} \ge V^{lim}_{h=\hat{H}})$ **then**
  $\alpha_t(...) \leftarrow$ Optimise (1) - (15), (18)
else if $(t_B \le t < t_D) \wedge (V_{h=\hat{H}} + Z_{h=\hat{H}} \ge V^{lim}_{h=\hat{H}})$ **then**
  $\alpha_t(...) \leftarrow$ Optimise (1) - (15), (17)
else if $t_D \le t < t_E$ **then**
  $\alpha_t(...) \leftarrow$ Optimise (1) - (15), (19)
else if $t < t_D \wedge \xi_t$ **then**
  $\alpha_t(...) \leftarrow$ Optimise (1) - (15), (16)
else
  $\alpha_t(...) \leftarrow$ Optimise (1) - (15)
end

Output: $\alpha_t(...)$

3. Case study

3.1. Case Description

This case study assesses the impact of the state-dependent maximum discharge regulation on water values, simulated reservoir operation and profit from the simulated operation of the system. First, water values are calculated in the SDP model, before optimal operation of the system is simulated for a selection of scenarios.

The described model is applied to the hydropower system shown in Fig. 3. The hydropower system is based on Bergsdalsvassdraget in Western Norway. The system comprise several hydropower reservoirs and power plants, of which the two upper reservoirs and power plants are modelled here. The modelled part of the system has a total generation capacity of approximately 55 MW and a reservoir storage capacity of up to 360 Mm^3.

The lower of the two modelled reservoirs has a state-dependent environmental maximum discharge constraint. The constraint is of

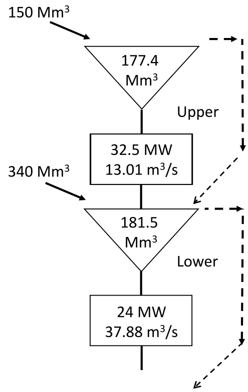


Fig. 3. Topology of the modelled system. Reservoirs (triangles), power plants (rectangles), and water routes for discharge (solid lines) and spillage (dashed lines) are shown. Maximal values for discharge (m^3/s), production (MW), reservoir volumes (Mm^3) and average yearly inflow (Mm^3) are given (not considering the environmental constraint).

the type described in Section 2.2. The discharge limitation can be activated by inflow above the weekly average from week 15 and, at the latest, in week 19. The discharge limitation is active until week 32, or until the storage volume in the reservoir is above 146 Mm^3. If the storage volume in the reservoir reaches 146 Mm^3, discharge is permitted as long as the water level stays above the threshold. From week 33 to week 35, the reservoir storage is not allowed to be reduced. The constraint is deactivated in week 35. In addition, a minimum discharge of 3 m^3/s is imposed on the lower reservoir.

Two cases are considered; without the environmental regulation, *wo/Env*, and with the environmental regulation, *w/Env*. In the *w/Env* case, the decision problem is solved with the environmental regulation, as given in Section 2.4. The SDP model is solved for one year of weekly decision stages, comprising three price periods of 56 h each. A high intra-week price variation is assumed. Each of the reservoirs are discretised into 20 equidistant points, giving 400 combinations of reservoir states. Since the focus of this research is on the modelling of the environmental constraint, a relatively coarse representation of uncertainty and time discretization is included. A discrete Markov chain with 10 nodes per stage is used, each comprising a unique price and inflow value. In the weeks when early activation of the environmental constraint could occur, the environmental state variable is added, leading to a total of 20 nodes per stage.

The discrete Markov chain is generated using inflow data from 58 historical years and power prices generated based on the same inflow data. Alternatively, forecasted weather data from climate models can be used, see e.g., Ref. [38]. The power prices were provided from the long-term hydropower scheduling model EMPS [25], based on a low emission dataset of the European power system for 2030 [39]. The penalty cost of spilling water is set low, $C^S = 10^{-3}\ \frac{€}{m^3/s}$. The cost of drawing down the reservoir below 10% of the storage capacity is set to approximately 150 $\frac{€}{Mm^3}$ and 580 $\frac{€}{Mm^3}$ for the lower and upper reservoirs, respectively.

The simulation is conducted as weekly decisions in a sequence, solving the decision problem formulated in Section 2.1 as a short-term operational problem for each week. The same technical details as in the SDP model are included. The water values calculated in the SDP model are used as input to the weekly decision problem to evaluate the value of the water in the reservoir at the end of each week. For the *w/Env* case, the logical conditions for activating the environmental constraint, as described in Section 2.2, are checked each time the weekly decision problem is solved. When (and if) the conditions are met, the associated constraints, i.e., (16), (17), (18) or (19), are added to the decision problem.

The model was implemented in Julia v1.5 using the Jump package [40] and the CPLEX 12.10 solver [41]. The relative MIP gap is set to zero and the absolute MIP gap to 10^{-10}.The case study was carried out on an Intel Core i7-8650U processor with 16 GB RAM. One iteration of the *wo/Env* case solved 208k decision problems in approximately 440 s. One iteration of the *w/Env* case solved 224k decision problems in approximately 1860 s, whereof approximately 40% of the decision problems were solved as MILP. By reducing the number of problems solved as MILP, the solution time of the *w/Env* case was reduced with around 30%. The algorithm converged in 16–20 iterations with a convergence criterion of 10^{-3} $\frac{€}{Mm^3}$. Advanced tuning of the applied MIP solver and use of parallel processing could serve to improve the computational efficiency [42].

3.2. Water values

The water values are the main result from the SDP model. We are especially interested in how the water values change when including the state-dependent maximum discharge constraint. This is of high importance in real-life hydropower scheduling, as the water values provide essential information for short-term decision making.

The upper reservoir is not directly impacted by the environmental regulation in the *w/Env* case but can be actively used to help manage the regulation. If it is optimal to adjust the reservoir management of the upper reservoir to reach the threshold in the lower reservoir more rapidly, this would be reflected in the water values of the upper reservoir. However, only minor or no changes were seen in the water values for the upper reservoir, implying that it is not economically profitable to release more water from the upper reservoir to reach the reservoir threshold in the lower reservoir earlier. This result is sensitive to several factors, such as the expected power prices in the weeks when the constraint is active, the strictness of the constraint and the efficiency of the lower power plant compared to the upper power plant. Since small or no changes were seen in the water values of the upper reservoir, the rest of this section only considers the water values of the lower reservoir. The water values presented for the lower reservoir are given for a medium storage level in the upper reservoir (i.e., $\sim 85Mm^3$).

Fig. 4 shows the calculated water values for the *wo/Env* case and the *w/Env* case. The water values change with the storage volume in the reservoir and the week of the year. In the *wo/Env* case, the water values are non-increasing with increasing storage volume in the reservoir. This will always be the result from linear hydropower scheduling models where the expected future profit is a concave function. For low storage volumes in the reservoir, the water value is high because of the risk of emptying the reservoir. For higher storage volumes in the reservoir, the water value decrease as the risk of spilling water increase. The water value is zero when water has to be spilled because of full reservoirs. In the *w/Env* case, the same behaviour of high and low water values can be observed for low and high storage volumes, respectively. However, the water values also sometimes increase with increasing storage volumes. For this case, the expected future profit is therefore a nonconcave function.

The increasing water values with increasing reservoir storage volumes in the *w/Env* case are a direct result of the state-dependent maximum discharge constraint. The largest differences in the water values between the two cases can be seen when the strictest part of the environmental regulation is active (week 18–32) and backwards in time (towards week 1). In the weeks when the constraint is active and the storage volume in the reservoir is lower than the threshold (146 Mm^3), the water values are higher in the *w/Env* case than in the *wo/Env* case. Since discharge from the reservoir is strictly limited over a longer period, the model cannot take advantage of the potential high prices within this period, unless the threshold is reached. As a result, the water values are higher in the *w/Env* case compared to the *wo/Env* case for storage volumes where the maximum discharge capacity restriction can be deactivated early.

The water values are calculated from the last to the first week of the year, hence the impact of the constraint on the water values from later weeks affects the earlier weeks. Week 32 is the last week when the maximum discharge capacity restriction is active. Fig. 5 compares the water values from the two cases for selected weeks. No large differences can be seen after the constraint is deactivated; this is, for example, shown in Fig. 5a. In week 32 (Fig. 5b), the difference between the water value curves for the two cases becomes more distinct. The local peak in the water value curve for the *w/Env* case in Fig. 5b is a result of discharge being permitted when the storage volume in the reservoir reaches the threshold. Moving forwards in time, this effect is being shifted towards lower storage volumes, as shown in Fig. 5c and d.

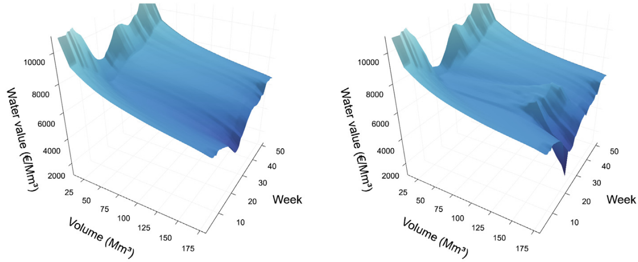
3.3. Simulation results

Simulations were run for 1000 scenarios, randomly selected from the originally sampled scenarios. The *wo/Env* case and the *w/Env* case were simulated for the same scenarios, using water values from the SDP model for each of the cases accordingly. The final simulations are conducted to test the calculated water values in an operational decision-making setting, as well as to demonstrate the effect of the environmental constraint on operation of the system.

The activation and deactivation of the maximum discharge capacity restriction varies between the scenarios because of the state-dependent nature of the conditions. Fig. 6 shows when the maximum discharge constraint is activated and deactivated in the *w/Env* case for the simulated scenarios. In approximately 85% of the scenarios, the storage volume in the reservoir reaches the threshold before week 33, deactivating the maximum discharge constraint. The discharge limitation is activated by high inflow before week 19 in 50% of the scenarios. Even so, inflow-dependent activation was found to only have muted impact on the strategy and simulated economic results for the case considered. Still, under other price assumptions inflow-dependent activation could be of higher importance.

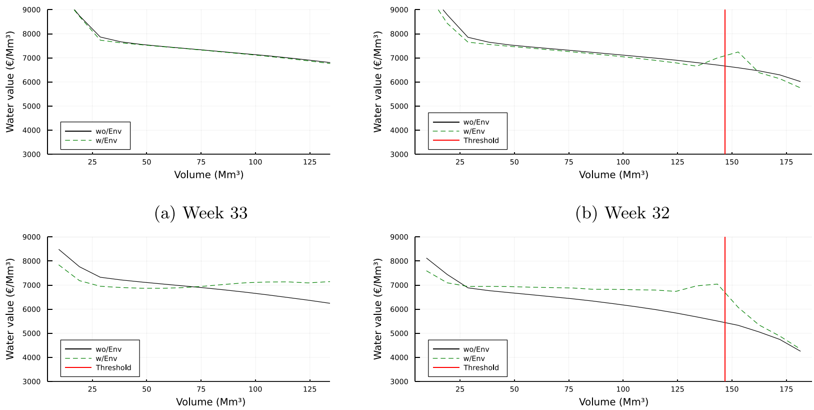
The results from the simulations show a considerable change in optimal operation when the environmental constraint is included. Fig. 7 compares the change in storage volume in the lower reservoir over a year for the *wo/Env* and *w/Env* cases. In general, the storage volume in the reservoir is kept higher in the *w/Env* case. The largest difference can be seen in the spring and summer weeks, when the environmental regulation is active. In this period, no discharge is permitted if the storage level is below the reservoir threshold. For several weeks in this period, the median reservoir storage volume is raised from below 100 Mm^3 in the *wo/Env* case to over 150 Mm^3 in the *w/Env* case, demonstrating the effectiveness of the constraint to achieve the underlying purpose of reaching the threshold.

For most of the simulated scenarios, the storage volume in the



(a) wo/Env (b) w/Env

Fig. 4. Calculated water values for the lower reservoir in the two cases plotted for the storage volume in the reservoir and week of the year.



(a) Week 33 (b) Week 32

(c) Week 25 (d) Week 20

Fig. 5. Water values calculated in the *w/Env* case (dashed lines) and the *wo/Env* case (solid lines). The vertical lines give the reservoir threshold.

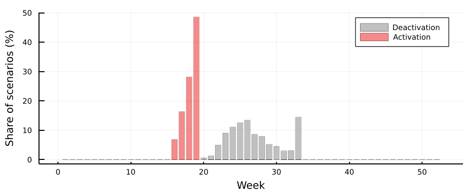


Fig. 6. Activation and deactivation of the maximum discharge restriction per week, given in share of scenarios.

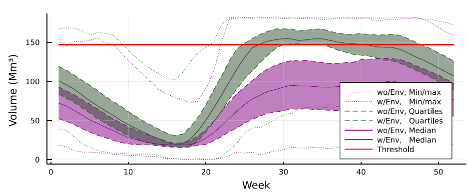


Fig. 7. Simulated storage volume in the lower reservoir in the *wo/Env* (purple) and *w/Env* (green) cases. Min/max (dotted lines), quartiles (dashed lines) and the medians (solid lines) are shown. The horizontal line gives the reservoir threshold.

lower reservoir reaches the reservoir threshold in week 25–30 in the *w/Env* case. This means that the optimal operation of the reservoirs lies within the reservoir volume segments where the maximum discharge capacity constraint has the largest impact on the water values, indicating the importance of including the constraint in the calculation of the water values. Furthermore, the reservoir storage volume is also kept higher in the autumn and winter weeks in the *w/Env* case compared to the *wo/Env* case. Higher storage volumes throughout the year, and not only when the constraint on discharge is active, can be explained by the

Table 1
Average profit and electricity generation.

Case	Reservoir	Profit [/yr]	Production [MWh/yr]	Profit week 19–35 []
wo/Env	Upper	5.16E+06	1.04E+05	1.20E+06
	Lower	4.19E+06	9.00E+04	1.16E+06
	Total	9.34E+06	1.94E+05	2.36E+06
w/Env	Upper	5.15E+06	1.04E+05	1.24E+06
	Lower	4.12E+06	8.98E+04	7.16E+05
	Total	9.27E+06	1.94E+05	1.95E+06
Difference	Upper	−0.10%	−0.0%	3.12%
	Lower	−1.60%	−0.22%	−38.46%
	Total	−0.77%	−0.11%	−17.23%

differences in water values. Higher water values for higher storage volumes in the *w/Env* case give the model an incentive to keep more water in the reservoir when coming into the constraint period.

A selection of average numeric results from the completed simulations are given in Table 1. The total yearly profit from the system is reduced by around 72 k(0.8%) in the *w/Env* case compared to the *wo/Env* case. In the period when the constraint is active, week 19–35, the total profit from electricity generation is reduced by approximately 17% or 406 k. By shifting the electricity generation, the model manages to keep the total generation in the *w/Env* case close to the total generation in the *wo/Env* case, significantly reducing the total loss in profit. This means that the loss in profit is mainly caused by a lower average realised price of electricity, and not reduced sales of electricity. Still, it should be mentioned that the economic results are sensitive to the power price assumptions used in the simulations. Higher power prices in the constrained period can increase the cost of restricting production in this period, and vice versa.

4. Conclusion

We present a medium-term hydropower scheduling model comprising an accurate representation of inflow- and volume-dependent environmental constraints on maximum discharge. Such constraints cause a pronounced nonconvexity in the scheduling problem. The proposed model can solve nonconvex model formulations for smaller systems, by applying an SDP-algorithm, where binary variables are only required to represent the nonconvex characteristics of the expected future value function. By dynamically checking for nonconvexities in the value function, we find that the number of weekly decision problems solved as MILPs can be reduced significantly. Still, the required discretization of the state space leads the SDP-algorithm to scale poorly for larger systems with more reservoirs.

The model is applied to a case study of a Norwegian hydropower system with multiple reservoirs. Simulations of the system with and without the environmental constraint show a substantial difference in operation of the reservoir to which the constraint is imposed. In the case with the environmental constraint, the storage volume in the reservoir reaches the wanted threshold for most of the scenarios. Still, the total electricity generation over the year is maintained and total loss in profit is limited to approximately 0.8%.

The calculated water values were found to change considerably when the state-dependent maximum discharge constraint was included in the SDP model. For the reservoir to which the constraint was imposed, the water values were found to both increase and decrease with increasing storage volumes in the reservoir, reflecting that the expected future profit function is nonconcave. The distinct changes in the calculated water values when the environmental regulation was considered show the importance of accurate modelling of such regulations. This conclusion is further strengthened by the optimal reservoir operation being within the nonconcave area of the expected future profit function for most of the simulated scenarios, as demonstrated by the simulation results. If the future profit function is used as boundary condition in operational short-term scheduling models, the nonconcave shape may impact the results substantially.

The substantial impact on the calculated water values and reservoir operation observed in this study support further research on nonconvex environmental constraints. To strengthen the findings from this study, future research should investigate the impact of using accurate water values, compared to water values based on simplified problem formulations, in operation of hydropower systems with environmental regulation. Furthermore, a wider selection of cases and hydropower watercourses with different variations of the state-dependent maximum discharge constraint could be analysed. Finally, a broader analysis to evaluate how well the constraint meets the underlaying purpose of the environmental regulation, as well as other unintended consequences like flood risk, could be of interest.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] The European green deal. https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en. (Accessed 3 June 2021).
[2] M. Mattmann, I. Logar, R. Brouwer, Hydropower externalities: a meta-analysis, Energy Econ. 57 (2016) 66–77.
[3] N.L. Poff, J.K. Zimmerman, Ecological responses to altered flow regimes: a literature review to inform the science and management of environmental flows, Freshw. Biol. 55 (1) (2010) 194–205.
[4] B. Köhler, A. Ruud, Ø. Aas, D.N. Barton, Decision making for sustainable natural resource management under political constraints – the case of revising hydropower licenses in Norwegian watercourses, Civ. Eng. Environ. Syst. 36 (1) (2019) 17–31.
[5] L.-R.D. Kosnik, Balancing environmental protection and energy production in the federal hydropower licensing process, Land Econ. 86 (3) (2010) 444–466.
[6] I. Guisández, J.I. Pérez-Díaz, J.R. Wilhelmi, Assessment of the Economic Impact of Environmental Constraints on Annual Hydropower Plant Operation, Energy Policy, 2013, pp. 1332–1343.
[7] E.G. Dimanchev, J.L. Hodge, J.E. Parsons, The role of hydropower reservoirs in deep decarbonization policy, Energy Pol. 155 (2021).
[8] A. Helseth, A.C.G. de Melo, Scheduling toolchains in hydro- dominated systems - evolution, current status and future challenges, SINTEF, Trondheim, Tech. Rep. (2020), 00757, 2020. [Online]. Available: https://hdl.handle.net/11250/2672581.
[9] M.V. Pereira, L.M. Pinto, Multi-stage stochastic optimization applied to energy

planning, Math. Program. 52 (1–3) (1991) 359–375.
[10] A. Gjelsvik, M. Belsnes, A. Haugstad, An algorithm for stochastic medium-term hydrothermal scheduling under spot price uncertainty, in: Proceedings. 13th Power Systems Computation Conference 2, 1999, pp. 1079–1085, 1999.
[11] R. Bellman, Dynamic programming and stochastic control processes, Inf. Control 1 (3) (1958) 228–239.
[12] A.L. Diniz, M.E. Piñeiro Maceira, A four-dimensional model of hydro generation for the short-term hydrothermal dispatch problem considering head and spillage effects, IEEE Trans. Power Syst. 23 (3) (2008) 1298–1308.
[13] W. van Ackooij, I. Danti Lopez, A. Frangioni, F. Lacalandra, M. Tahanan, Large-scale unit commitment under uncertainty: an updated literature survey, Ann. Oper. Res. 271 (1) (2018) 11–85.
[14] A. Helseth, M. Fodstad, B. Mo, Optimal medium-term hydropower scheduling considering energy and reserve capacity markets, IEEE Trans. Sustain. Energy 7 (3) (2016) 934–942.
[15] S. Cerisola, J.M. Latorre, A. Ramos, Stochastic dual dynamic programming applied to nonconvex hydrothermal models, Eur. J. Oper. Res. 218 (3) (2012) 687–697.
[16] Q. Goor, R. Kelman, A. Tilmant, Optimal multipurpose-multireservoir operation model with variable productivity of hydropower plants, J. Water Resour. Plann. Manag. 137 (3) (2011) 258–267.
[17] E. Pereira-Bonvallet, S. Püschel-Løvengreen, M. Matus, R. Moreno, Optimizing hydrothermal scheduling with non-convex irrigation constraints: case on the Chilean electricity system, in: Energy Procedia, vol. 87, 2016, pp. 132–140, plus 0.5em minus 0.4emElsevier Ltd.
[18] A. Helseth, M. Fodstad, M. Askeland, B. Mo, O.B. Nilsen, J.I. Pérez-Díaz, M. Chazarra, I. Guisández, Assessing hydropower operational profitability considering energy and reserve markets, IET Renew. Power Gener. 11 (13) (2017) 1640–1647.
[19] M.N. Hjelmeland, J. Zou, A. Helseth, S. Ahmed, Nonconvex medium-term hydropower scheduling by stochastic dual dynamic integer programming, IEEE Trans. Sustain. Energy 10 (1) (2019) 481–490.
[20] A. Helseth, B. Mo, H.O. Hågenvik, Nonconvex environmental constraints in hydropower scheduling, in: International Conference on Probabilistic Methods Applied to Power Systems, PMAPS), 2020.
[21] J.D.C. Little, The use of storage water in a hydroelectric system, J. Oper. Res. Soc. Am. 3 (2) (5 1955) 187–197.
[22] J. Lindqvist, Operation of a hydrothermal electric system: a multistage decision process, Trans. Am. Inst. Electr. Eng.Part III: Power Apparatus and Systems 81 (3) (1962) 1–6.
[23] J.A. Tejada-Guibert, S.A. Johnson, J.R. Stedinger, Comparison of two approaches for implementing multireservoir operating policies derived using stochastic dynamic programming, Water Resour. Res. 29 (12) (1993) 3969–3980.
[24] A. Turgeon, R. Charbonneau, An aggregation-disaggregation approach to long-term reservoir management, Water Resour. Res. 34 (1998) 3585–3594.
[25] O. Wolfgang, A. Haugstad, B. Mo, A. Gjelsvik, I. Wangensteen, G. Doorman, Hydro reservoir handling in Norway before and after deregulation, Energy 34 (10) (2009) 1642–1651.
[26] N.V. Arvanitidis, J. Rosing, Composite representation of a multireservoir hydroelectric power system, IEEE Trans. Power Apparatus Syst. PAS-89 (2) (1970) 319–326.
[27] M.A. Olivares, J. Haas, R. Palma-Behnke, C. Benavides, A framework to identify Pareto-efficient subdaily environmental flow constraints on hydropower reservoirs using a grid-wide power dispatch model, Water Resour. Res. 51 (5) (2015) 3664–3680.
[28] I. Guisández, J.I. Pérez-Díaz, J.R. Wilhelmi, Approximate formulae for the assessment of the long-term economic impact of environmental constraints on hydropeaking, Energy 112 (2016) 629–641.
[29] S. Steinschneider, A. Bernstein, R. Palmer, A. Polebitski, Reservoir management optimization for basin-wide ecological restoration in the Connecticut river, J. Water Resour. Plann. Manag. 140 (9) (2014).
[30] L.E. Schäffer, A. Adeva-Bustos, T.H. Bakken, A. Helseth, M. Korpås, Modelling of environmental constraints for hydropower optimization problems – a review, in: 2020 17th *International Conference On the European Energy Market (EEM)*. Plus 0.5em Minus 0.4emIEEE, 2020, pp. 1–7.
[31] I. Guisández, J.I. Pérez-Díaz, W. Nowak, J. Haas, Should environmental constraints be considered in linear programming based water value calculators? Int. J. Electr. Power Energy Syst. 117 (2020).
[32] I. Guisández, J.I. Pérez-Díaz, J.R. Wilhelmi, The influence of environmental constraints on the water value, Energies 9 (6) (2016).
[33] J.H. Halleraker, W. Van De Bund, M. Bussettini, R. Gosling, S. Döbbelt-Grüne, J. Hensman, J. Kling, V. Koller-Kreimel, P. Pollard, Working group ECOSTAT report on common understanding of using mitigation measures for reaching good ecological potential for heavily modified water bodies - Part 1: impacted by water storage, Publications Office of the European Union, Luxembourg, Tech. Rep. EUR 28413 EN, 2016. [Online]. Available: https://www.ecologic.eu/14545.
[34] I. Guisández and J. I. Pérez-Díaz, "Mixed integer linear programming formulations for the hydro production function in a unit-based short-term scheduling problem," Int. J. Electr. Power Energy Syst., vol. 128, 2021.
[35] R. Misener, C.A. Floudas, Piecewise-linear approximations of multidimensional functions, J. Optim. Theor. Appl. 145 (2010) 120–147.
[36] C. D'Ambrosio, A. Lodi, S. Martello, Piecewise linear approximation of functions of two variables in MILP models, Oper. Res. Lett. 38 (1) (2010) 39–46.
[37] P.H. Williams, Model Building In Mathematical Programming, 5th Edition – Wiley, fifth ed., 2013 plus 0.5em minus 0.4emWest Sussex: Wiley.
[38] B. Mo, O. Wolfgang, J. Styve, The Nordic power system in 2020 – impacts from changing climatic conditions, in: H.H. Pikkarainen (Ed.), Conference on Future Climate and Renewable Energy: Impacts, Risks and Adaptation Conference Proceedings Conference Proceedings, plus 0.5em minus 0.4emOslo: Norwegian Water Resources and Energy Directorate, 2010, pp. 44–45.
[39] L.E. Schäffer, B. Mo, I. Graabak, Electricity prices and value of flexible generation in Northern Europe in 2030, in: International Conference on the European Energy Market, EEM, 2019.
[40] I. Dunning, J. Huchette, M. Lubin, JuMP: a modeling language for mathematical optimization, SIAM Rev. 59 (2) (2015) 295–320.
[41] IBM CPLEX optimizer. http://www-01.ibm.com/software/. (Accessed 1 July 2021).
[42] Y. Ma, P.-a. Zhong, B. Xu, F. Zhu, Y. Xiao, Q. Lu, Multidimensional parallel dynamic programming algorithm based on spark for large-scale hydropower systems, Water Resources Management 2020 34:11 34 (11) (2020) 3427–3444.

Paper III

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Optimal operation of hydropower systems with environmental constraints on reservoir management

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Abstract

Hydropower systems' unique capability to provide flexibility and long-term energy storage makes the low-carbon technology a key contributor to cost-effective and reliable decarbonisation of power systems. To ensure sustainable operation, environmental regulations are normally imposed on the plants. Some of these regulations can be difficult to model in existing scheduling tools based on optimisation because of their non-convex and logical characteristics. This study assesses the operational impacts of two types of environmental reservoir constraints, as well as the economic impacts of considering these constraints in medium-term hydropower scheduling. The results show that optimal reservoir management may change considerably due to these types of constraints. Furthermore, improved planning results in a decent increase in expected profit to the power producer under certain price assumptions in several of the simulated cases.

Keywords: Environmental constraints, Hydropower scheduling, Reservoir management, Stochastic optimisation

1 Introduction

Successful transition to low-carbon power systems relies on a rapid transition into and efficient use of renewable energy resources. Hydropower is the only large-scale renewable electricity-generating technology that can provide both short-term system flexibility and long-term energy storage [1]. By rapidly responding to fluctuations in intermittent power generation and load, regulated hydropower can act as an enabler of cost-efficient integration of larger shares of wind and solar power generation, thereby playing an important role in the green transition [2].

In liberalised power markets, such as the Nordic power market, efficient use of power plants rely on competition between power producers to sell electricity in the market. Hydropower producers aim to maximise profit by optimising the use of water for power generation while honouring technical and regulatory constraints. Regulatory constraints, such as environmental constraints, are imposed to accommodate considerations conflicting with power production, i.e., to preserve environmental qualities and mitigate adverse effects due to hydropower production. These constraints are normally given in the licensing terms of the power plants and revised periodically (often with 30-50 years intervals). Many hydropower plants in Europe and the US will go through revision of terms over the next decade [3–5], providing the opportunity to adjust or impose new environmental constraints.

While environmental constraints play an important role in protecting the diverging interests of life in and close to regulated watercourses, they often come with an associated cost. The constraints restrict the operational flexibility of the power producers and may reduce the total energy supply and the power plants' capability to deliver power system services. The regulator, therefore, has to weigh the requirements for environmental constraints towards the power system's needs. These trade-off decisions often require extensive analyses, which can lead to time-consuming revision processes [6]. Especially in hydro-dominated systems, like the Nordic, Canadian and Brazilian systems, the consequences on power system operations and security of supply of imposing new constraints have to be properly considered by the regulators.

1.1 Environmental constraints on the operation of hydropower

Land use changes caused by energy production are identified as one of the main pressures on the environment and the ecosystems [7]. Hydropower is a technology that makes direct use of natural resources and is built into the river at specific locations where the water resources are abundant and topography favourable for power production. Despite the site-specific character of hydropower, environmental impacts from the development and operation of hydropower projects can to some extent be generalised. Hydropower projects typically introduce barriers and fragmentation and lead to changes in the natural flow regime [8]. Parts of the river system might experience dramatically reduced flow or large changes in the natural flow regime. In the reservoir area, large and unnatural fluctuations in water level are recognised as a main ecological stressor.

Environmental constraints can be imposed on hydropower systems to mitigate the environmental impacts of river regulations. The constraints are normally defined to sustain important environmental qualities in the rivers and lakes, while also considering the need for a reliable supply of renewable energy from hydropower. Environmental constraints exist in many versions, and some are more widely applied than others. A variety of river flow constraints can be used to preserve certain flow characteristics in bypass sections or downstream hydropower plants. Most frequently applied are minimum flows, also known as environmental flows, which are used to preserve flow in rivers downstream points of water abstractions, i.e., downstream of dams and intakes, and downstream of hydropower outlets in periods the power plant is not in operation. A large set of methods are available to set ecologically sound minimum flow regimes in bypass sections [9–11]. Furthermore, maximum ramping rates on discharge are frequently used to reduce the negative effects of rapid and frequent changes in the flow downstream of the hydropower outlets (also known as hydropeaking operations). Several studies have been carried out to propose ecologically acceptable flow regimes in downstream river sections exposed to hydropeaking operations, see for example [12, 13]. The operational and economic consequences of minimum flows and maximum ramping rates have been extensively studied in the literature by the use of hydropower scheduling models (see e.g., [14–16]), as well as the implications for optimal long-term reservoir management [17].

Reservoir constraints restrict reservoir management directly or indirectly to preserve certain conditions in reservoirs and dams. There are different reasons for imposing restrictions on the operation of the reservoirs, such as ecologic preservation of important spawning grounds, the risks of landslides and erosion along the shorelines, and to facilitate multiple water use (e.g., irrigation and recreational use). Perhaps the most common are reservoir constraints aimed at achieving certain water levels in the reservoirs in specific periods for landscape, recreational or agricultural reasons. Target filling degrees can be achieved by imposing hard limits on the water level, or by imposing restrictions on the discharge to implicitly restrict the water level in the reservoir. A few recent studies have analysed the ecological impacts of changing conditions in hydropower reservoirs (see e.g., [18, 19]), and a set of possible constraints on variation in the water level of reservoirs have been proposed in [20].

In this paper we consider two types of reservoir constraints: soft reservoir filling constraints and maximum reservoir ramping. Both constraints are state-dependent in the sense that they depend on the reservoir volume which is a state variable in the scheduling model to be used. The soft reservoir filling constraint induces a discharge limitation when the reservoir filling is below a given target and is therefore sometimes also referred to as a state-dependent maximum discharge constraint in the research literature. In the Nordic region, soft reservoir filling constraints are commonly imposed due to landscape considerations and recreational use. The recreational aspects are usually most pronounced in areas of popular tracking routes, where cabins are numerous and/or the reservoirs are used for fishing from boats. The reservoir constraints are often assigned to specific dates, aiming to reach certain levels of reservoir fillings before the high season for recreational use (the summer season). In other regions, similar types of constraints can be used to ensure sufficient water supply for drinking water or agricultural use. On the other hand, maximum reservoir ramping constraints are not commonly applied on Nordic hydropower plants today but may be required in the near future to reduce the magnitude and frequency of changes in the water level in the reservoirs. That the constraints depend on the water level in the reservoirs (i.e., are state-dependent) make them non-convex and thereby more challenging to model in linear programming based hydropower scheduling models.

1.2 Hydropower scheduling and modelling complexities

Because of the computational complexity of the hydropower scheduling (HS) problem, the problem is normally solved for different planning horizons and technical details [21]. Short-term models provide daily operational decision support by optimising operations over a short time horizon (days to weeks) including a high level of technical detail, but with no uncertainty. In contrast, long- and medium-term HS typically consider reservoir management under uncertainty over a planning horizon of several months up to several years, but comprise fewer details than the short-term models. The division between short- and medium/long-term is mainly to ensure reasonable computation times.

We are in this paper concerned with modelling simplifications of environmental constraints in medium-term hydropower scheduling (MTHS). In the Nordic region, the MTHS models optimise reservoir management for a single watercourse from the perspective of a price-taking, risk-neutral producer [22]. One of the main uses of MTHS is to calculate the opportunity cost of water (i.e., the water values) for use in the short-term models. In the short-term models, the water values (or cuts) represent the value of storing water in the reservoirs at the end of the planning horizon, which is crucial for the efficient use of water resources in the long run.

The computational efficient stochastic dual dynamic programming (SDDP) algorithm in [23] is the state-of-the-art method for solving stochastic, large-scale HS problems. However, a major drawback of SDDP is the need for a convex model formulation of the problem. This limits the method's ability to represent certain characteristics of the problem accurately, such as the complex interaction between power output and water [24] and unit commitment of generators [25]. Non-convex relationships in the problem are normally approximated (see e.g., [26, 27]) or omitted from the medium-term problem formulation, potentially leading to loss of precision in the water values. Since deterministic short-term models are designed to handle non-convexities, the operational decisions will respect technical functionality that was not considered when computing water values. Consequently, short-term operational decisions become inconsistent with the strategy applied when making the decisions, as discussed in [28, 29] in the context of approximate representation of transmission grid constraints. Similarly, some types of environmental constraints are difficult to incorporate when computing water values and may therefore lead to unnecessary operational inefficiencies [30]. Soft reservoir filling constraints are one type of environmental constraint that is often omitted or approximated in medium-term hydropower scheduling, due to the non-convex characteristics of the constraints [31].

1.3 Research scope and contribution

Our research considers environmental constraints on reservoir management. The research is motivated by the ongoing revisions of hydropower licenses in Norway, where reservoir constraints will likely be imposed in several hydropower systems. Recent revision processes have demonstrated the challenges of assessing diverging needs and pointed to a knowledge gap concerning the consequences of environmental constraints for power system operation. Furthermore, hydropower producers report challenges in handling complex environmental constraints in strategic reservoir management. In other words, improved modelling and knowledge of these types of constraints are needed both from a regulatory perspective considering revisions of licensing terms and from the producer's perspective considering hydropower system operation.

An underlying question is whether complex environmental constraints should be included in MTHS models, and what the operational implications of improving this aspect in the modelling could be. In [32] stochastic dynamic programming (SDP) [33] based modelling framework is used to accurately represent soft reservoir filling constraints (also referred to as state-dependent maximum discharge constraints) in the MTHS problem. The study demonstrates that the constraint has a significant impact on the water value curves and leads to a non-concave expected future profit function. Furthermore, an advancement of the SDDP algorithm (SDDiP [34, 35]) has been used to model this type of complex constraints in [36], demonstrating that more detailed modelling holds a potential for improved operational decision-making. Finally, the use of a tight linear approximation of the constraint in linear programming based MTHS models has been shown to give a good economic performance in [37].

We contribute to the existing literature by presenting a thorough assessment of the operational and economic implications of treating two types of environmental reservoir constraints, namely soft reservoir filling constraints and reservoir ramping rates, in the MTHS. To the best of our knowledge, few studies include reservoir ramping constraints in the hydropower scheduling problem and none consider the impacts of this type of constraint on the water value curves. Both constraints are state-dependent and may introduce significant non-convexities in the scheduling model. For this purpose, we apply a modelling framework based on SDP. The case study is conducted for two Norwegian water courses and six different power price expectations.

The remaining of this article is structured as follows. The methodology is presented in Section 2, including a description of the hydropower scheduling model, the environmental constraints and the case study. The results from the strategy phase, i.e., the water value curves from the SDP-model, are presented and discussed in Section 3, while the simulation results are presented in Section 4 (including a discussion of the value of using improved water values) before the article is concluded in Section 5.

2 Methodology

2.1 Hydropower Scheduling Model

The MTHS problem can be formulated as a multi-stage stochastic optimisation problem. The goal is to find the optimal operation planning policy to maximise profit under uncertainty, over a planning horizon of months to years. We assume a risk-neutral, price-taking hydropower producer who optimises operation given a presumed stationary future system state. Two exogenous stochastic variables are considered; the total weekly inflow into the system and the weekly average energy price. In our model setup, we assume that the stochastic variables can be described by discrete nodes using a Markov decision process. This objective and model setup are in line with standard practice by most Nordic hydropower producers.

The SDP-based modelling framework used in this study is well suited for accurate scheduling of hydropower systems with pronounced non-convexities. The method scales poorly due to the "curse of dimensionality", but is suitable for small hydropower systems. The main features of the modelling framework are presented here, while a more detailed description can be found in [32]. The scheduling problem is solved in two phases; a strategy phase and an operational simulation phase. In the strategy phase, the expected future value of storing water is calculated for a discrete set of system states using stochastic dynamic programming (SDP). The solution algorithm is based on SDP to allow for non-convex characteristics to be included in the problem formulation. In the SDP algorithm, the problem is decomposed into weekly decision problems, formulated as linear programming (LP) or mixed integer linear programming (MILP) problems, which are solved in sequence using backward recursion. The resulting strategy, namely the water values, is the computed expected marginal value of storing water for power production at a later time. In the simulation phase, a simulation of the system operation is conducted using the strategy calculated in the strategy phase. Here the weekly decision problems are optimised in a forward sequence for different inflow and price scenarios. The simulation phase serves as a proxy for simulating the short-term scheduling using water values computed in the strategy phase. The water values represent the alternative cost of production and are used as the marginal cost of hydropower production in the simulation. This is the only available information about the future in the simulation and without it, the model would not see any reason to save water for later periods.

2.1.1 Stochastic variables

Uncertainty in price and inflow is considered. A Markov chain with 10 nodes per stage is used in the SDP-algorithm, each node comprising a unique price and inflow value. An auto-regressive model is used to draw 10 000 scenarios, which are then clustered together using K-means clustering to create the Markov model, following the procedure described in [32].

2.1.2 The weekly decision problem

The weekly decision problem is solved in a backwards recursion in the strategy phase and a forward sequence in the simulation phase. Each decision problem is solved as a deterministic problem, where the stochastic state S^u (i.e., a defined weekly inflow and weekly average power price) and the reservoir state s^p (i.e., the reservoir volume at the beginning of the week) is given before the problem is solved. In the strategy phase, the decision problem is solved for all discrete stochastic states in the Markov model and a predefined set of discrete reservoir states. In the simulation phase, the decision problem is solved in a sequence for a range of scenarios, where the stochastic state is given by the weekly scenario values and the reservoir volume is given by the end reservoir state in the previous week. The base of the decision problem is equal in the strategy and simulation phase, while the inclusion of environmental constraints may vary between the phases, as further described in section 2.2. Both the environmental constraints considered in this work are dependent on the reservoir volume and can thus be classified as state-dependent constraints. That is, information related to these constraints is passed between decision stages (weeks) in the SDP algorithm through the reservoir volume state variable. The environmental constraints are described in detail in sections 2.1.3 and 2.1.4.

The weekly decision problem optimises the operation of the hydropower system to maximise profit while honouring all physical and regulatory constraints. The objective function (1) maximises the profit of the hydropower plants h over all time-steps k within the week, as well as the expected future profit of storing water for the remaining of the planning horizon, given by α_{t+1}. The income of the power producer is given by the power price λ_k in each time-step k, and the power production $p_{k,h}$, scaled for the number of hours in each time-step by F_k^H. The expected future profit α_{t+1} is a function of the resulting storage volume in the reservoirs at the end of the stage, as well as the stochastic state of the system. Each stage (week) is divided into K time steps of 3 hours.

$$\alpha_t(s^p, s_t^u) = \max\left\{ \sum_{k\in\mathcal{K}} F_k^H \lambda_k \sum_{h\in\mathcal{H}} p_{k,h} + \alpha_{t+1}(v_{h\in\mathcal{H},k=K}, s_t^u) \right\} \qquad (1)$$

The energy production is a function of the discharge, $q_{k,h,d}$, divided into $d \in D$ discharge segments with an associated efficiency $\eta_{h,d}$, as given in (2). The total discharge in each time-step is limited in (3) by the maximum discharge capacity $Q^{max}_{h,d}$ of each discharge segment d. The reservoir volume $v_{k,h}$ is bounded in (4) by the maximum and minimum reservoir volumes (V^{min}_h and V^{max}_h). The reservoir balance (5) keeps track of the change in water volume in each reservoir. Water may enter the reservoir as inflow $Z_{k,h}$ or as discharge from the reservoir above in the cascade H^{up}_h, and may exit the reservoir either as discharge $q_{k,h,d}$ or spillage $f_{k,h}$. F^C is a factor for converting the units. The decision variables are defined as positive variables, except α_{t+1} which is a free variable (6).

$$p_{k,h} - \sum_{d \in \mathcal{D}_h} \eta_{h,d} q_{k,h,d} = 0 \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{2}$$

$$q_{k,h,d} \leq Q^{max}_{h,d} \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H}, d \in \mathcal{D}_h \tag{3}$$

$$V^{min}_h \leq v_{k,h} \leq V^{max}_h \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{4}$$

$$\begin{aligned} v_{k,h} - v_{k-1,h} &+ F^C \Big(\sum_{d \in \mathcal{D}_h} q_{k,h,d} + f_{k,h} \Big) \\ -F^C &\sum_{j \in \mathcal{H}^{up}_h} \Big(\sum_{d \in \mathcal{D}_j} q_{k,j,d} \Big) = \; Z_{k,h} \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \end{aligned} \tag{5}$$

$$p, v, q, f \in \mathbb{R}^+, \quad \alpha_{t+1} \in \mathbb{R} \tag{6}$$

The expected future profit function is represented by convex combination of the expected future value points calculated in the previous stage $(t+1)$, as described in [32]. If the expected future value function is non-concave, special ordered sets of order 2 (SOS2) are used to ensure that adjacent points are used, turning the problem into a MILP [38]. Both the environmental constraints considered in this work are state-dependent and may introduce non-convex characteristics into the problem, which may result in a non-concave expected future value function in the weekly decision problem.

2.1.3 Modelling of the soft reservoir filling constraint

Soft reservoir filling constraints are frequently used in Norway to facilitate so-called "summer filling" requirements. The goal is to reach a certain filling degree in the reservoirs before the summer season for aesthetic, recreational and, sometimes, ecological reasons. The constraint is activated in spring, around the snow-melting, to ensure that the spring inflow is retained in the reservoirs for the summer season. Because of the large variations in seasonal and yearly inflow, discharge is constrained rather than imposing minimum restrictions on the water level in the reservoirs. This way, the power producers are not punished for not reaching the target filling degree in low inflow years. If an explicit reservoir limit had been used, the power producers could be forced to withhold water through winter to be sure to reach the reservoir threshold before summer. This could result in higher operational costs for the power system in the low-inflow period, as well as increased flood risk in high-inflow years. Instead, the regulation allows the hydropower producers to operate as normal through the winter season.

The soft reservoir filling constraints are formulated as logical conditions dependent on the water level in the reservoir, introducing nonlinear and non-convex relationships into the problem. The constraints are therefore challenging for hydropower producers to incorporate in stochastic models based on linear programming. A general formulation of the constraint is illustrated in Fig. 1.

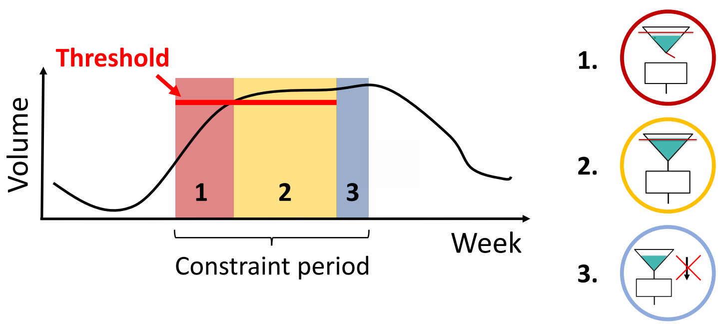


Fig. 1 Illustration of the soft reservoir filling constraints. The constraint period can be divided into three phases: (1) if the reservoir level is below the threshold, discharge from the reservoir is restricted, (2) if the reservoir level is above the threshold, the threshold becomes the minimum allowed reservoir level, and (3) the reservoir can not be drawn down, only filled up.

The soft reservoir filling constraint is defined for a specific period of the year, $t \in \tau \subset \mathcal{T}$, where $\mathcal{T}$ represent the entire planning horizon. This period is normally the spring/snow-melting and summer seasons in Norway. In the first phase of the constraint period, discharge is restricted to be below a given limit, Q_h^{lim}, as given in (7). The discharge limit is normally set to either zero discharge (i.e., stop the station) or minimum discharge (i.e., environmental flow). The discharge limitation is a requirement only if the water level in the reservoir is below a target level, V_h^{lim}. If the storage level in the reservoir reaches a given threshold within the constraint period, constraint (7) is replaced with a minimum reservoir level restriction (8). The constraint can also be followed by a period where no decrease in the reservoir level is permitted, as given by (9). Note that (9) not is state-dependent but defined for a part of the constraint period (time-dependent), as illustrated in Fig. 1.

$$\sum_{d \in \mathcal{D}_h} q_{k,h,d} \leq Q_h^{lim} \mid v_{k=1,h} < V_h^{lim} \qquad \forall \quad k \in \mathcal{K}, h = \hat{H} \tag{7}$$

$$v_{k,h} \geq V_h^{lim} \mid v_{k=1,h} \geq V_h^{lim} \qquad \forall \quad k \in \mathcal{K}, h = \hat{H} \tag{8}$$

$$v_{k,h} \geq v_{k-1,h} \qquad \forall \quad k = K, h = \hat{H} \tag{9}$$

The state-dependent logic in the regulation is handled in the SDP algorithm. In the strategy phase, the reservoir volume and the inflow at the beginning of the week are checked and, if the respective conditions are met, constraints (7) or (8) are added to the decision problem.

2.1.4 Modelling of the reservoir ramping constraint

The reservoir ramping constraint is imposed to avoid rapid draw-down of the water level in the reservoir. When water is drawn from the reservoir, the shoreline is left dry. The area of the dried-up shoreline depends on the shape of the reservoir. Reservoir ramping limitations are often given as the maximum permitted change in water level given in meters over a period. This can be converted into a maximum volume of water that can be discharged over a period. The amount of water that can be withdrawn for power production varies according to the shape of the reservoir making the constraint non-convex. The ramping constraint (10) is modelled as a volumetric constraint where the maximum allowed change in reservoir volume, $\delta_h^{max}(v_{k=1})$, is a function of the reservoir volume at the beginning of the week. The functional relationship between the ramping limit and the reservoir level is represented by a piece-wise linear function. The ramping limit is updated in the SPD-algorithm based on the reservoir state in each stage before the weekly decision problem is solved.

$$v_{k-1,h} - v_{k,h} \leq \delta_h^{max}(v_{k=1}) \qquad \forall \quad k \in \mathcal{K}, h = \hat{H} \tag{10}$$

2.2 Modelling framework and simulation set-up

The modelling framework is divided into two phases: a strategic phase and a simulation phase, as illustrated in Fig. 2. To evaluate the operational impacts of the environmental constraints, the SDP algorithm solves the decision problem formulated in 2.1.2 without and with the environmental constraints presented in section 2.1.3 and 2.1.4. The resulting water values are then used in a set of final simulations to assess the technical and economical impact of following the resulting strategies (see Fig. 2). The simulations are conducted for 1000 scenarios in a series. The model framework is implemented in Julia v1.5 using the Jump package [39] and the CPLEX 12.10 solver [40].

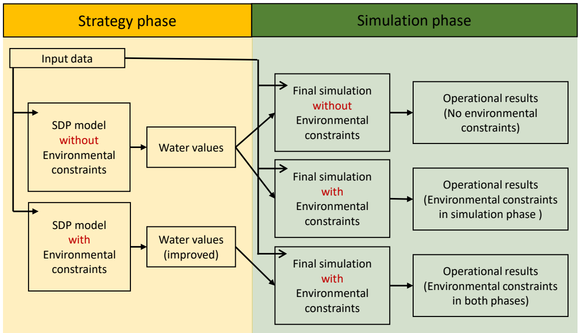


Fig. 2 Flow chart of the strategy phase and final simulation.

2.3 Case Study Description

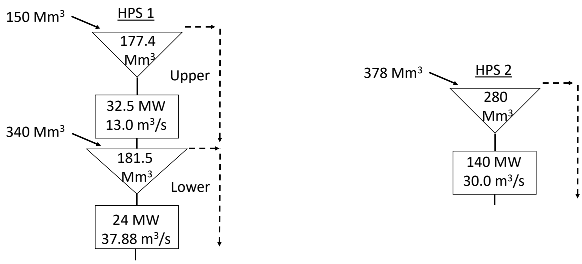
A case study of two different Norwegian water courses (HPS 1 and HPS 2) constrained by two types of environmental reservoir constraints is conducted to evaluate the operational and economic impacts of the constraints. Section 2.3.1 describes the two hydropower systems, the environmental regulation imposed on each of the systems and the set-up of the environmental cases, while section 2.3.2 describes the power price assumptions.

2.3.1 Description of the hydropower systems and the environmental regulation

The topology of HPS 1 is based on the Bergsdalen water course located in the west of Norway. The real system comprises several hydropower reservoirs and power plants, of which the two upper reservoirs and power plants are modelled here. HPS 2 is based on the Driva water course located in Trøndelag in mid-Norway. The technical specifications and topology of the two modelled systems are shown in Fig. 3. Data describing Norwegian hydropower systems are openly available from the Norwegian regulator (NVE) [1].

Both hydropower systems used in this case study are restricted by a soft reservoir filling constraint. For HPS 1, the lower of the two modelled reservoirs is constrained by the regulation. The regulation states that discharge is not permitted from when the "low-inflow period" ends (earliest in week 15 or at the latest from week 19). The discharge limitation is active until week 32, or until the storage volume in the reservoir is above the threshold; $V_h^{lim} = 146$ Mm^3. If the storage volume in the reservoir reaches 146 Mm^3, discharge is permitted as long as the water level stays above the threshold. From week 33 to week 35 the reservoir storage is not allowed to be reduced. In the model,

[1] https://www.nve.no/energi/energisystem/vannkraft/Modell-av-det-norske-vannkraftsystemet/

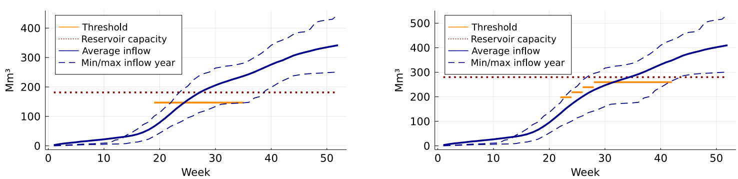


(a) HPS 1 (b) HPS 2

Fig. 3 Topology of HPS 1 (left) and HPS 2 (right). Reservoirs (triangles), plants (rectangles), and waterways for discharge (solid lines) and spillage (dashed lines) are shown, as well as maximal discharge (m^3/s), production (MW) and reservoir volumes (Mm^3), and average yearly inflow (Mm^3).

the soft reservoir filling constraint is assumed to be active from weeks 19-33, and from weeks 33-35, the reservoir management is restricted to ensure a non-decreasing water level in the reservoir. The constraint is illustrated in Fig. 4a.

The configuration of the soft reservoir filling constraint on HPS 2 differs somewhat from the regulation of HPS 1. The soft reservoir filling constraint is here defined from week 22 to week 42 but has a step-wise increasing threshold as illustrated in Fig. 4b. As described earlier, discharge is permitted if the water level reaches the defined thresholds, as long as the water level is kept above the threshold for the rest of the constraint period. If and when the threshold is met, depends on the reservoir filling when the constraint is activated and the inflow. The average accumulated inflow (historic data) and the most extreme high and low inflow-years are plotted together with the thresholds in Fig. 4. The plots show that the threshold should be possible to meet in average- and high-inflow years, but that it can be challenging in low-inflow years.



(a) HPS 1 (b) HPS 2

Fig. 4 Illustration of the reservoir thresholds (orange lines) given in the soft reservoir filling constraints for HPS 1 (left) and HPS 2 (right) together with an accumulated plot of the average historic inflow (blue lines) and the reservoir capacity (red dotted line).

Contrary to the soft reservoir filling constraints, the reservoir ramping constraints are not currently imposed in the concessions of the two case systems.

Reservoir ramping constraints have not traditionally been imposed on Norwegian reservoirs, but may become more relevant in the following years as new research on environmental conditions in hydropower reservoirs become available. Furthermore, reservoir ramping may become a problem in systems where turbine capacity and/or pump expansions are of interest. To the best of our knowledge, quantitative levels for acceptable water level variations in hydropower reservoirs are not available for different time scales. However, recent research classifies daily water level variations of $0.10 - 0.50\ m$ to represent a slightly modified reservoir [20]. Based on this, we have set a ramping restriction of $0.013\ m/3h$. Table 1 and 2 gives the ramping restriction in Mm^3 for HPS 1 and HPS 2 respectively.

Table 1 Reservoir segments and maximum down-ramping constraint HPS 1.

Reservoir volume $[Mm^3]$	Reservoir level [M.o.h]	Max ramping $[m/3h]$	Max ramping $[Mm^3/3h]$
00.0 - 25.2	560.2 - 570.0	-0.013	-0.0334
25.2 - 58.5	570.0 - 575.0	-0.013	-0.0868
58.6 - 99.5	575.0 - 580.0	-0.013	-0.1063
99.5 - 181.5	580.0 - 588.0	-0.013	-0.1333

Table 2 Reservoir segments and maximum down-ramping constraint HPS 2.

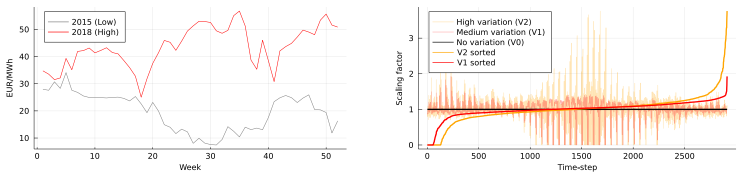
Reservoir volume $[Mm^3]$	Reservoir level [M.o.h]	Max ramping $[m/3h]$	Max ramping $[Mm^3/3h]$
00.0 - 53.6	645.0 - 649.0	-0.013	-0.1742
53.6 - 116.6	649.0 - 652.5	-0.013	-0.2340
116.6 - 202.0	652.5 - 657.0	-0.013	-0.2467
202.0 - 280.0	657.0 - 660.8	-0.013	-0.2668

Table 3 Definition of the environmental cases

Case name	Description
NoEnv	No environmental constraints are included in the modelling
ResFillSim	The soft reservoir filling constraint is included in the simulation phase
ResFill	The soft reservoir filling constraint is included in both the strategy and the simulation phase
RampSim	The reservoir ramping constraint is included in the simulation phase
Ramp	The reservoir ramping constraint is included in both the strategy and the simulation phase

2.3.2 Power price assumptions

Six different price models are used in the case study, as given in Table 4. The prices are based on two different historical price profiles and three levels of intra-week price variation. The price assumptions are used to evaluate the impact of different price expectations in medium-term scheduling. The Markov model and the sampled scenarios have been scaled so the average expected price matches the historical price series shown in Fig. 5a. In addition, the three different levels of price variations illustrated in Fig 5b are used. The price-variation plots show the scaling factors used to convert the weekly stochastic prices into a price per time-step in the decision problem.



(a) Seasonal profiles (b) Intra-week price scaling

Fig. 5 Plot of historical weekly power prices (left) from Nordpool for price-zone NO5 and the assumed intra-week price variation (right). The historical price series are chosen for their differences in seasonal profiles.

Table 4 Summary of the power price assumptions included in the case study

Price model	Yearly price profile	Intra-week price variation
High-V0	2018	No price variation
High-V1	2018	Medium price variation
High-V2	2018	High price variation
Low-V0	2015	No price variation
Low-V1	2015	Medium price variation
Low-V2	2015	High price variation

3 Results from the strategy phase

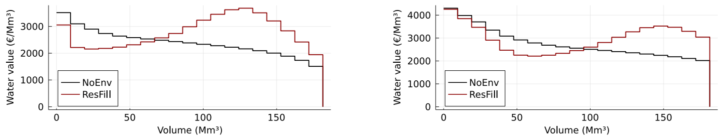
The main result from the strategy phase is the expected future value of storing water given different combinations of reservoir fillings and stochastic outcomes. The water values are the change in the expected future value with a marginal change in reservoir volume and are calculated under the different price assumptions for the two hydropower systems without any environmental constraints (NoEnv) and with each of the two environmental constraints (ResFill and Ramp cases). We here discuss the water value curves obtained for HPS 1 and HPS 2 for the reservoirs where the environmental constraints are imposed. The water values in the lower reservoir of HPS 1 depend on the reservoir filling in the upper and lower reservoir. The plots in this section are given for a medium filling degree of the upper reservoir.

Constraints on the operation of hydropower plants reduce the operational flexibility of the power plants in different ways. If the maximum discharge capacity is reduced (directly or implicitly), the operational time of the plant needs to increase to maintain a reasonable reservoir operation. For flexible hydropower plants, this normally implies that parts of the production may be shifted to periods with lower power prices, generally leading to lower water values. However, the constraints may also change the shape of the functional relation between water value and reservoir volume, and have varying impacts in different weeks.

3.1 Soft reservoir filling constraints

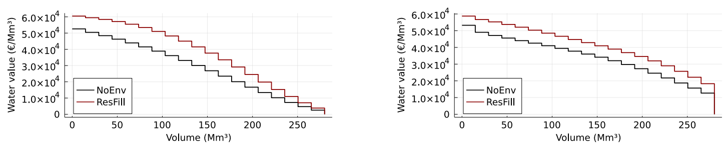
The water value curves are found to change considerably when the soft reservoir filling constraint is included in the strategy calculation. In the period when the environmental regulation is active, the water values are higher for reservoir fillings close to (from below) the reservoir level threshold compared to when the environmental constraint is not included in the modelling. This indicates a non-concave expected future profit function, as has previously been discussed in [32]. The non-concave characteristics are a result of the power production being limited below the threshold but permitted as soon as the threshold is reached. The magnitude of the changes in the water value curves depends on the price assumptions, the hydropower system and the configuration of the environmental constraint. For HPS 1, considerable changes are seen for all the price assumptions, as can be seen in Appendix A.1, but the largest impact is found for High seasonal price and high price variation (High-V2). Also for HPS 2 the largest changes are found for the High-V2 price, while smaller changes are seen for the Low seasonal price, see Appendix B.1.

The operation of the constrained reservoir is severely restricted when the soft reservoir filling constraint is active and the water level in the reservoir is below the threshold. In this period, no production is allowed and the strategy does therefore not impact the operation of the constrained reservoirs. However, the above-discussed changes in the water value curves can propagate back to earlier stages in the SDP backward recursion and change the optimal reservoir management before the constraint becomes active. Fig. 6 and Fig. 7 show the water value curves in selected weeks before the constraint becomes active assuming the Low-V0 price for HPS 1 and the High-V2 price for HPS 2. For both price assumptions, we see a distinct difference in the water value curves when the environmental constraint is considered. For HPS 2 under the High-V2 price assumption, we see a general increase in the water values, indicating a higher value of storing water to reach the reservoir threshold sooner. For HPS 1, under the Low-V0 price, there is a higher water value for high reservoir fillings close to the activation of the constraint, but a lower water value for low reservoir fillings. This indicates that, if the reservoir filling is low, the model finds it optimal to use more water before the constraint period starts, potentially making it more challenging to reach the threshold. Since weeks 15 and 18 are at the end of the winter period (low inflow period), the reservoir filling is normally low at this point, implying that the model in most scenarios (under the given assumptions) would produce more in the winter period rather than save water to try and reach the threshold earlier. This can be explained by the low expected power prices in the summer (i.e., constraint period), and thereby a low economic value of holding back production in the winter (high price period) to reach the threshold earlier.



(a) Week 18 (b) Week 15

Fig. 6 Water value curves for the lower reservoir in HPS 1 in the noEnv and ResFill cases under the Low-V0 price assumption.



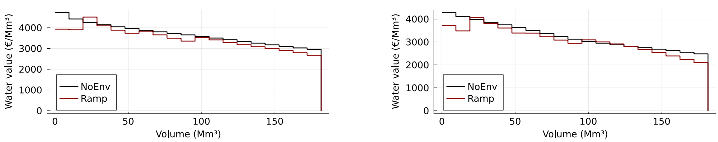
(a) Week 20 (b) Week 15

Fig. 7 Water value curves for the reservoir in HPS 2 in the noEnv and ResFill cases under the High-V2 price assumption.

3.2 Reservoir ramping constraint

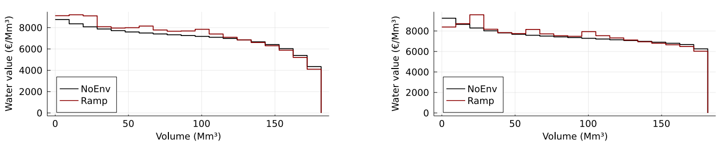
The reservoir ramping constraint limits how rapidly the reservoir can be drawn down, effectively imposing an upper discharge limitation that depends on the water level in the reservoir and the amount of incoming water to the reservoir (inflow and discharge from reservoirs higher up in the cascade). The results from the strategy calculation show some modifications on the water value curves, but not as distinct as for the soft reservoir filling constraint. For HPS 1, the water values are lower for high and low reservoir fillings in many of the weeks, as shown for weeks 6 and 11 for the Low-V2 price in Fig. 8. For high reservoir fillings, the water values may be reduced due to an increased risk of spillage. As a consequence of the ramping constraint, it may take longer to draw down the reservoir before high inflow periods, increasing the risk of spillage. The reduced water values for low reservoir fillings are a consequence of the strictness of the constraint for low reservoir fillings. Since the maximum ramping rate is a function of the reservoir filling, as given by Equation (10), the reservoir filling (in meters) changes more rapidly per volumetric unit of water for lower reservoir fillings. The ramping constraint thereby becomes stricter for low reservoir fillings, which results in lower water values for low reservoir fillings. For some weeks and price assumptions, the water values may also be higher when the ramping constraint is considered than when not, as shown for weeks 26 and 31 for HPS 1 for the High-V2 price in Fig. 9. The water values may also increase with increasing water levels in certain situations, however, the behaviour is much more subtle than for the ResFill cases. The non-convex behaviours of the expected future value functions are a result of the reservoir level-dependent ramping rate in Equation (10). Since the reservoir is divided into segments with different ratios between the water volume (Mm^3) and water level (m), the water value may increase when the water level reaches a new segment, as a consequence of the change this induces in the environmental constraint.

For HPS 2, the water value curves only change slightly when including the reservoir ramping constraint compared to when the constraint is not considered (Ramp cases compared to the NoEnv cases). The water values are close to equal, and in some cases slightly lower, than in the NoEnv cases. More water value curves for HPS 1 and HPS 2 are provided in Appendix A.2 and B.2.



(a) Week 6 (b) Week 11

Fig. 8 Water value curves for HPS 1 in the NoEnv and Ramp cases for the Low-V2 price assumption.



(a) Week 26 (b) Week 31

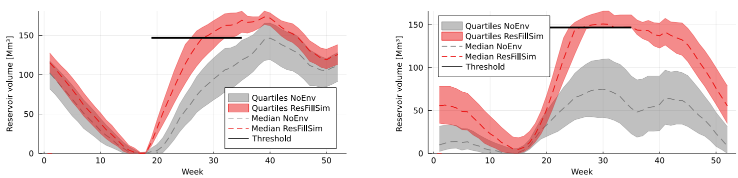
Fig. 9 Water value curves for HPS 1 in the NoEnv and Ramp cases for the High-V2 price assumption.

4 Results from the simulation phase

This section discusses the operation of the hydropower plants considering the two types of environmental constraints separately. We first discuss the implications of the constraints in cases ResFillSim and RampSim. Secondly, we discuss the impacts of improved planning, i.e., cases ResFill and Ramp. The presented results are for 1000 simulated scenarios with different price and inflow realisations. Average income, production and spillage for all the cases under different price assumptions are given in Table C1 and Table C2 in Appendix C.

4.1 Soft reservoir filling constraints

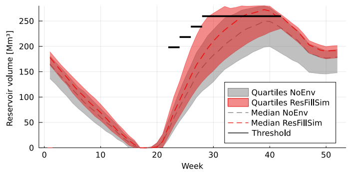
Fig. 10 and Fig. 11 show that the reservoir management change considerably when the soft reservoir filling constraint is considered in the simulation (ResFillSim cases). This is a consequence of the discharge being restricted from a given date until the reservoir threshold is met. Still, we also see that the changes vary under different price expectations. For the Low-V2 price, the changes in the reservoir management are less pronounced than for the High-V2 price. The reservoirs are drawn down almost completely during the winter for the Low seasonal price because of high power prices in the winter, while the lower power prices in the spring/summer period cause the reservoirs to fill up during the high inflow period (spring). This trend is also seen in the NoEnv cases (see Fig. 10a and Fig. 11a), even though production is not restricted in these cases. On the contrary, we see that the reservoirs are not filled up as much in the NoEnv cases for the High seasonal price (see Fig. 10a and Fig. 11a). This is a result of higher power prices in the spring/summer period, making it optimal to produce more in this period if the power production is not restricted (NoEnv case). This causes a larger difference in the reservoir management between the ResFillSim cases and the NoEnv cases for the High seasonal price than for the Low seasonal price.



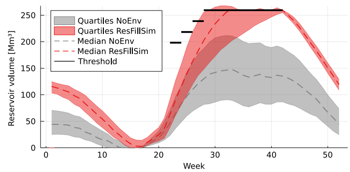
(a) Low-V2 price (b) High-V2 price

Fig. 10 Simulated reservoir storage levels over the year for reservoir 2 in HPS 1, without (grey) and with (red) the soft reservoir filling constraint.

Even though it is not a violation of the constraint to not meet the threshold, the purpose of the constraint is only fully achieved when the water level reaches the threshold. Fig. 12 shows the share of the scenarios that are above the threshold for each of the cases per week. For most of the price assumptions, only a small share of the scenarios reach the threshold when the environmental constraint is not included (NoEnv cases). By including the soft reservoir filling constraint in the simulation phase (ResFillSim cases), the water levels are lifted and at least 60% of the scenarios reach the threshold within the end of the



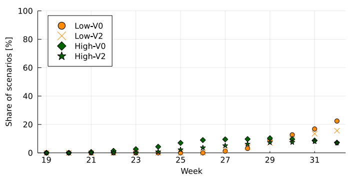
(a) Low-V2 price



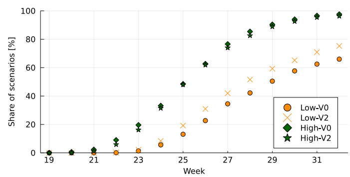
(b) High-V2 price

Fig. 11 Simulated reservoir storage levels over the year for HPS 2, without (grey) and with (red) the soft reservoir filling constraint.

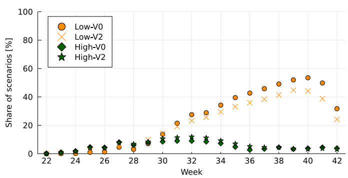
constraint period for all the price assumptions. The improvement of including the constraint is especially large for the High seasonal price.



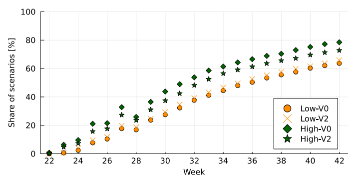
(a) HPS 1, NoEnv



(b) HPS 1, ResFillSim



(c) HPS 2, NoEnv



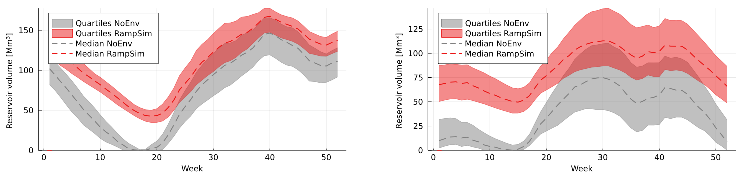
(d) HPS 2, ResFillSim

Fig. 12 The share of the scenarios (in %) for which the reservoir filling is above the threshold in each week within the constraint period.

The economic costs (i.e., the losses in profit) associated with the soft reservoir filling constraint are found to vary considerably depending on the price assumptions. In general, the loss in profit is highest when there are high power prices during the summer period (the High seasonal price profile) and increase with higher price variation. For the High price with different levels of intra-week price variation, the loss associated with the soft reservoir filling constraint varies from 1.5-2.7% for HPS 1 and from 8-14.7% for HPS 2. For the Low price, on the other hand, the economic loss is considerably smaller: from 0.8-1.5% for HPS 1 and 0.8-2.4% for HPS 2. It is reasonable that the larger economic impacts are found for the price assumptions with relatively high prices within the constraint period (the price cases with the High seasonal profile and/or high price variations). Furthermore, we notice that HPS 2 has a higher associated loss (in percent) of the constraint than HPS 1. This can be explained by the physical and regulatory differences between the systems. In short, the reservoir threshold is more difficult to reach in HPS 2, and the system is therefore restricted by the discharge limitation for longer periods.

4.2 Reservoir ramping constraint

The water level in the reservoir in HPS 1 is kept considerably higher for all the price cases when the reservoir ramping constraint is included in the simulation phase (RampSim), as shown for the Low-V2 and High-V2 prices in Fig. 13. For HPS 2, on the other hand, the ramping constraint only leads to minor changes in reservoir management. The different impacts of the ramping constraint on the two systems are a consequence of the shapes of the reservoirs, implicitly leading to a stricter limitation of the discharge capacity for low reservoir fillings in HPS 1 than in HPS 2. The impact of the ramping constraint on the reservoir management is found to be slightly stronger for higher price variability.

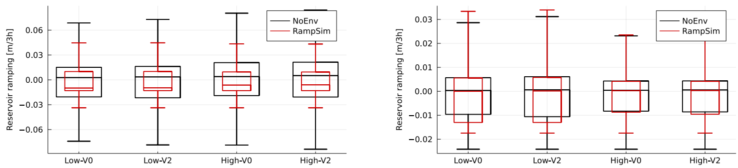


(a) Low-V2 price (b) High-V2 price

Fig. 13 Simulated reservoir storage levels over the year for reservoir 2 in HPS 1, without (grey) and with (red) the soft reservoir filling constraint.

The reservoir ramping constraint ensures that the reservoir is drawn down more carefully for lower reservoir fillings to avoid rapid changes in water level, resulting in higher reservoir fillings. Fig. 14 shows that the ramping constraint (the RampSim cases) effectively reduces the most extreme reductions in water level for both the hydropower systems, but especially for HPS 1. Even though the (negative) extremes are reduced, we notice that there is some down-ramping violating the constraint ($< -0.013\frac{m}{3h}$). This is a consequence of inaccurate modelling of the state-dependencies of the constraint, where the volumetric boundary for the ramping constraint is set for a week at the time, based on the reservoir filling at the beginning of the week.

Even though the reservoir management is changed considerably as a consequence of the ramping constraint, the economic loss due to the constraint is considerably lower than what was found for the soft reservoir filling constraint. The loss in profit ranges from 0.74-1.95% for HPS 1 and from 0.5-2.49% for HPS 2. The economic losses are found to be highest for the Low seasonal price and increase slightly with the level of price variability.

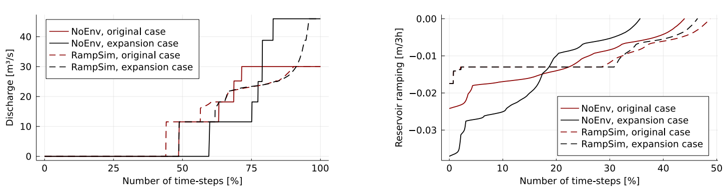


(a) HPS 1 (b) HPS 2

Fig. 14 Change in reservoir volume per time step (3h) without (NoEnv in black) and with (RampSim in red) the reservoir ramping constraint.

4.2.1 Expansion case HPS 2

To further investigate the impacts of the reservoir ramping constraint, an expansion case was conducted for HPS 2, increasing the turbine capacity by 50% compared to the original system design. By drastically increasing the discharge and power production capacity, the hydropower plant's capability to respond to short-term price variations is improved. At the same time, this implies that more water can be drawn from the reservoir in each time step, potentially resulting in a more severe ramping of the water level in the reservoir. The expansion case is evaluated for the Low-V2 price. Fig. 15a shows the duration curve of the discharge in the original and the extension cases without and with the ramping constraint. Fig. 15b shows the duration curve of the down-ramping of the reservoir for the same cases. We see that the increased discharge capacity is utilised in 15-20% of the hours in the NoEnv (extension) case, but only in about 5% of the hours in the RampSim case because of the ramping constraint. The profit increases by 7.2 % in the expansion case if no environmental constraints are considered (comparing the NoEnv cases), but only with 1.7 % when the ramping constraint is included in the simulation (comparing the RampSim cases). In other words, the ramping constraint drastically reduces the potential value of a turbine capacity expansion for this system.



(a) Discharge (b) Reservoir ramping

Fig. 15 Duration curves of the discharge and reservoir ramping over all simulated scenarios for the Original NoEnv case (red, solid line), the Original RampSim case (red, dashed line), the Expansion NoEnv case (black, solid line) and the Expansion RampSim case (black, dashed line).

4.3 Impacts of improved planning

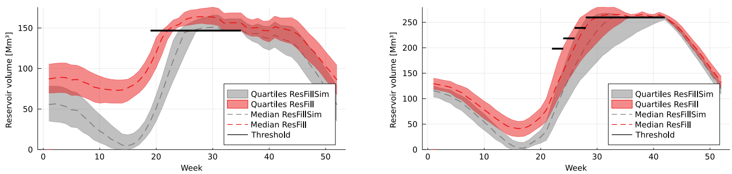
The impact of improved planning can be evaluated by comparing the simulated operation in the cases where the environmental constraint only are included in the simulation (ResFillSim and RampSim cases) to the cases where the constraints are considered in both the strategy and simulation phase (ResFill and Ramp cases). Average results for all the cases are given in Table C1 and Table C2 in Appendix C. The above-discussed economic impacts are based on the assumption that the hydropower producers ignore the environmental constraints in the medium-term reservoir scheduling (i.e., do not plan for the constraints in advance). If the producers can include the environmental constraints in the strategy phase, either accurately as discussed here or by the use of approximations as in [37], the associated loss could potentially be reduced.

4.3.1 Soft reservoir filling constraints

The economic gain from improved planning strongly depends on the price assumptions. For the High seasonal price (with different levels of price variation), we find that the expected profit of HPS 1 is improved by 0.5-1.4% by considering the soft reservoir filling constraint in the medium-term scheduling, at the most reducing the economic loss of the constraint with around 50%. For HPS 2 the economic performance improves by 0.6-2.6%, reducing the loss by up to 15%. For the Low seasonal price (with different levels of price variations), we found a lower economic impact of the soft reservoir filling constraint. Under these price assumptions, no significant economic gain is found from improved modelling. For some price expectations, we even get a slightly reduced profit when planning for the constraint (<0.1%). This is likely to be a result of a slight under-representation of the probability of low inflow scenarios in the Markov chain used in the SDP-model. As the Markov model is made by K-means clustering, the most extreme scenarios may have lower inflows than what is captured in the stochastic model, resulting in a slight underestimate of extreme inflows and a modest underestimation of the risk of running out of water in the strategy.

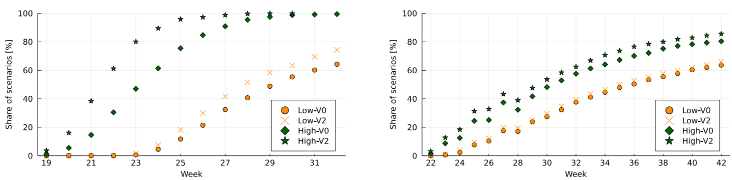
The High-V2 price gives the largest economic gain of improved planning for both HPS 1 and HPS 2. In these cases, the water levels in the reservoirs are kept higher through the winter when planning for the constraint compared to when not planning for the constraint (ResFill compared to ResFillSim), as shown in Fig. 16. The same tendency, but with a lower magnitude is found for the High-V1 and High-V0 prices. For the case runs with a High seasonal price expectation, the reservoir threshold is met in 80-100% of the scenarios for both HPS 1 and HPS 2 when planning for the constraint, as shown in Fig. 17. This is an improvement compared to the number of scenarios that reach the threshold in the constraint period when the constraint only is included in the simulation, as shown in Fig. 18. Furthermore, the threshold is met earlier in the constraint period for HPS 1 when planning for the constraint.

For the Low seasonal price, only small adjustments in the reservoir management are found. For HPS 1 slightly lower reservoir fillings can be observed when planning for the constraint. This is in line with the differences in the calculated water values, as discussed in section 3.1. As a consequence, the effectiveness of the environmental constraint is not found to improve with improved planning. For HPS 1, the fulfilment of the constraint is even slightly worse when a low seasonal price is expected (when comparing the ResFill to the ResFillSim results), as shown in Fig. 18.



(a) HPS 1, High-V2 (b) HPS 2, High-V2

Fig. 16 Simulated reservoir storage levels when considering the soft reservoir filling constraint in the simulation (ResFillSim in grey) compared to when considering the constraint in the strategy and simulation phase (ResFill in red).

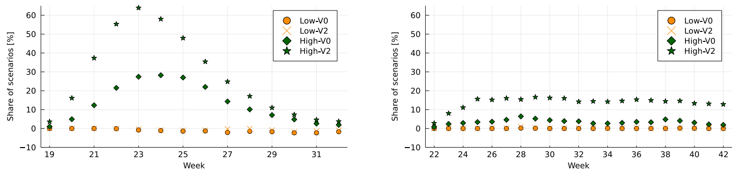


(a) HPS 1 (b) HPS 2

Fig. 17 The share of the scenarios (in %) for which the reservoir filling is above the threshold in each week within the constraint period.

4.3.2 Reservoir ramping constraint

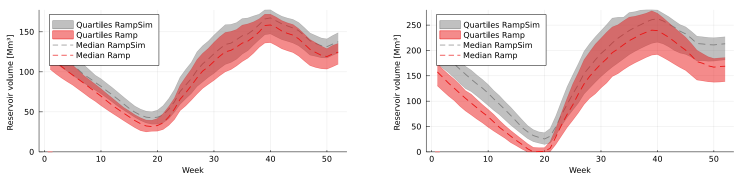
Only small to no economic improvements are achieved by including the reservoir ramping constraint in the medium-term scheduling. For HPS 1, the profit is increased by 0.12-0.22%, while for HPS 2 a slightly reduced profit is found for all the price assumptions (<0.1%). As discussed for the soft reservoir filling constraint, this is a result of the discretised inflow model leading to a slight underestimate of extreme inflows in the strategy. In the HPS 2 expansion case, on the other hand, an increased profit of 0.53% is achieved when planning for the reservoir ramping constraint. An economic gain of including the reservoir ramping constraint in the medium-term scheduling, even though



(a) HPS 1 (b) HPS 2

Fig. 18 The increase in the share of scenarios for which the reservoir filling is above the threshold in each week within the constraint period when considering the constraint in the strategy (i.e., the difference between the ResFill case and the ResFillSim case).

small, is found for the price expectations with the highest relative cost of the ramping constraint. In these situations, a change in reservoir management can be observed. For the Low-V2 price, the reservoir filling is kept a bit lower when planning for the constraint, as shown in Fig. 19a for HPS 1. A similar trend is seen for the HPS 2 Expansion case, where the reservoir filling is kept lower when the ramping constraint is considered in the planning compared to when the constraint only is considered in the simulation, as shown in Fig. 19b. Finally, as the reservoir ramping constraint is a hard constraint directly targeting the underlying goal of the constraint, the fulfilment of the constraint is not impacted by if the constraint is included in the strategy phase or not.



(a) HPS 1, Low-V2 price (b) HPS 2 Expansion case, Low-V2 price case

Fig. 19 Simulated reservoir storage levels for the RampSim case (in grey) and the Ramp case (in red).

5 Conclusion

We have studied the operational and economic implications of two types of environmental reservoir constraints: a soft reservoir filling constraint and a reservoir ramping constraint, and evaluated the value of including the constraints in the medium-term hydropower scheduling. We find that a framework combining strategy computation by SDP and system simulation is useful to assess the impact of non-convex and nonlinear elements in medium-term hydropower scheduling. The impacts of the two environmental constraints are evaluated for two different hydropower systems under six different price model assumptions.

The results from the strategy calculations show that the water value curves change considerably for some of the cases, but that the magnitude depends on the expected power price, the hydropower system and the type of constraint. The soft reservoir filling constraint gives higher water values for reservoir fillings close to the constraint threshold, in line with what has been shown in previous studies [32]. Furthermore, the impacts increase with increasing price variation and are found to be strongly dependent on the seasonal profile of the power price. The reservoir ramping constraint, on the other hand, is only found to induce smaller changes in the water value curves. Still, also for this constraint, the state-dependent and non-convex characteristics of the constraint cause the water values to increase with increasing reservoir levels in certain situations, demonstrating a non-concave expected future value function.

For the soft reservoir filling constraints the simulation results demonstrate a considerable change in reservoir management due to the constraint. The difference in reservoir management and economic performance is found to vary between the different price assumptions. In most cases, the economic loss associated with the constraint is partly reduced when the constraint is included in the medium-term scheduling, as also has been shown in previous research [36, 37]. The economic gain from improved planning is found to be strongly dependent on the expected seasonal profile of the power price and the level of price variation. Furthermore, we find that the achievement of the constraint also is impacted by the price expectations. A higher expected cost of the constraint (i.e., of being below the reservoir threshold) gives a stronger incentive to save water through the winter, resulting in a better fulfilment of the purpose of the constraint.

The reservoir ramping constraint is found to have small economic impacts, even though the reservoir management changes considerably under certain price assumptions. The highest costs of this type of constraint are found for a "traditional" seasonal profile with high prices in winter and lower prices in spring/summer. The economic loss increases slightly with higher price variation. Furthermore, the costs depend on the shape of the reservoir (which impacts the strictness of the constraint) and the operational flexibility of the power plant. A considerably higher cost of the constraint was found when the turbine capacity was increased by 50% for one of the hydropower plants in the case study (HPS 2). Improved planning, by including the reservoir ramping constraint in the medium-term scheduling model was found to give small to no economic improvements.

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References

[1] IEA. Hydropower Special Market Report. Paris: IEA; 2021. Available from: https://www.iea.org/reports/hydropower-special-market-report/executive-summary.

[2] Dimanchev EG, Hodge JL, Parsons JE. The role of hydropower reservoirs in deep decarbonization policy. Energy Policy. 2021 8;155. https://doi.org/10.1016/j.enpol.2021.112369.

[3] Köhler B, Ruud A, Aas Ø, Barton DN. Decision making for sustainable natural resource management under political constraints – the case of revising hydropower licenses in Norwegian watercourses. Civil Engineering and Environmental Systems. 2019;36(1):17–31. https://doi.org/10.1080/10286608.2019.1615475.

[4] Kosnik LRD. Balancing Environmental Protection and Energy Production in the Federal Hydropower Licensing Process. Land Economics. 2010;86(3):444–466. https://doi.org/10.2139/ssrn.1004572.

[5] Glachant JM, Saguan M, Rious V, Douguet S, Gentzoglanis E. Regimes for granting rights to use hydropower in Europe. European University Institute; 2014. Available from: https://cadmus.eui.eu/bitstream/handle/1814/33653/2014_RR_Hydropower.pdf.

[6] Pracheil BM, Levine AL, Curtis TL, Aldrovandi MSP, Uría-Martínez R, Johnson MM, et al. Influence of project characteristics, regulatory pathways, and environmental complexity on hydropower licensing timelines in the US. Energy Policy. 2022 3;162:112801. https://doi.org/10.1016/J.ENPOL.2022.112801.

[7] IPBES. Summary for policymakers of the global assessment report on biodiversity and ecosystem services; 2019. Available from: https://zenodo.org/record/3553579.

[8] World Commission on Dams. Dams and development: a new framework for decision-making - The report of the World Commission on Dams. London: Earthscan; 2000. Available from: https://www.routledge.com/Dams-and-Development-A-New-Framework-for-Decision-making---The-Report-of/Dams/p/book/9781853837982.

[9] Poff NL, Allan JD, Bain MB, Karr JR, Prestegaard KL, Richter BD, et al. The Natural Flow Regime. BioScience. 1997;47(11):769–784. https://doi.org/10.2307/1313099.

[10] Acreman M, Dunbar MJ. Defining environmental river flow requirements – a review. Hydrology and Earth System Sciences. 2004;8(5):861–876.

https://doi.org/10.5194/HESS-8-861-2004.

[11] Linnansaari T, Monk W, Baird D, Curry R. Review of approaches and methods to assess Environmental Flows across Canada and internationally. Canada: DFO Canadian Science Advisory Secretary Research Document 2012/039; 2012. Available from: www.dfo-mpo.gc.ca/csas-sccs/.

[12] Moreira M, Hayes DS, Boavida I, Schletterer M, Schmutz S, Pinheiro A. Ecologically-based criteria for hydropeaking mitigation: A review. Science of the Total Environment. 2019;657:1508–1522. https://doi.org/10.1016/j.scitotenv.2018.12.107.

[13] Bakken TH, Harby A, Forseth T, Ugedal O, Sauterleute JF, Halleraker JH, et al. Classification of hydropeaking impacts on Atlantic salmon populations in regulated rivers. River Research and Applications. 2021;https://doi.org/10.1002/RRA.3917.

[14] Guisández I, Pérez-Díaz JI, Wilhelmi JR. Assessment of the economic impact of environmental constraints on annual hydropower plant operation. Energy Policy. 2013;p. 1332–1343. https://doi.org/10.1016/j.enpol.2013.05.104.

[15] Guisández I, Pérez-Díaz JI, Wilhelmi JR. Approximate formulae for the assessment of the long-term economic impact of environmental constraints on hydropeaking. Energy. 2016;112. https://doi.org/10.1016/j.energy.2016.06.076.

[16] Olivares MA, Haas J, Palma-Behnke R, Benavides C. A framework to identify Pareto-efficient subdaily environmental flow constraints on hydropower reservoirs using a grid-wide power dispatch model. Water Resources Research. 2015;51(5):3664–3680. https://doi.org/10.1002/2014WR016215.

[17] Guisández I, Pérez-Díaz JI, Nowak W, Haas J. Should environmental constraints be considered in linear programming based water value calculators? International Journal of Electrical Power and Energy Systems. 2020;117. https://doi.org/10.1016/j.ijepes.2019.105662.

[18] Hirsch PE, Eloranta AP, Amundsen PA, Brabrand Å, Charmasson J, Helland IP, et al. Effects of water level regulation in alpine hydropower reservoirs: an ecosystem perspective with a special emphasis on fish. Hydrobiologia. 2017 6;794(1):287–301. https://doi.org/10.1007/S10750-017-3105-7/TABLES/1.

[19] Eloranta AP, Finstad AG, Helland IP, Ugedal O, Power M. Hydropower impacts on reservoir fish populations are modified by environmental variation. Science of The Total Environment. 2018 3;618:313–322. https:

//doi.org/10.1016/J.SCITOTENV.2017.10.268.

[20] Bakken TH, Beck V, Schönfelder LH, Charmasson J, Thrane JE, Lindholm M, et al. Testing and evaluation of a HYMO classification system for lakes and reservoirs - Proposed new and modified hydromorphological (HYMO) classification system. Trondheim, Norway: SINTEF-report: 01365; 2019. Available from: https://ntnuopen.ntnu.no/ntnu-xmlui/handle/11250/2642179.

[21] Helseth A, de Melo ACG. Scheduling Toolchains in Hydro- Dominated Systems - Evolution, Current Status and Future Challenges. Trondheim: SINTEF; 2020. Available from: https://www.sintef.no/publikasjoner/publikasjon/1823349/.

[22] Gjelsvik A, Belsnes M, Haugstad A. An algorithm for stochastic medium-term hydrothermal scheduling under spot price uncertainty. Proceedings 13th Power Systems Computation Conference, 1999, Vol2. 1999;p. 1079–1085.

[23] Pereira MVF, Pinto LMVG. Multi-stage stochastic optimization applied to energy planning. Mathematical Programming. 1991;52(1-3):359–375. https://doi.org/10.1007/BF01582895.

[24] Diniz AL, Piñeiro Maceira ME. A four-dimensional model of hydro generation for the short-term hydrothermal dispatch problem considering head and spillage effects. IEEE Transactions on Power Systems. 2008;23(3):1298–1308. https://doi.org/10.1109/TPWRS.2008.922253.

[25] van Ackooij W, Danti Lopez I, Frangioni A, Lacalandra F, Tahanan M. Large-scale unit commitment under uncertainty: an updated literature survey. Annals of Operations Research. 2018 12;271(1):11–85. https://doi.org/10.1007/s10479-018-3003-z.

[26] Pereira-Bonvallet E, Püschel-Løvengreen S, Matus M, Moreno R. Optimizing Hydrothermal Scheduling with Non-Convex Irrigation Constraints: Case on the Chilean Electricity System. In: Energy Procedia. vol. 87. Elsevier Ltd; 2016. p. 132–140. Available from: https://doi.org/10.1016/j.egypro.2015.12.342.

[27] Cerisola S, Latorre JM, Ramos A. Stochastic dual dynamic programming applied to nonconvex hydrothermal models. European Journal of Operational Research. 2012 5;218(3):687–697. https://doi.org/10.1016/j.ejor.2011.11.040.

[28] Brigatto A, Street A, Valladão DM. Assessing the cost of time-inconsistent operation policies in hydrothermal power systems. IEEE Transactions on Power Systems. 2016;32(6):4541–4550. https://doi.org/10.1109/TPWRS.

2017.2672204.

[29] Rosemberg AW, Street A, Garcia JD, Valladao DM, Silva T, Dowson O. Assessing the Cost of Network Simplifications in Long-Term Hydrothermal Dispatch Planning Models. IEEE Transactions on Sustainable Energy. 2022 1;13(1):196–206. https://doi.org/10.1109/TSTE.2021.3106810.

[30] Schäffer LE, Adeva-Bustos A, Bakken TH, Helseth A, Korpås M. Modelling of Environmental Constraints for Hydropower Optimization Problems - A Review. International Conference on the European Energy Market, EEM. 2020 9;2020-September. https://doi.org/10.1109/EEM49802.2020.9221918.

[31] Helseth A. Environmental Constraints in Seasonal Hydropower Scheduling - Survey and Feasibility. Trondheim: HydroCen; 2019. Available from: https://ntnuopen.ntnu.no/ntnu-xmlui/handle/11250/2609531.

[32] Schäffer LE, Helseth A, Korpås M. A stochastic dynamic programming model for hydropower scheduling with state-dependent maximum discharge constraints. Renewable Energy. 2022 7;194:571–581. https://doi.org/10.1016/J.RENENE.2022.05.106.

[33] Bellman R. Dynamic programming and stochastic control processes. Information and Control. 1958 9;1(3):228–239. https://doi.org/10.1016/S0019-9958(58)80003-0.

[34] Zou J, Ahmed S, Sun XA. Stochastic dual dynamic integer programming. Mathematical Programming. 2019;175(1-2):461–502. https://doi.org/10.1007/s10107-018-1249-5.

[35] Hjelmeland MN, Zou J, Helseth A, Ahmed S. Nonconvex Medium-Term Hydropower Scheduling by Stochastic Dual Dynamic Integer Programming. IEEE Transactions on Sustainable Energy. 2019;10(1):481–490. https://doi.org/10.1109/TSTE.2018.2805164.

[36] Helseth A, Mo B, Hagenvik HO. Nonconvex Environmental Constraints in Hydropower Scheduling. 2020 International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2020 - Proceedings. 2020 8;https://doi.org/10.1109/PMAPS47429.2020.9183590.

[37] Helseth A, Mo B, Hans, Hågenvik O, Schäffer LE. Hydropower Scheduling with State-Dependent Discharge Constraints: An SDDP Approach. Journal of Water Resources Planning and Management. 2022 9;148(11):04022061. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001609.

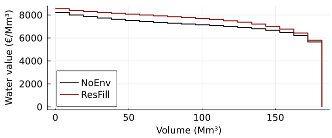
[38] D'Ambrosio C, Lodi A, Martello S. Piecewise linear approximation of functions of two variables in MILP models. Operations Research Letters. 2010 1;38(1):39–46. https://doi.org/10.1016/j.orl.2009.09.005.

[39] Dunning I, Huchette J, Lubin M. JuMP: A Modeling Language for Mathematical Optimization. SIAM Review. 2015 8;59(2):295–320. https://doi.org/10.1137/15M1020575.

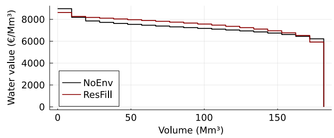
[40] IBM.: CPLEX optimizer. IBM. Last accessed 02.03.2023. https://www.ibm.com/academic/topic/data-science?ach_id=6fe17098-43df-4a9d-8412-3377286841a3.

Appendix A Water Value curves HPS 1

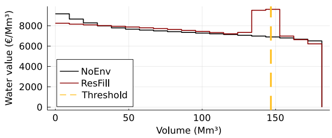
A.1 Soft reservoir filling constraint



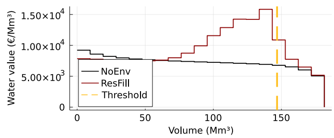
(a) HPS 1 week 40



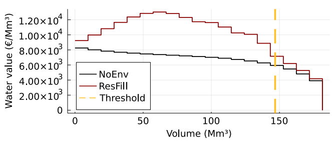
(b) HPS 1 week 35



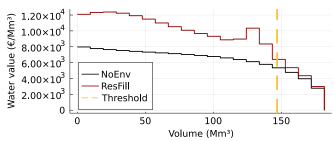
(c) HPS 1 week 32



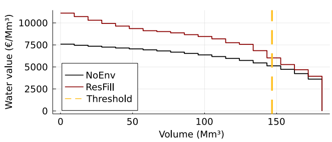
(d) HPS 1 week 28



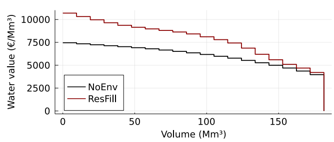
(e) HPS 1 week 24



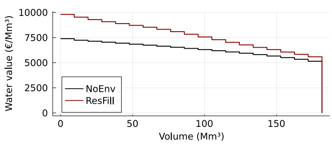
(f) HPS 1 week 22



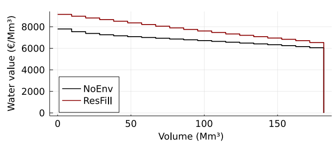
(g) HPS 1 week 19



(h) HPS 1 week 18

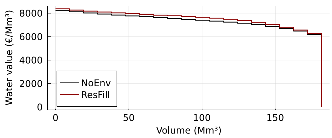


(i) HPS 1 week 15

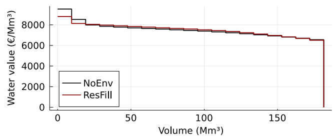


(j) HPS 1 week 10

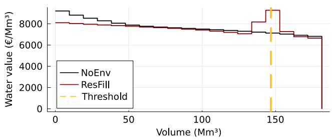
Fig. A1 Water value curves for the lower reservoir in HPS 1 in the NoEnv and ResFill cases under the High-V2 price assumption.



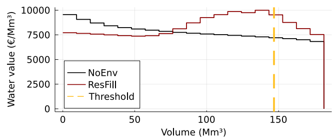
(a) HPS 1 week 40



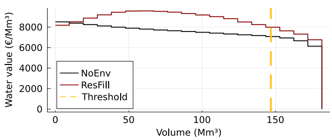
(b) HPS 1 week 35



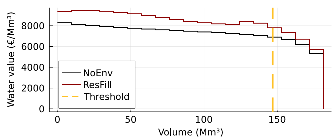
(c) HPS 1 week 32



(d) HPS 1 week 28



(e) HPS 1 week 24



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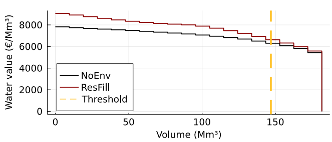
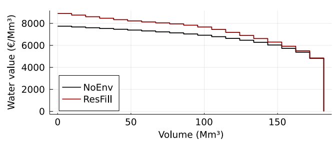
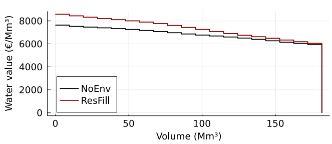


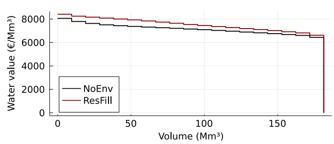
(g) HPS 1 week 19



(h) HPS 1 week 18

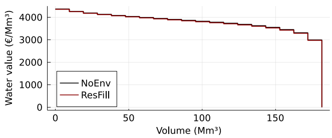


(i) HPS 1 week 15

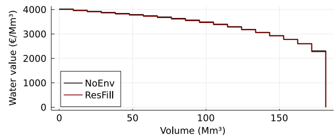


(j) HPS 1 week 10

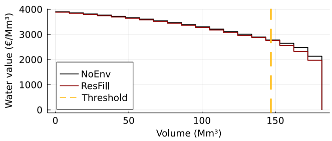
Fig. A2 Water value curves for the lower reservoir in HPS 1 in the NoEnv and ResFill cases under the High-V0 price assumption.



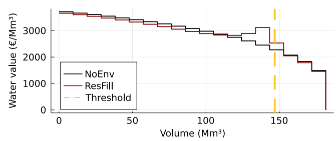
(a) HPS 1 week 40



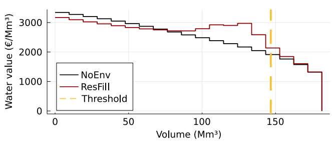
(b) HPS 1 week 35



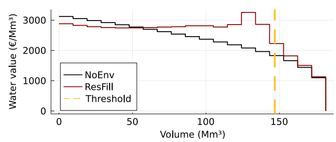
(c) HPS 1 week 32



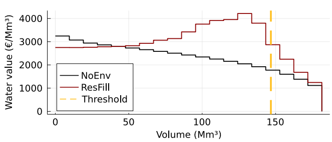
(d) HPS 1 week 28



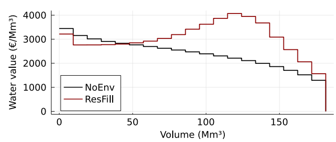
(e) HPS 1 week 24



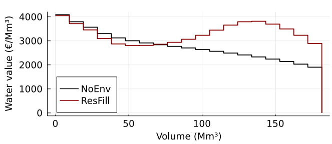
(f) HPS 1 week 22



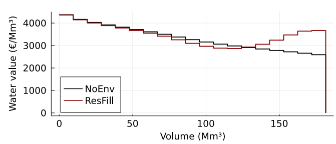
(g) HPS 1 week 19



(h) HPS 1 week 18

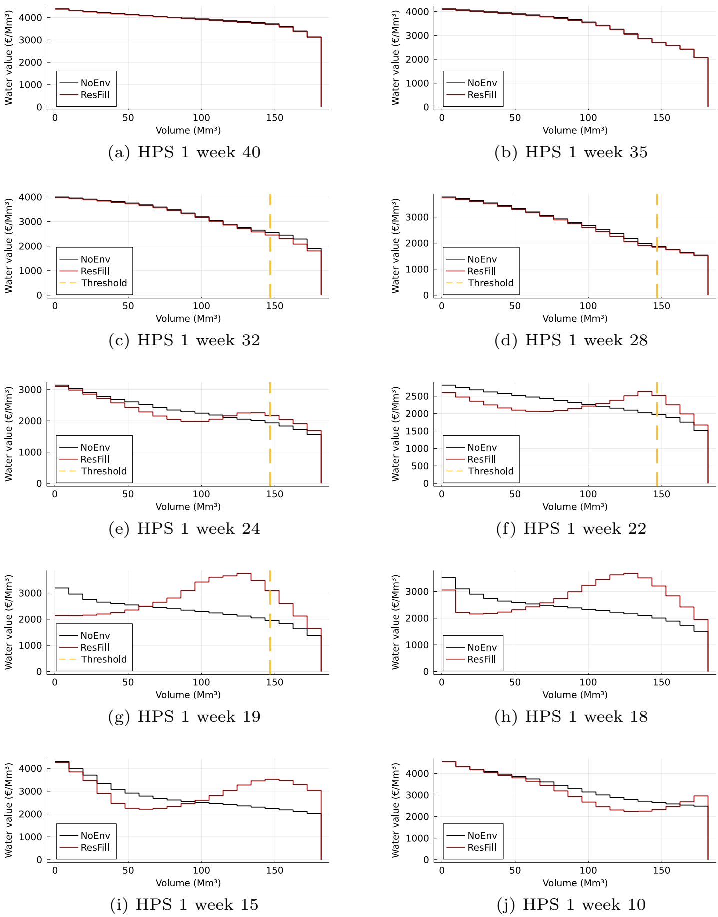


(i) HPS 1 week 15



(j) HPS 1 week 10

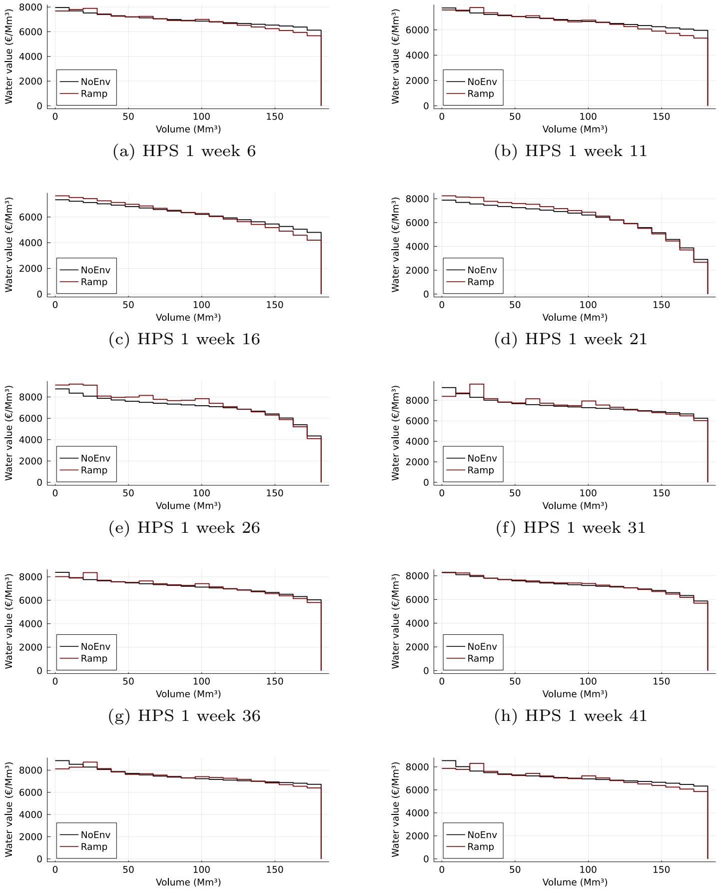
Fig. A3 Water value curves for the lower reservoir in HPS 1 in the NoEnv and ResFill cases under the Low-V2 price assumption.



(a) HPS 1 week 40
(b) HPS 1 week 35
(c) HPS 1 week 32
(d) HPS 1 week 28
(e) HPS 1 week 24
(f) HPS 1 week 22
(g) HPS 1 week 19
(h) HPS 1 week 18
(i) HPS 1 week 15
(j) HPS 1 week 10

Fig. A4 Water value curves for the lower reservoir in HPS 1 in the NoEnv and ResFill cases under the Low-V0 price assumption.

A.2 Reservoir ramping constraint



(a) HPS 1 week 6 (b) HPS 1 week 11

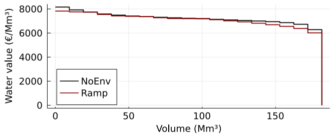
(c) HPS 1 week 16 (d) HPS 1 week 21

(e) HPS 1 week 26 (f) HPS 1 week 31

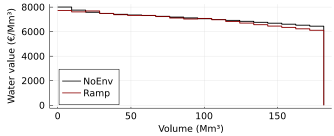
(g) HPS 1 week 36 (h) HPS 1 week 41

(i) HPS 1 week 46 (j) HPS 1 week 51

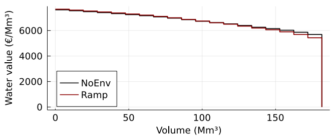
Fig. A5 Water value curves for the lower reservoir in HPS 1 in the NoEnv and Ramp cases under the High-V2 price assumption.



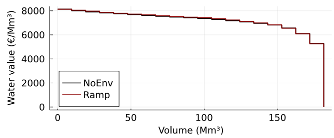
(a) HPS 1 week 6



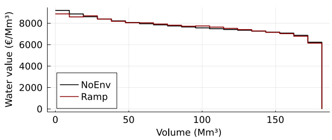
(b) HPS 1 week 11



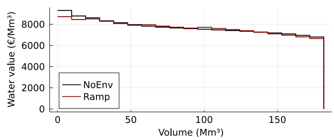
(c) HPS 1 week 16



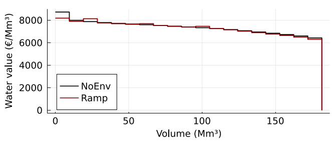
(d) HPS 1 week 21



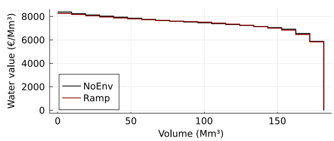
(e) HPS 1 week 26



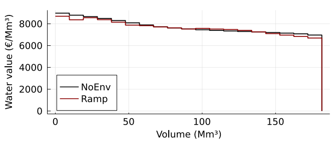
(f) HPS 1 week 31



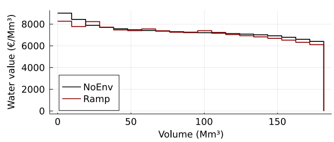
(g) HPS 1 week 36



(h) HPS 1 week 41

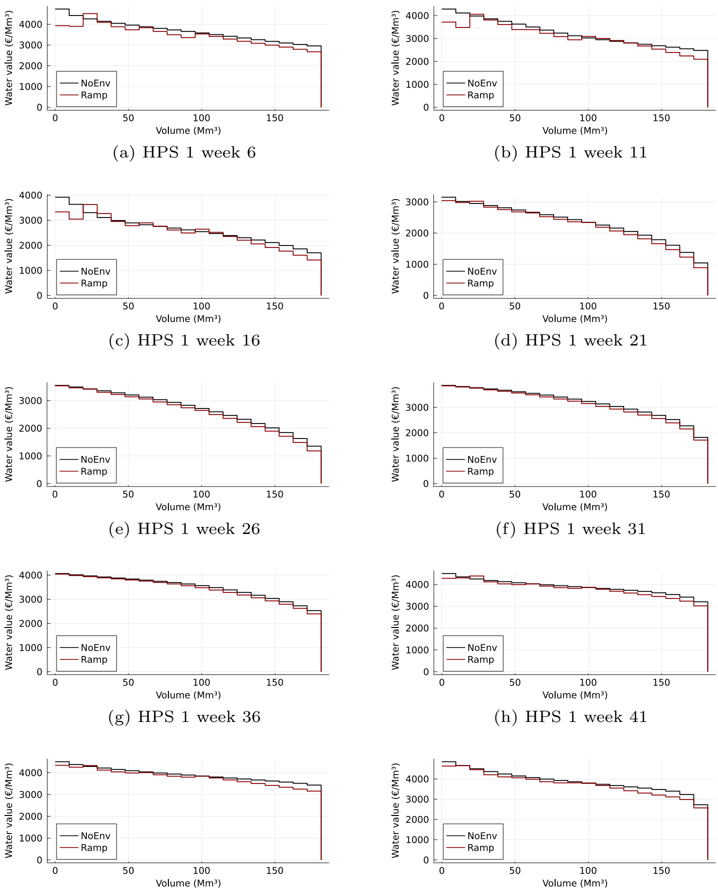


(i) HPS 1 week 46



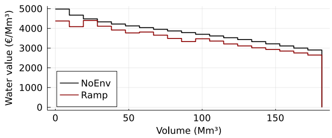
(j) HPS 1 week 51

Fig. A6 Water value curves for the lower reservoir in HPS 1 in the NoEnv and Ramp cases under the High-V0 price assumption.

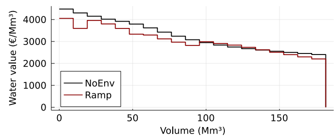


(a) HPS 1 week 6
(b) HPS 1 week 11
(c) HPS 1 week 16
(d) HPS 1 week 21
(e) HPS 1 week 26
(f) HPS 1 week 31
(g) HPS 1 week 36
(h) HPS 1 week 41
(i) HPS 1 week 46
(j) HPS 1 week 51

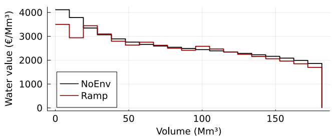
Fig. A7 Water value curves for the lower reservoir in HPS 1 in the NoEnv and Ramp cases under the Low-V2 price assumption.



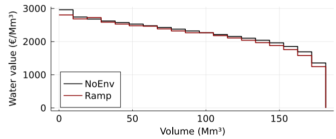
(a) HPS 1 week 6



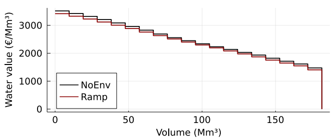
(b) HPS 1 week 11



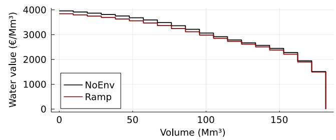
(c) HPS 1 week 16



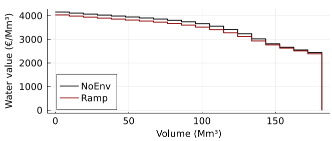
(d) HPS 1 week 21



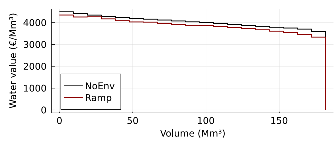
(e) HPS 1 week 26



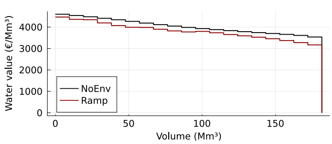
(f) HPS 1 week 31



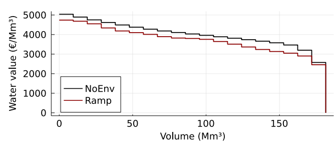
(g) HPS 1 week 36



(h) HPS 1 week 41



(i) HPS 1 week 46

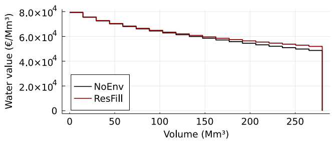


(j) HPS 1 week 51

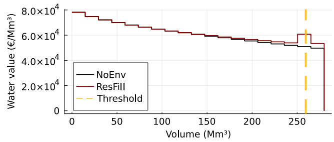
Fig. A8 Water value curves for the lower reservoir in HPS 1 in the NoEnv and Ramp cases under the Low-V0 price assumption.

Appendix B Water Value curves HPS 2

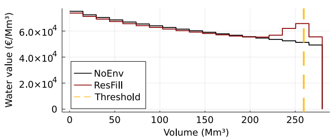
B.1 Soft reservoir filling cosntraint



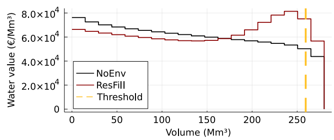
(a) HPS 2 week 44



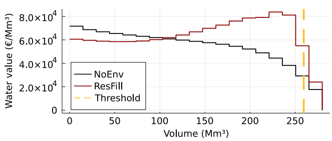
(b) HPS 2 week 42



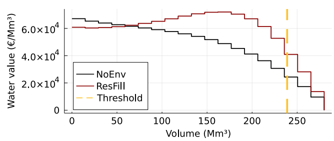
(c) HPS 2 week 38



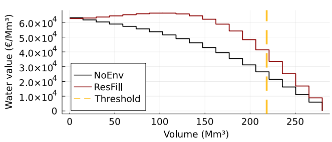
(d) HPS 2 week 32



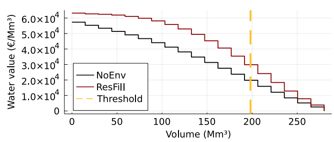
(e) HPS 2 week 28



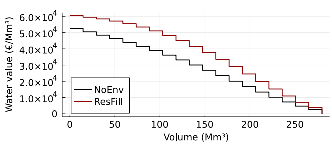
(f) HPS 2 week 26



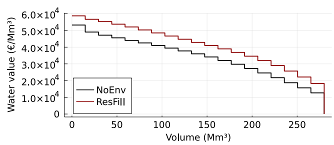
(g) HPS 2 week 24



(h) HPS 2 week 22

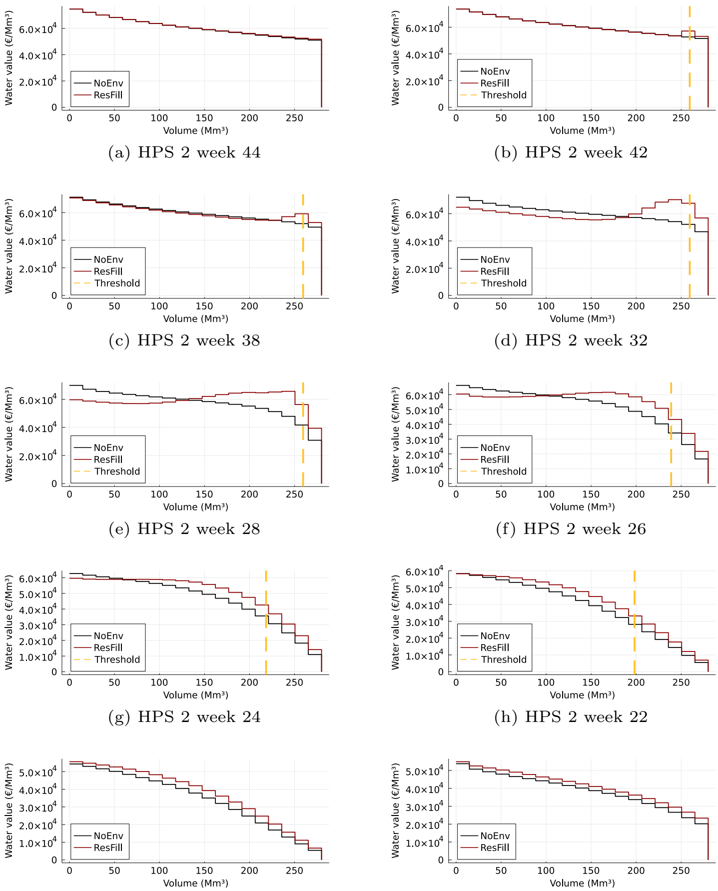


(i) HPS 2 week 20



(j) HPS 2 week 15

Fig. B9 Water value curves for the reservoir in HPS 2 in the NoEnv and ResFill cases under the High-V2 price assumption.



(a) HPS 2 week 44 (b) HPS 2 week 42

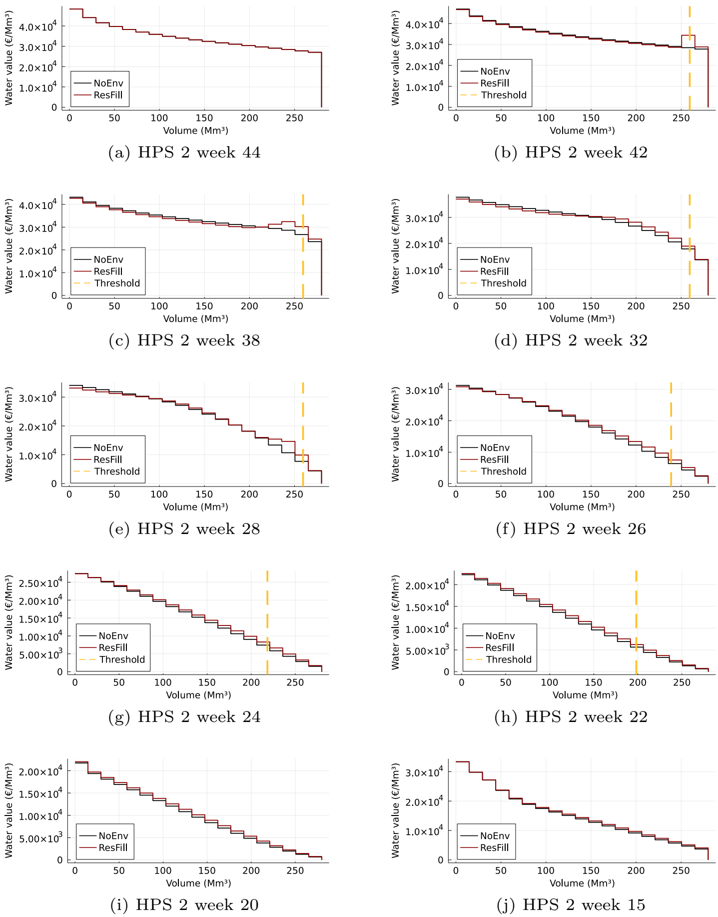
(c) HPS 2 week 38 (d) HPS 2 week 32

(e) HPS 2 week 28 (f) HPS 2 week 26

(g) HPS 2 week 24 (h) HPS 2 week 22

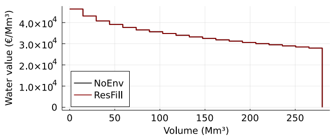
(i) HPS 2 week 20 (j) HPS 2 week 15

Fig. B10 Water value curves for the reservoir in HPS 2 in the NoEnv and ResFill cases under the High-V0 price assumption.

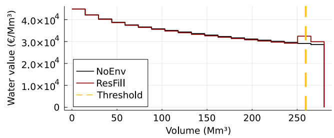


(a) HPS 2 week 44
(b) HPS 2 week 42
(c) HPS 2 week 38
(d) HPS 2 week 32
(e) HPS 2 week 28
(f) HPS 2 week 26
(g) HPS 2 week 24
(h) HPS 2 week 22
(i) HPS 2 week 20
(j) HPS 2 week 15

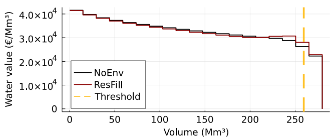
Fig. B11 Water value curves for the reservoir in HPS 2 in the NoEnv and ResFill cases under the Low-V2 price assumption.



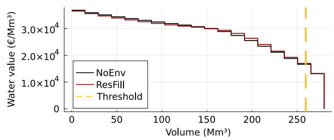
(a) HPS 2 week 44



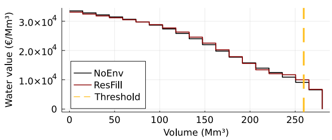
(b) HPS 2 week 42



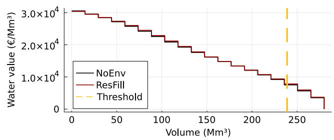
(c) HPS 2 week 38



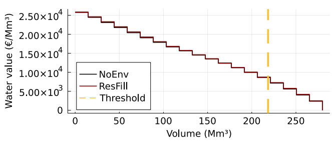
(d) HPS 2 week 32



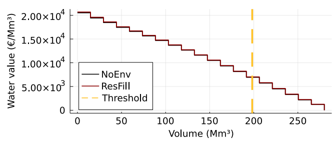
(e) HPS 2 week 28



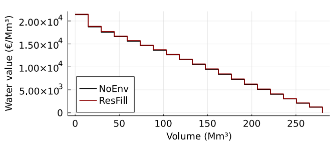
(f) HPS 2 week 26



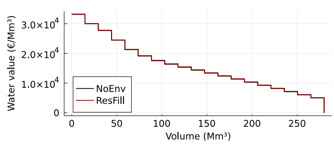
(g) HPS 2 week 24



(h) HPS 2 week 22



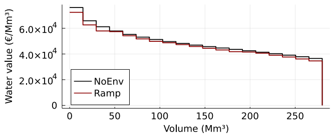
(i) HPS 2 week 20



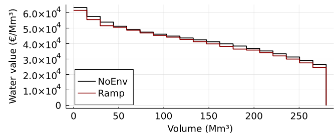
(j) HPS 2 week 15

Fig. B12 Water value curves for the reservoir in HPS 2 in the NoEnv and ResFill cases under the Low-V0 price assumption.

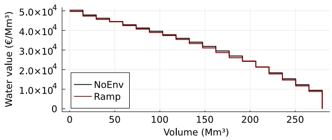
B.2 Reservoir ramping constraint



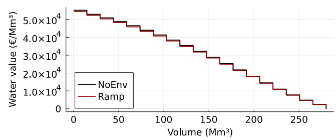
(a) HPS 2 week 6



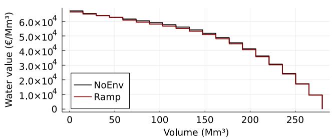
(b) HPS 2 week 11



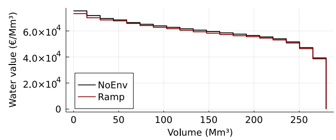
(c) HPS 2 week 16



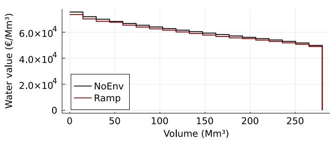
(d) HPS 2 week 21



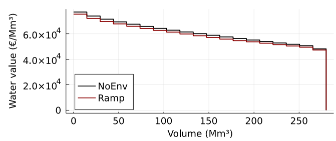
(e) HPS 2 week 26



(f) HPS 2 week 31



(g) HPS 2 week 36



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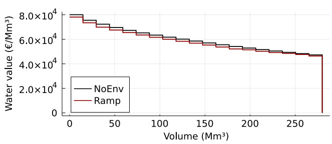
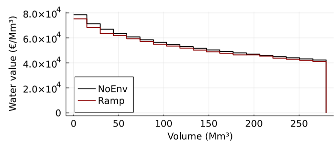


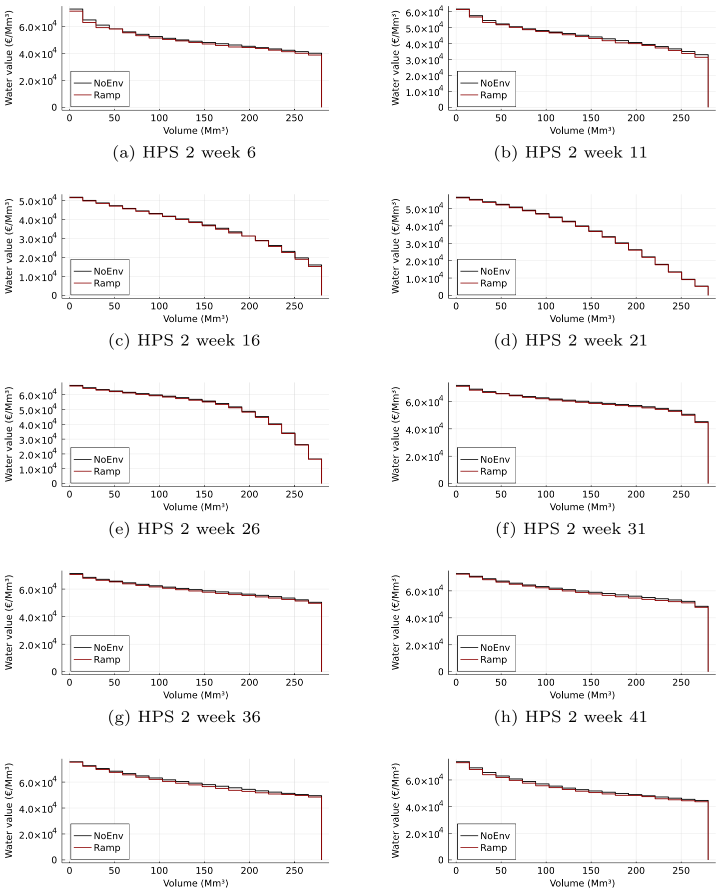
(i) HPS 2 week 46



(j) HPS 2 week 51

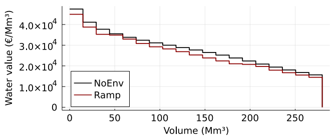
Fig. B13 Water value curves for the reservoir in HPS 2 in the NoEnv and Ramp cases under the High-V2 price assumption.

Appendix C Simulation results



(a) HPS 2 week 6
(b) HPS 2 week 11
(c) HPS 2 week 16
(d) HPS 2 week 21
(e) HPS 2 week 26
(f) HPS 2 week 31
(g) HPS 2 week 36
(h) HPS 2 week 41
(i) HPS 2 week 46
(j) HPS 2 week 51

Fig. B14 Water value curves for the reservoir in HPS 2 in the NoEnv and Ramp cases under the High-V0 price assumption.



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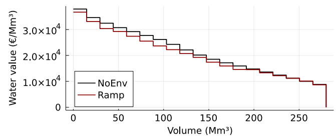

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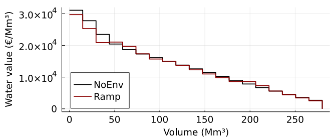

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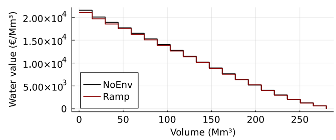

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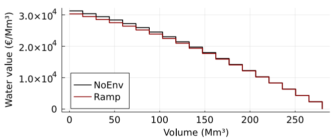

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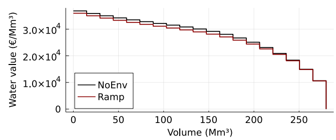

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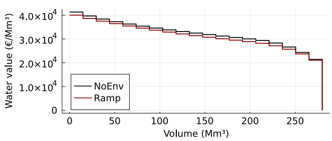
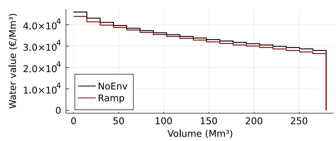


(g) HPS 2 week 36



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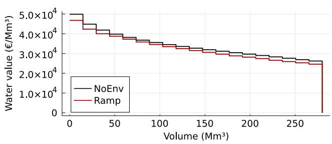

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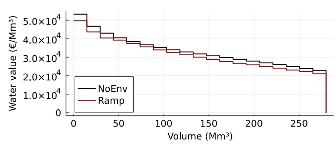
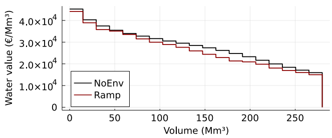


(j) HPS 2 week 51

Fig. B15 Water value curves for the reservoir in HPS 2 in the NoEnv and Ramp cases under the Low-V2 price assumption.



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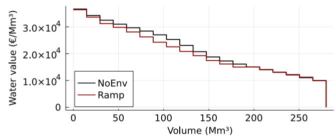

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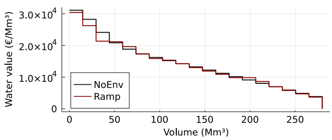

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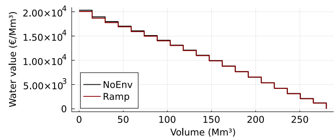

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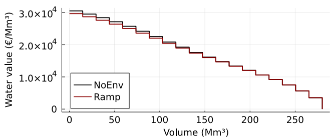

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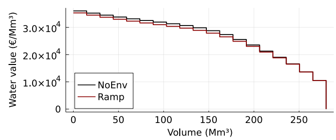

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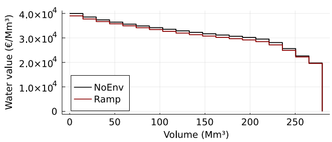
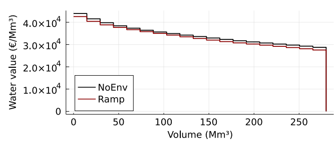
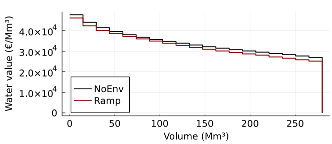


(g) HPS 2 week 36



(h) HPS 2 week 41



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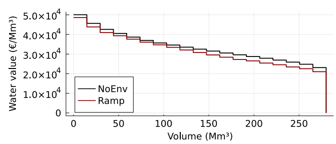

(j) HPS 2 week 51

Fig. B16 Water value curves for the reservoir in HPS 2 in the NoEnv and Ramp cases under the Low-V0 price assumption.

Table C1 Simulation results soft reservoir filling constraint cases

			Income [M.Eur/yr]			**Production [GWh/yr]**			**Spillage [Mm]**		
			NoEnv	*ResFillSim*	*ResFill*	*NoEnv*	*ResFillSim*	*ResFill*	*NoEnv*	*ResFillSim*	*ResFill*
HPS 1	Low	V0	5.09	5.05	5.04	191.33	191.28	191.24	0.04	0.07	0.06
		V1	5.19	5.14	5.13	191.11	191.04	191.01	0.03	0.07	0.06
		V2	5.38	5.30	5.30	190.74	190.65	190.63	0.02	0.08	0.08
	High	V0	10.02	9.86	9.91	191.78	191.79	191.80	0.04	0.13	0.31
		V1	10.74	10.52	10.61	191.26	191.26	191.18	0.02	0.14	0.47
		V2	11.60	11.29	11.45	190.76	190.68	190.51	0.00	0.13	0.61
HPS 2	Low	V0	12.70	12.60	12.61	503.08	499.58	499.57	1.05	2.86	2.89
		V1	13.02	12.87	12.87	500.56	496.63	496.61	1.33	3.34	3.37
		V2	13.53	13.21	13.22	497.68	493.91	493.87	1.59	3.62	3.67
	High	V0	25.97	23.89	24.04	504.14	495.60	494.23	1.95	4.98	6.04
		V1	27.66	24.54	24.84	500.05	493.54	491.31	2.04	5.21	7.07
		V2	29.67	25.32	25.98	497.86	491.95	487.87	2.03	4.98	8.54

Table C2 Simulation average results reservoir ramping constraint cases

			Income [M.Eur/yr]			**Production [GWh/yr]**			**Spillage [Mm]**		
			NoEnv	*RampSim*	*Ramp*	*NoEnv*	*RampSim*	*Ramp*	*NoEnv*	*RampSim*	*Ramp*
HPS 1	Low	V0	5.09	5.00	5.01	191.33	192.05	192.09	0.04	0.05	0.05
		V1	5.19	5.10	5.11	191.11	191.90	191.93	0.03	0.05	0.04
		V2	5.38	5.28	5.29	190.74	191.63	191.67	0.02	0.08	0.05
	High	V0	10.02	9.95	9.96	191.78	192.15	192.16	0.04	0.12	0.11
		V1	10.74	10.64	10.66	191.26	191.72	191.75	0.02	0.11	0.09
		V2	11.60	11.46	11.48	190.76	191.42	191.44	0.00	0.10	0.09
HPS 2	Low	V0	12.70	12.44	12.44	503.08	507.78	508.46	1.05	1.26	1.10
		V1	13.02	12.72	12.72	500.56	505.49	506.26	1.33	1.63	1.42
		V2	13.53	13.19	13.18	497.68	503.22	503.91	1.59	1.90	1.69
	High	V0	25.97	25.84	25.82	504.14	507.75	507.71	1.95	2.21	2.04
		V1	27.66	27.47	27.45	500.05	504.02	504.02	2.04	2.27	2.13
		V2	29.67	29.33	29.31	497.86	502.78	502.69	2.03	2.30	2.14

Paper IV

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Paper IV

Optimal Operation of Hydro-Dominated Power Systems with Environmental Constraints

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***Abstract*—This paper studies the operation of a small renewable and hydro-dominated power system when introducing environmental constraints. The risk of rationing and the local price formation is investigated using a stochastic, cost-minimising optimisation model for long-term operation of a regional renewable power system with reservoir hydropower. The model is applied to a case study based on Norwegian hydropower plants with state-dependent, environmental constraints on reservoir management. The results demonstrate the reduced operational flexibility of the hydropower system and an increased risk of rationing, when the environmental constraint is imposed. In some of the case runs, the long-term management of the constrained reservoir is found to change considerable, but is also shown to be sensitive to the value of lost load, the transmission capacity and the total wind power generation.**

***Index Terms*—Electricity Price, Environmental Constraints, Hydropower, Flexible Power Generation, Security of Electricity Supply**

I. Introduction

The European Green Deal defines ambitious targets for both climate change mitigation and broader environmental sustainability. A sustainable power system must ensure affordable, high quality power supply at the lowest possible environmental and social costs. Environmental requirements are often imposed on power plants to ensure sustainable operation by preserving ecological, social and recreational interests of the surrounding area. Such requirements may reduce the plants' operational flexibility, thereby reducing the plants' capability to adjust production according to the market.

The operation of hydropower plants modify the surrounding ecosystems by altering the flow regime downstream the hydropower outlet and the water levels in the reservoirs. Flow alterations and associated ecological consequences are major environmental concerns [1], [2]. Minimum flows and maximum ramping rates are among the most commonly applied mitigation measures, but a wide range of environmental constraints may be imposed on hydropower plants to limit the negative impacts of operation [3].

While important to preserve ecological and social interests, environmental constraints may in some situations be conflicting with security of power supply. Many existing power systems, such as the Norwegian, rely on hydropower plants to deliver load-following power generation and reserve capacity to avoid blackouts and maintain the power quality in situations of unexpected events [4]. The trade-off between environmental and economic considerations is one of the core challenges when deciding on new terms in revision processes for hydropower licenses in Northern Europe [5]. Furthermore, available flexibility in the power system and concerns for secure power system operations have become more pressing in recently conducted revisions. Because of hydropower plants' importance for security of electricity supply in the whole Nordic region, the consequences of new or adjusted environmental constraints to the power system should be thoroughly assessed on local, regional, and national levels.

Limited research addresses the implications of environmental constraints in competitive power markets dominated by hydropower, and less so the importance of accurate representation of such constraints in the long-term operations of hydropower. Existing research mainly consider environmental constraints in the form of minimum flow requirements and ramping restrictions. Reduced profit for hydropower producers due to such constraints have been assessed using both short- and long-term scheduling models, see e.g. [6]–[8]. A framework to evaluate the cost to the power system has also been suggested [9]. While ramping restrictions have been found to impact strategies for reservoir management under certain conditions [10], such constraints mainly limit the short-term flexibility. Only a few publications consider environmental constraints that include state-dependencies in long-term hydropower scheduling. Such constraints have been found to have a considerable impact on the water value curves used for reservoir management, [11], [12], and may significantly impact the seasonal flexibility.

We evaluate the impacts of environmental requirements for hydropower reservoirs on the risk of scarcity situations and price formation in a competitively operated power system reliant on hydropower. Especially, environmental, state-dependent reservoir constraints that are imposed on Nordic hydropower plants are considered. To the best of our knowledge, this has not been addressed in the research literature previously. A multi-stage stochastic model for operation of small renewable electricity systems is presented and used to investigate the impact on the formation of the electricity price. The modelled part of the power system relies on hydropower, and is only weakly linked to a the larger power system. The model is formulated from a system perspective with an objective to minimise the cost of meeting local electricity demand and is solved using stochastic dynamic programming (SDP) [13]. The main contribution of this work lies in the modelling of the state-dependent environmental constraint, and in the assessment of the impact on the operation of the system and the local electricity price formation for a case study based on a Norwegian hydropower system. The local price formation is directly impacted by the risk of rationing [14] and is a measure of the stress in the local system.

The remainder of this article is structured as follows: the stochastic power system model and the modelling of the environmental constraint is presented in Section II, the case study is presented in Section III, before the results and the final conclusion is presented in Section IV and V accordingly.

II. Power System Model

This section presents the multi-stage, stochastic model used to optimise operation, and determine the corresponding electricity price, of a renewable electricity system dependent on hydropower plants constrained by environmental requirements. A more thorough description of the use of SDP in hydropower scheduling can be found in [12], [15], [16]. We here emphasize on describing the stage-wise (weekly) decision problem.

The defined optimisation problem optimises operation of the system illustrated in Fig. 1, i.e. determines electricity generation, storage of water in the reservoirs, and utilisation of the weak transmission link in order to meet the local electricity demand at the lowest possible cost. The hydropower reservoirs are the only form of energy storage in the system and determine the ability of the hydropower plants to generate electricity during the year. The option to store water in the reservoirs couple the decision variables in time, making the problem dynamic. Furthermore, the problem depends on uncertain weather parameters, making the problem stochastic.

A. Multi-stage, stochastic programming model

To solve the large multi-stage, stochastic problem at hand, we use SDP [13]. SDP is a mature solution method based on decomposing the problem into smaller stage-wise independent problems which can be solved sequentially. The method allows for nonconvex characteristics to be included in the model formulation, but can only be used for smaller or aggregated hydropower systems due to the need to discretise the state variables, making the problem grow exponentially in size with the number of reservoirs considered.

The SDP model solves the problem for a yearly time-horizon, broken down to 52 weekly decision stages ($t \in \mathcal{T}$). In each stage, the model solves the weekly problem for a set of discrete stochastic states ($s_t^u \in \mathcal{S}^u$) and a set of discrete reservoir states ($s^p \in \mathcal{S}^p$). Three stochastic variables are considered; the total weekly inflow to the reservoirs, the weekly average wind power production and a temperature dependent weekly load. The reservoir states give the start filling of the reservoir in each stage. Each time the weekly decision problem is solved, the sum of the immediate cost and the expected future cost is minimised to find the optimal operation of the system.

To account for end-of-horizon-effects, the SDP algorithm iterates until convergence. When the model has converged, the calculated strategy (water values) are used in a final forward simulation of the same system, optimising system operation for a range of scenarios.

B. Weekly decision problem

The weekly decision problem is solved for every discrete system state. The uncertainty is reflected by the stochastic states and corresponding transition probabilities in the SDP algorithm. The weekly decision problems are deterministic as the stochastic variables for each week are known at the beginning of the week. Each problem consist of K time steps, allowing for intra-week variation in weather parameters and load profiles.

The objective of the decision problem (1) is to minimise the sum of the immediate and expected future cost. The immediate cost is determined by the cost of energy import/export at a deterministic market price ($\lambda_k e_k$), and the cost of load rationing ($C^{ls} ls_k$), in each time step k. The expected future cost (α_{t+1}) is a function of the current stochastic state of the system (s_t^u) and the resulting reservoir state at the end of the stage ($v_{t,h\in\mathcal{H},k=K}$).

$$\alpha_t(s^p, s_t^u) = \min \left\{ \sum_{k\in\mathcal{K}} (\lambda_k e_k + C^{ls} ls_k) + \alpha_{t+1}(v_{h\in\mathcal{H},k=K}, s_t^u) \right\} \tag{1}$$

The power balance (2) state that the electricity generation from hydropower ($p_{k,h}$) and net import (e_k) of electricity has to equal the net local electricity demand in all time steps ($k \in K$), i.e. the electricity consumption of households (D_k^C) and industry (D_k^I) minus the wind power generation (W_k). If required, load can be rationed (ls_k) at a high cost (C^{ls}) or wind power can be curtailed (w_k^c) for free.

$$\sum_{h\in\mathcal{H}} p_{k,h} + e_k + ls_k - w_k^c = D_k^C + D_k^I - W_k \quad \forall \quad k \in \mathcal{K} \tag{2}$$

The electricity generation from each of the hydropower plants $h \in \mathcal{H}$ is given by the discharge ($q_{k,h,d}$) from each plant and the efficiency $\eta_{h,d}$ of each discharge segment $d \in \mathcal{D}$, as given in (3). Discharge per segment is restricted by (4). The water level in the reservoir $v_{k,h}$ is restricted by upper and lower limits in (5).

$$p_{k,h} - \sum_{d\in\mathcal{D}_h} \eta_{h,d} q_{k,h,d} = 0 \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{3}$$

$$q_{k,h,d} \leq Q^{max}_{h,d} \quad \forall \quad k \in \mathcal{K}, h \in \mathcal{H}, d \in \mathcal{D}_h \tag{4}$$

$$V^{min}_h \leq v_{k,h} \leq V^{max}_h \quad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{5}$$

Constraint (6) provides a mass balance for the water stored in the reservoirs. Water is drawn from the reservoir as discharge ($q_{k,h,d}$) or spillage ($f_{k,h}$), and can be added to the reservoir as inflow ($\phi_k Z_h$) or through discharge from the reservoirs above. Water that is spilled is lost from the system. The factor ϕ_k distributes the weekly total inflow (Z_h) to the time steps, while F^C is a conversion factor from $\frac{m^3}{s}$ to mm^3.

$$\begin{aligned} v_{k,h} - v_{k-1,h} + F^C(\sum_{d \in \mathcal{D}_h} q_{k,h,d} + f_{k,h}) \\ -F^C \sum_{j \in \mathcal{H}^{up}_h} \sum_{d \in \mathcal{D}_j} q_{k,j,d} = \phi_k Z_h \quad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \end{aligned} \tag{6}$$

C. Environmental requirements

Many hydropower reservoirs in Norway are also used for recreational purposes in the summer. In this period, low water levels in the reservoirs can make it difficult to access the water surface. In order to meet ecological and recreational needs for high water levels in summer, constraints may be imposed on the operation of selected reservoirs. The purpose of the considered constraint is to enforce rapid filling of the reservoirs ($h \in \hat{H}$) in order to reach a target water level within a given period. Because of large inflow-variations, a hard reservoir constraint may induce high socioeconomic cost in low-inflow years and is therefore not suitable. Instead, a dynamic formulation that restricts discharge from the reservoir is used. The constraint is formulated as a requirement to stop any discharge, except to meet minimum flow obligations, within a certain period $t \in \hat{T}$, if the water level in the reservoir is below a given threshold (V^{lim}_h), as given in (7). If there are no minimum flow obligations $Q^{min} = 0$.

$$\sum_{d \in \mathcal{D}_h} q_{k,h,d} \leq Q^{min} \quad | \quad v_{k,h} < V^{lim}_h \quad \forall \quad k \in \mathcal{K}, h \in \hat{H} \tag{7}$$

If, the water level reach the threshold at any time within the restriction period, the water level in the reservoir has to stay above the threshold for the rest of the period $\hat{T}$, adding (8) to the weekly decision problem (and removing (7)).

$$v_{k,h} \geq V^{lim}_h \quad \forall \quad k \in \mathcal{K}, h \in \hat{H} \tag{8}$$

Since the activation of (7) depends on the reservoir level ($v_{k,h}$), the environmental constraint introduces a state-dependency, making the scheduling problem nonconvex. This type of constraints are imposed on several Nordic hydropower plants and can have a considerable impact on the seasonal reservoir management [12].

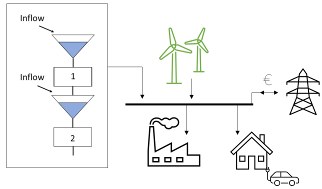

Fig. 1. Illustration of the system used in the case study.

TABLE I
HYDROPOWER SYSTEM

Power Plant	Reservoir Capacity $[Mm^3]$	Generation Capacity $[MW]$	Discharge Capacity $[m^3/s]$	Average Inflow $[Mm^3/yr]$
Upper (1)	195	15.0	26.0	536.0
Lower (2)	179	126.6	37.5	276.3

III. Case Study

The SDP model is applied to a small renewable system, illustrated in Fig. 1, resembling a region that is weakly linked to the rest of the power system. The model is run with 52 weekly stages and an 3-hour resolution within each stage. The electricity demand within the region can be met by wind- and hydropower, and partly by import at a deterministic price. The transmission capacity is not sufficient to meet the power demand at all times.

The wind power generation is represented by weekly energy series, which is evenly distributed between the intra-week time-steps. The total electricity demand is divided into a household consumption and an industry consumption. The household consumption is assumed to follow a weekly load profile, while the industry consumption is constant.

The hydropower system is based on the Gråsjø and Trollheim power plants in Folldalen, Norway. Details are given in Table I. The weekly inflow is assumed to be distributed evenly throughout the week. The environmental reservoir constraint is active from week 18-35 on the lower reservoir, and states that no generation is permitted from the lower reservoir if the filling of the reservoir is below 85% of maximum [1].

Historical inflow data, wind power generation, temperature adjusted load profiles and an exogenous power price for mid-Norway is taken from a 2030 low emission dataset [17] run with the EMPS model [14] [2] . To create a suitable test system, the data was scaled to match the capacity of the chosen hydropower system.

[1]This type of constraint has been suggested for this power plant, but was not imposed in the recently finished revision of the licensing terms.

[2]A market model designed for systems dominated by reservoir hydro, used in the Nordic power market. https://www.sintef.no/en/software/emps-multi-area-power-market-simulator/

TABLE II
CASE DETAILS

Case	Total Load $[GWh]$	Wind Power $[GWh]$	Transmission $[MW]$	VOLL $[\text{€}\backslash MWh]$
Base	1 403	474	100	500
HighTrans	1 403	474	300	500
LowTrans	1 403	474	50	500
VOLL 300	1 403	474	100	300
VOLL 100	1 403	474	100	100
HighWind	1 403	949	100	500

A. Representation of uncertainty

Uncertainty is considered for inflow, wind power generation and electricity demand from households (temperature dependent). Serial- and cross-correlations in the stochastic variables are accounted for by the use of a vector auto-regressive model of order one (VAR(1)) to draw scenarios [18]. Each scenario consist of 52 weekly values for each of the stochastic variables. In the SDP-algorithm, the stochastic variables are represented by a Markov-model. The final simulations were conducted for 100 of the originally sampled scenarios.

B. Case runs

In total, 12 case-runs are presented as part of this work. Sensitivities are conducted on the transmission capacity, value of lost load (VOLL) and wind power generation, as given in Table II. In addition, the different configurations of the system is considered both with and without the environmental reservoir constraint.

IV. RESULTS AND DISCUSSION

This section present results from solving the cases described in Table II. We compare results from optimal operation of the Base and HighWind case with and without constraints on operation of the reservoir, and comment on the sensitivity to the value of lost load (VOLL) and the transmission capacity. Finally, we discuss the implications of the reservoir constraint on resource utilisation, local price formation and security of supply.

A. Operational results

The environmental constraint has a considerable impact on the operation of the system. If the reservoir level is below the threshold in the constraint period, the lower hydropower plant is not allowed to produce, which drastically reduce the generation capacity in the system. Combined with unfavorable wind conditions, this can lead to a shortage of generation and rationing of load. Table III presents average yearly results for operation of the system for the different case runs. In general, the operational costs increase when including the environmental constraint, due to higher imports of energy and (in most cases) increased rationing of load. Furthermore, spillages from the hydropower reservoirs increase for all cases when the reservoir constraint is included, reducing the total energy generation from the hydropower plants.

TABLE III
AVERAGE YEARLY RESULTS

Case	Reservoir Constraint	Cost $[10^6$ €$]$	Rationing [GWh]	Spillage [Mm3]	Net Import [GWh]
Base	NO	2.16	0.37	11.44	76.85
VOLL300	NO	2.08	0.37	11.44	76.85
VOLL100	NO	2.00	0.43	11.43	76.76
LowTrans	NO	2.70	0.47	12.58	78.12
HighTrans	NO	1.93	0	11.64	77.29
HighWind	NO	-15.83	0.09	16.28	- 387.94
Base	YES	3.61	0.46	28.95	94.59
VOLL300	YES	3.50	0.47	28.87	94.49
VOLL100	YES	2.81	6.53	18.58	77.60
LowTrans	YES	4.80	1.55	35.58	101.12
HighTrans	YES	2.33	0	18.09	83.44
HighWind	YES	-14.98	0.99	23.78	-381.07

1) Base case: Fig. 2 (upper) shows the operation of the lower reservoir (where the constraint is imposed). The reservoir management throughout the year changes completely when considering the environmental constraint, in order to keep both hydropower plants in operation. With high reservoir fillings throughout the year, spillage would be expected to increase, reducing the total generation from hydropower. The average spillage increase from 1.4% to 3.5% percent of the average total inflow when the constraint is included. There is no curtailment of wind power.

2) High wind case: In this case, the total wind generation is doubled, resulting in a net export of energy and a negative total system cost, as given in Table III. The system still has some rationing of load, but less than in the Base case. In some hours curtailment of wind power occur, but on average less than 0.5% of the total wind generation is curtailed. The high share of wind gives a high variation in total energy availability between the scenarios, increasing the spread in the operation of the hydropower plants. This can be seen comparing the High Wind case Fig. 2 (lower) to the Base case in Fig. 2 (upper). Due to the increased availability of energy, rationing is lower than in the Base case when the environmental constraint is not included, while the spillage of water is higher. When the environmental constraint is included, we find that the seasonal reservoir operation of the reservoirs are less changed than in the Base case. As a result, there is more rationing and less spillage.

3) Value of lost load: The results are sensitive to the expected cost of rationing, which is impacted by two factors: VOLL (EUR/MWh) and the amount of rationing (MWh). The VOLL can be seen as a calibration parameter, and the optimal value used in this type of models is not easily defined. Ideally, it should vary with type of consumption and duration of the rationing of load [19]. From Table III we see that a low VOLL (VOLL100) gives more rationing of load, but equal or less spillage of water from the reservoirs than in the Base case. More rationing is accepted in the VOLL 100 case, as the system cost of rationing in this case is quite low. Fig. 3 shows that the reservoir management is more similar to the operation without the reservoir constraint for VOLL 100, giving lower spillage than in the Base and VOLL 300 cases. VOLL up to

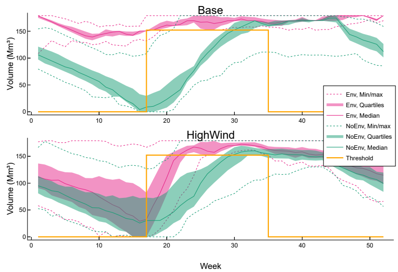

Fig. 2. Water filling in the lower reservoir for the Base case (upper) and Highwind case (lower) for all scenarios.

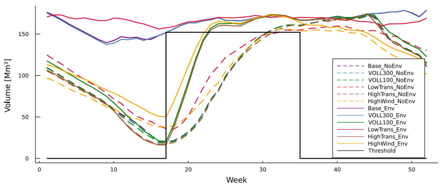

Fig. 3. Average water filling in the lower reservoir for all cases.

4000 EUR/MWh was also tested, but gave similar results to the Base and VOLL 300 cases.

4) Transmission capacity: The transmission capacity to the larger system is vital for security of supply. If the transmission capacity is reduced (LowTrans), the system becomes more vulnerable to uncertainty and variation, which again increase the probability of rationing. This is reflected in the operation of the reservoirs by that the water level in the reservoirs are kept higher, as shown in Fig. 3 for the lower reservoir. The differences in operation are particular apparent for the cases with the environmental constraint, having higher rationing and spillage compared to the Base case. This is due to the restrictions on operation combined with low import capacity and high reservoir levels, accordingly.

If the transmission capacity is unconstrained (higher than peak demand), scarcity will never be a problem (no rationing), and the power generation can be optimised towards the larger system. Comparing the HighTrans cases with and without the environmental constraint, we see only small differences in the operation of the hydropower reservoirs in the weeks before the environmental constraint is activated, as illustrated in Fig. 3. We have assumed a constant transmission capacity, the actual capacity can vary with the operation and state of the system.

B. Local price formation

The dual value of the power balance gives the marginal cost of covering one more unit of load, and represents the

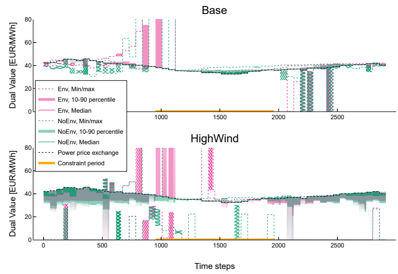

Fig. 4. The dual value (local price) in the Base Case (upper) and HighWind case (lower) plotted over one year for all scenarios. The highest dual values reach (500 EUR/MWh), but for readability the y-axis is capped in the plots.

theoretical power price in competitive power markets. In the defined system, one additional unit of load would in most hours either be covered by increasing the hydropower generation or adjusting the import/export. If the local system is not constrained, the local price is equal to the exogenous market price on the other side of the transmission cable. However, when there is an increased risk of load rationing, spillage of water or curtailment of wind power, the local price formation will increase or decrease accordingly. The resulting local price for the Base and HighWind case are given in Fig. 4. For both cases, there are more hours with high local prices when including the environmental constraint.

In the Base case, the highest local prices can be found before and in the beginning of the constraint period (before time-step 1000) when including the environmental constraint. Since the water level in the lower reservoir is below the threshold for some scenarios (week 18 in Fig. 2), rationing of load becomes necessary, resulting in local prices up to the VOLL (i.e. 500 EUR/MWh). The higher local prices before the constraint becomes active is due to the increased risk of rationing, which gives higher marginal costs of using water. In the HighWind case, the high local prices occur later than in the Base case. This is because the water level in the lower reservoir stays below the threshold for a longer period for many of the scenarios (see Fig. 2). Still, due to the relatively high wind power generation there are only a few scenarios where rationing is required. Furthermore, the local price falls to zero in more periods, due to curtailment of wind power or spillage from the reservoirs.

V. Conclusion and Further Work

An SDP-model for long-term scheduling of small hydro-dominated systems is presented and applied to a case study based on two Norwegian hydropower plants. The small test model is found to be useful to evaluate area-specific aspects of power system operation, such as the conducted case study. The case study results demonstrate how operation of the system is restricted when an environmental reservoir constraint is included, increasing the risk of rationing in certain periods. The magnitude and frequency of rationing strongly depend on the configuration of the system and the assumptions of VOLL used in the operational planning. Furthermore, both increased transmission capacity and higher wind power generation are found to reduce the impact of the constraint on the reservoir management.

The results, in the form of price formation and rationing, show that the system becomes more stressed when the environmental constraint is added. The local price is found to be higher within the constraint period in many of the scenarios. In some of the scenarios, the increased risk of rationing also lifts the local price in the weeks leading up to constraint period. To dampen the negative impacts, the operations of the hydropower resources are adjusted, significantly changing the reservoir management. The sensitivity to the VOLL demonstrates the importance of correctly pricing this parameter and alternative flexibility resources in the system, such as demand flexibility.

Further work should include demand side flexibility, short-term variations in wind generation and reserve capacity requirements. In addition, impacts on local flexibility of different types of environmental constraints could be considered.

VI. Acknowledgments

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References

[1] N. L. Poff and J. K. Zimmerman, "Ecological responses to altered flow regimes: A literature review to inform the science and management of environmental flows," *Freshwater Biology*, vol. 55, no. 1, pp. 194–205, 2010.

[2] D. M. Carlisle, D. M. Wolock, and M. R. Meador, "Alteration of streamflow magnitudes and potential ecological consequences: a multiregional assessment," *Frontiers in Ecology and the Environment*, vol. 9, no. 5, pp. 264–270, 2011.

[3] L. E. Schäffer, A. Adeva-Bustos, T. H. Bakken, A. Helseth, and M. Korpås, "Modelling of Environmental Constraints for Hydropower Optimization Problems – a Review," in *2020 17th International Conference on the European Energy Market (EEM)*. IEEE, 9 2020, pp. 1–7. [Online]. Available: https://ieeexplore.ieee.org/document/9221918/

[4] G. L. Doorman, K. Uhlen, G. H. Kjølle, and E. S. Huse, "Vulnerability analysis of the nordic power system," *IEEE Transactions on Power Systems*, vol. 21, no. 1, pp. 402–410, 2 2006.

[5] B. Köhler, A. Ruud, Ø. Aas, and D. N. Barton, "Decision making for sustainable natural resource management under political constraints – the case of revising hydropower licenses in Norwegian watercourses," *Civil Engineering and Environmental Systems*, vol. 36, no. 1, pp. 17–31, 2019.

[6] J. I. Pérez-Díaz and J. R. Wilhelmi, "Assessment of the economic impact of environmental constraints on short-term hydropower plant operation," *Energy Policy*, vol. 38, no. 12, pp. 7960–7970, 2010.

[7] S. Niu and M. Insley, "On the economics of ramping rate restrictions at hydro power plants: Balancing profitability and environmental costs," *Energy Economics*, vol. 39, pp. 39–52, 2013.

[8] I. Guisández, J. I. Pérez-Díaz, and J. R. Wilhelmi, "Assessment of the economic impact of environmental constraints on annual hydropower plant operation," *Energy Policy*, pp. 1332–1343, 2013.

[9] M. A. Olivares, J. Haas, R. Palma-Behnke, and C. Benavides, "A framework to identify Pareto-efficient subdaily environmental flow constraints on hydropower reservoirs using a grid-wide power dispatch model," *Water Resources Research*, vol. 51, no. 5, pp. 3664–3680, 2015.

[10] I. Guisández, J. I. Pérez-Díaz, W. Nowak, and J. Haas, "Should environmental constraints be considered in linear programming based water value calculators?" *International Journal of Electrical Power and Energy Systems*, vol. 117, 2020.

[11] A. Helseth, B. Mo, and H. O. Hågenvik, "Nonconvex Environmental Constraints in Hydropower Scheduling," in *International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2020.

[12] L. E. Schäffer, A. Helseth, and M. Korpås, "A stochastic dynamic programming model for hydropower scheduling with state-dependent maximum discharge constraints," *Renewable Energy*, vol. 194, pp. 571–581, 7 2022.

[13] R. Bellman, "Dynamic programming and stochastic control processes," *Information and Control*, vol. 1, no. 3, pp. 228–239, 9 1958.

[14] O. B. Fosso, A. Gjelsvik, A. Haugstad, B. Mo, and I. Wangensteen, "Generation scheduling in a deregulated system. the norwegian case," *IEEE Transactions on Power Systems*, vol. 14, no. 1, pp. 75–80, 1999.

[15] P. Côté and R. Arsenault, "Efficient Implementation of Sampling Stochastic Dynamic Programming Algorithm for Multireservoir Management in the Hydropower Sector," *Journal of Water Resources Planning and Management*, vol. 145, no. 4, p. 05019005, 4 2019. [Online]. Available: http://ascelibrary.org/doi/10.1061/%28ASCE%29WR.1943-5452.0001050

[16] A. Helseth, M. Fodstad, M. Askeland, B. Mo, O. B. Nilsen, J. I. Pérez-Díaz, M. Chazarra, and I. Guisández, "Assessing hydropower operational profitability considering energy and reserve markets," *IET Renewable Power Generation*, vol. 11, no. 13, pp. 1640–1647, 11 2017.

[17] L. E. Schäffer, B. Mo, and I. Graabak, "Electricity Prices and Value of Flexible Generation in Northern Europe in 2030," in *International Conference on the European Energy Market, EEM*, 2019.

[18] C. T. Larsen, G. Doorman, and B. Mo, "Joint Modelling of Wind Power and Hydro Inflow for Power System Scheduling," *Energy Procedia*, vol. 87, pp. 189–196, 2016.

[19] M. Ovaere, E. Heylen, S. Proost, G. Deconinck, and D. Van Hertem, "How detailed value of lost load data impact power system reliability decisions," *Energy Policy*, vol. 132, pp. 1064–1075, 9 2019.

Paper V

The paper **"Implications of environmental constraints in hydropower scheduling for a power system with limited grid and reserve capacity"** was submitted for review to **Springer** in the journal **Energy Systems** in November 2023. A revised version of the manuscript was submitted for 2^{nd} round of revision in the same journal in April 2023. The revised version is included here.

Implications of environmental constraints in hydropower scheduling for a power system with limited grid and reserve capacity

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Abstract

The negative impacts of power systems on biodiversity have to be mitigated, while simultaneously ensuring affordable and secure electricity supply for the future. This may lead to trade-off situations where ecological, recreational or social needs are weighted against the need for flexible power supply. This paper explores the interaction between the security of electricity supply and environmental constraints on the operation of flexible hydropower plants in the Norwegian renewable-based power system. A long-term, stochastic scheduling model of a wind- and hydropower-dominated power system is used to assess the implications of environmental constraints and reserve capacity requirements in combination. The model is used for a representative case study where three types of environmental constraints are imposed on the operation of the hydropower plants in a region of the congested Norwegian power system. In addition, requirements for spinning and non-spinning reserve capacity have to be met. The case study results demonstrate varying impacts on the operation of the hydropower plants, curtailment of demand and provision of reserve capacity depending on the type of environmental constraint being imposed.

Keywords: Hydro-dominated power systems, Hydropower scheduling, Environmental constraints, Reserve capacity, Renewable power systems

Nomenclature

Sets

$\mathcal{D}_h$	Set of discharge segments for hydropower plant h
$\mathcal{H}$	Set of hydropower plants
$\hat{\mathcal{H}}$	Subset of hydropower plants with environment restrictions, in $\mathcal{H}$
$\mathcal{H}_h^{up}$	Set of hydropower plants that discharge to plant h
$\mathcal{K}$	Set of time steps within a stage (week)
$\mathcal{N}$	Set of discrete reservoir segments
$\mathcal{S}$	Set of scenarios
$\mathcal{S}^p$	Set of reservoir states
$\mathcal{S}^u$	Set of stochastic states
$\mathcal{T}$	Set of stages (weeks) in the planning horizon
$\bar{\mathcal{T}}$	Subset of stages (weeks) where an environmental constraint is active, in $\mathcal{T}$
Θ_h	Set of weighting variables $\gamma_{n,m}$ defined for each hydropower plant h

Decision variables

α_{t+1}	The future expected operating cost for stage $t+1$
$b_{k,h}$	Bypass in time step k from plant h
$c_{k,h}$	Cost of start-up in time step k for plant h
e_k	Exchange of energy (import/export) in time step k
$f_{k,h}$	Spillage in time step k from plant h
$\gamma_{n,m}$	Weighting variable allocated to the discrete reservoir segment combination n, m
ls_k	Rationing of demand in time step k
$p_{k,h}$	Generated electricity in time step k from plant h
$q_{k,h,d}$	Discharge in time step k from plant h allocated to discharge segment d
$q_{k,h}$	Total discharge in time step k from plant h
$q_{k,h}^{min}$	Amount of discharge allocated to meet the minimum release requirement in time step k from plant h
$r_{k,h}^{s+}$	Provisions of upwards spinning reserves in time step k from plant h

$r_{k,h}^{s-}$	Provisions of downwards spinning reserves in time step k from plant h
$r_{k,h}^{ns+}$	Provisions of upwards non-spinning reserves in time step k from plant h
s_k^{s+}	Slack variable for upwards spinning in time step k
s_k^{s-}	Slack variable for downwards spinning in time step k
s_k^{ns}	Slack variable for non-spinning in time step k
$\theta_{l,h}$	Sum of weighting variables for reservoir segment l for hydropower plant h
$u_{k,h}$	Commitment (running) variable in time step k from plant h
$v_{k,h}$	Reservoir level in time step k in reservoir h
w_k	wind power generation in time step k
w_k^c	curtailment of wind power in time step k

Parameters

$\boldsymbol{B}$	coefficient matrix
C^{ls}	Cost of rationing of demand
C^r	Penalty cost for unmet reserve capacity requirements
C_h^{start}	Start-up cost of hydropower plant h
δ_h^{env}	Maximum allowed ramping rates of discharge for plant h
D_k^I	Industry electricity demand in time step k
D^C	Average weekly household electricity demand
ϵ	Convergence criterion in the SDP algorithm
$\eta_{h,d}$	Efficiency of hydropower plant h for discharge segment d
η_h^{max}	Maximum efficiency of hydropower plant h
η_h^{min}	Efficiency of operating at the minimum output for plant h
F^C	Conversion factor from flow to volume
F_k^H	Factor to scale for the number of hours in time step k
H	Number of hydropower plants
K	Number of time steps
λ_k	Power price in time step k
μ	mean of data the series
M	Number of nodes in the Markov model
N	Number of discrete reservoir states
ω_k^Z	Profile to distribute weekly inflow to each time step k
ω_k^D	Profile to distribute weekly household demand to each time step k
ω_k^W	Profile to distribute weekly wind power to each time step k
P_h^{min}	Minimum power output of hydropower plant h
Φ	Matrix comprising the expected future cost for each reservoir state

Ψ	Matrix comprising the water values for each reservoir state
Q_h^{min}	Minimum discharge of hydropower plant h
$Q_{h,d}^{max}$	Maximum capacity of discharge segment d for hydropower plant h
$\underline{Q}_h^{env}$	Minimum discharge for plant h given by environmental restrictions
R^{S+}	Requirement for upwards spinning reserves
R^{S-}	Requirement for downwards spinning reserves
R^{NS+}	Requirement for upwards non-spinning reserves
s^p	reservoir state
s_t^u	stochastic state
σ	standard deviation of data series
σ_h^{up}	Helping parameter to discourage operation to occur below minimum output due to upward spinning requirements
σ_h^{down}	Helping parameter to discourage operation to occur below minimum output due to downward spinning requirements
σ_h^{min}	Helping parameter to discourage operation below minimum output
T	Number of stages in the planning horizon
$V_{n,m}$	Discrete reservoir state, where n, m denotes the combination of discrete reservoir fillings in the two reservoirs
V_h^{lim}	Target water level (threshold) for reservoir h given by the state-dependent maximum discharge constraint
W	Wind power potential
X	Data point
$\boldsymbol{y}$	noise vectors
Z	Total weekly inflow
Z_h	Total weekly inflow scaled to hydropower plant h

1 Introduction

The transformation towards more sustainable power systems concerns abating the negative impacts on the climate and biodiversity, while simultaneously providing an affordable and secure electricity supply. To achieve this, efficient use of renewable energy resources and storage is a prerequisite [1]. Power systems with larger shares of variable renewable energy resources have higher variability and uncertainty in power generation than thermal power systems, thereby increasing the need for balancing power and reserve capacity [2]. Hydropower is anticipated to be a key enabler for the green transition in many parts of the world as a provider of renewable power production and energy storage. The potential for long-term energy storage combined with the ability to rapidly adjust generation distinguishes reservoir hydropower from all other renewable energy resources [3]. In power systems with high shares of renewable energy resources, the operational flexibility of hydropower plants may therefore be imperative to the security of supply.

On the other hand, negative impacts are associated with all types of power production, including hydropower. Land use changes have had the largest relative negative impact on nature since 1970 and power production contributes substantially to this [4]. Many of the world's watercourses are regulated for the purpose of hydropower generation, leading to interruption of natural flow conditions, fragmentation of ecosystems and changes in habitat conditions [5–7]. Furthermore, hydropower operations may also limit the access to water for other important functions, such as agriculture, drinking water supply, flood control, tourism or recreation, while in several cases these functions can also co-exist and benefit from each other. To mitigate the negative impacts of power generation, environmental regulations may be imposed, such as the goals for improved ecological status of freshwater ecosystems defined in the European Water Framework Directive [8].

To protect the interests of local ecosystems and communities, environmental restrictions are often imposed through concessions for hydropower plants. In the Nordic region, hydropower concessions may be revised after 30-50 years in operation. In this process, environmental constraints can be updated or added to improve the environmental conditions of the watercourse. There is considerable potential for ecological improvements in many Norwegian watercourses used for hydropower generation [9]. For hydropower plants considered to have a high ecological priority by the Norwegian regulator (NVE) [10], it is expected that stricter environmental restrictions will be imposed during the revision of the concessions. At the same time, higher shares of wind power, electrification and more cross-border transmission capacity are expected to result in higher requirements for balancing power in the Nordic power market [11]. The Norwegian transmission system operator (TSO), Statnett, has emphasised that several of the hydropower plants with a "high ecological priority" also are important contributors of flexibility services to the Nordic power system [11]. Particularly, some of these plants are essential to the security of supply in congested regions of the power system. This may lead to trade-off situations where ecological and recreational needs are weighted against the need for a flexible power supply.

It is the TSOs that are responsible for maintaining security of supply by balancing out short-term imbalances in the Nordic power market. Reserve capacity may be acquired in advance to ensure that flexible resources can be activated when required. The requirements for reserve capacity are categorised depending on response time and required duration. Reserve capacities with short activation time (fast-responding reserves) are often referred to as spinning reserves (e.g., FCR and aFRR in the Nordic and European power markets) [12]. Reserve capacities that are slower to activate, also referred to as non-spinning reserves (e.g., mFRR and RR in the Nordic and European power markets), are used to release the fast-responding reserves and may be required for a longer duration [13]. An overview of the Nordic balancing markets and the procurement procedure are presented in [14].

Hydropower can provide non-spinning and spinning reserves. The latter requires that the plants are running (i.e., to respond fast) and may therefore require a higher level of detail to be included in the scheduling models, such as unit commitment and minimum production levels. Procurement of spinning-reserve capacity has previously been considered for the Nordic power system in combination with fundamental long-term planning models in [15] and [16], and in a fundamental short-term hydrothermal scheduling model in [12]. Furthermore, procurement of spinning reserve capacity has been considered in medium-term hydropower scheduling from the perspective of a producer operating as a price-taker in [17, 18] and a price-maker in [19]. Accurate representation of unit commitment introduces non-convexities into the problem as discussed in [18] and [19]. Such details are therefore often linearised, like in [17] and [20], which may lead to an overestimation of available reserve capacity [20] and inaccurate estimations of costs [12]. A review of methods for solving large-scale unit commitment problems with uncertainty is provided in [21], but with a focus on short-term problems. Accurate modelling of unit commitment is rarely considered in large-scale, stochastic hydropower scheduling problems for long planning horizons.

In this paper, we explore the interaction between security of electricity supply and environmental constraints on operation of hydropower plants in congested regions of power systems with high shares of wind- and hydropower generation. This is relevant for the congested Nordic power system where parts of the system may be weakly linked to the rest of the system. Traditionally, these regions rely on large, flexible hydropower plants, but in recent years several of these areas have also seen new developments in wind power. It is well established that large amounts of wind power, above 50% of the capacity, can be integrated into hydropower-dominated power systems like the Nordic power system [22, 23], while also considering limited transmission capacity [24]. Furthermore, coordinated operation of wind and hydropower has been shown to ease congestion problems [25]. Still, to the best of our knowledge, modern environmental regulations of hydropower plants combined with reserve capacity requirements have not previously been considered in the long-term operational planning of hydropower-dependent systems with wind power. Previous research that considers both reserve capacity requirements and environmental constraints on hydropower is based on short-term modelling. A weekly hydropower scheduling model for the day-ahead and spinning reserve markets that includes environmental constraints on the operation of hydropower is presented in [26]. Similarly, environmental constraints on hydropower operations are included in the short-term hydrothermal scheduling model used to assess the benefits of exchanging spinning reserve capacity in the Nordic market in [12]. Still, the implications for long-term operational planning under uncertainty have not been considered, nor has the interplay between reserve capacity requirements and environmental regulation been assessed.

We consider three types of environmental constraints on the operation of hydropower plants in this paper: 1) discharge constraints with dependencies on the water level in the reservoir (here referred to as state-dependent discharge constraints), 2) ramping restrictions on flow, and 3) minimum flow requirements. The economic impacts of environmental minimum flow requirements and ramping rates have been extensively studied in the existing literature, see e.g., [27–29]. These types of environmental constraints have also been shown to have a significant impact on medium-term hydropower scheduling [30, 31]. Constraints that introduce binary logic or nonconvex characteristics are often omitted or simplified in long-term operational planning under uncertainty, due to the trade-off between accuracy and computational complexity [32]. Non-convex constraints with dependencies on the water level in the reservoir can be challenging to include in long-term scheduling models that require a convex model formulation. However, such constraints have previously been demonstrated to have a considerable influence on medium-term hydropower scheduling in [33, 34]. Furthermore, linear approximations for discharge constraints with dependencies on the water level in the reservoir are suggested in [35].

The novelty of this work lies in the modelling of modern environmental constraints on hydropower operation in combination with reserve capacity requirements in a wind- and hydropower-dominated power system. A stochastic optimisation model for the long-term scheduling of a hydropower-dominated power system is used to assess the implications of environmental constraints on the security of electricity supply in a wind- and hydropower-dependent region. The system relies on flexible hydropower generation to meet the variable electricity demand and the spinning and non-spinning reserve capacity requirements. Uncertainty in inflow to the hydropower reservoirs, wind power generation and temperature-dependent electricity demand are considered in the model. To the best of our knowledge, no previous model for long-term stochastic scheduling of a hydro- and wind power system which considers both state-dependent environment constraints and reserve capacity requirements has been presented in the literature. Furthermore, limited work considers environmental constraints in combination with reserve capacity requirements. The main contributions of this work are twofold:

1. The formulation of a stochastic optimisation model for long-term scheduling which balance environmentally-constrained hydropower, wind power and exchange with an external power system to meet variable demand and reserve capacity requirements. Environmental constraints on hydropower discharge are modelled, including reservoir-level dependent maximum discharge, maximum ramping of discharge and minimum release.
2. A thorough assessment of the interplay between environmental constraints on hydropower and the system's reserve capacity constraints in long-term operation planning. Both types of constraints limit the operational flexibility of hydropower plants. A representative Norwegian case study is

presented, including a sensitivity study of certain characteristics of the hydropower system.

The rest of this article is structured as follows. The long-term scheduling model is presented in section 2. The environmental constraints are described in section 3, including a discussion of the flexibility implications and the mathematical formulations. The case study is described in section 4, before the results are presented in section 5. Finally, the paper is concluded in section 6.

2 Stochastic scheduling model

We consider the long-term scheduling of a wind- and hydropower-dependent region in the Nordic power system. By regional, we mean that the model represents a limited geographical area, for example, a part of a price area in the Nordic power system with a weak transmission link to the larger power system, or a small-scale equivalent. The problem is formulated as a cost-minimizing operational problem, where electricity demand is met by wind- and hydropower plants, or import. In addition, reserve capacity requirements and environmental constraints are imposed on the system. Two large reservoir hydropower plants provide short-term operational flexibility and seasonal energy storage in the system. The optimal use of the hydropower reservoirs for energy storage is strongly dependent on the meteorological conditions (i.e., water inflow and wind) and the electricity demand. The ability to store water in the reservoirs couples the dispatch decisions in time, while the large variations in inflow, wind power generation and electricity demand on multiple time scales make the problem stochastic in nature.

The resulting stochastic and dynamic optimisation problem calls for efficient decomposition methods and is solved using stochastic dynamic programming (SDP) [36]. SDP is an established solution method for long-term hydropower scheduling problems (see e.g., [37]), that decomposes the problem into smaller stage-wise problems, here referred to as weekly decision problems. The overall aim is to optimise the operation of the reservoirs and power plants in the system to meet the electricity demand and the reserve capacity requirements at the lowest possible cost, while respecting the physical and regulatory constraints. We assume that the problem can be decomposed into weekly decision stages for a planning horizon of one year, with an intra-week time resolution of three hours. Furthermore, we assume that the stochastic variables can be represented by a discrete Markov chain as briefly described in section 2.1. The weekly decision problem is described in detail in section 2.2 before an overview of the modelling framework and the SDP-model are described further in section 2.3. The Markov model and scenario generation method used in the case study is explained in section 4.2.

2.1 Representation of uncertainty

We consider uncertainty over a weekly resolution for three variables: inflow of water to the reservoirs, wind power generation and temperature-dependent electricity demand of households. A weekly time resolution is considered suitable for describing uncertainty in inflow for hydropower in the Nordic system [38, 39], but may not be ideal for the modelling of short-term uncertainty and variations in wind power. However, the model aims to model the scheduling of hydropower with reservoirs over a long planning horizon, which in itself is a difficult problem to solve. Short-term uncertainty should instead be handled in the short-term modelling.

In general, we assume that the stochastic variables are correlated in time and between themselves. The stochastic variables are represented by a discrete Markov chain, allowing the conditional probability distribution of future states to only depend on the current state. Markov chains are frequently used to represent stochastic variables in SDP-based models for hydropower scheduling [40]. Correlations of one lag are considered by including a stochastic state variable in the SDP algorithm. A Markov model with M nodes in each stage is generated for use in the SDP model. Each node comprises a value for each of the stochastic variables, namely inflow, wind power generation and temperature-dependent electricity demand. The Markov model used in the case study is described further in section 4.2, together with the scenario generation procedure.

2.2 The weekly decision problem

The weekly decision problem for the scheduling of wind- and hydropower generation is described in the following. The model aims to meet electricity demand, which consists of a deterministic industry demand and a stochastic household demand, as well as requirements for spinning and non-spinning reserve capacity at the lowest possible cost. The weekly decision problem is solved for every stage (week), discrete reservoir state and stochastic state (i.e., node in the Markov model) in the SDP model. The model solves the weekly decision problems over a yearly planning horizon ($t \in \mathcal{T}$), from the last week (T) to the first. The uncertain nature of the problem is represented in the SDP algorithm by the stochastic states and corresponding transition probabilities in the Markov chain. All uncertain variables are assumed known at the beginning of the week and the weekly decision problem is therefore deterministic. This implies that the total weekly inflow (Z), the average weekly wind power generation (W) and the average weekly household demand (D^C) are known at the beginning of the week (t).

The decision problem is formulated as a linearised (i.e., continuous) unit commitment model, jointly optimising the energy generation and procurement of reserve capacity from the hydropower plants. This implies that all the hydropower functions are linearised in the decision problem. The weekly problem is solved for K time steps of three hours, allowing for intra-week variations in the input parameters, i.e., inflow, wind power, electricity demand and power price, to be considered in the decision-making. For the stochastic variables, the intra-week variations are modelled by weekly profiles which scale the stochastic input parameters to each time step. For brevity of the mathematical formulation, the index denoting the stage (week), t, is only used to indicate the change of stage (week). The presented formulation is for a hydropower system with two reservoirs.

2.2.1 Objective function

The objective function (1) minimises the cost of operating the system in the current week and the expected future cost of operating the system. The current cost is determined by import/export (e_k) at the price (λ_k), rationing of demand (ls_k) at the cost (C^{ls}), a penalty cost (C^r) of relaxing the spinning and non-spinning reserve requirements (s_k^{s+}, s_k^{s-}, s_k^{ns}) and a start-up cost ($c_{k,h}$) of each hydropower plant h in each time step k. Some cost elements are scaled for the number of hours in each time step (F_k^H). The future expected operating cost (α_{t+1}) is a function of the current stochastic state (s_t^u) and the reservoir state at the end of the week (given by $v_{h\in\mathcal{H},k=K}$).

$$\alpha_t(s^p, s_t^u) = \min\Bigg\{\sum_{k\in\mathcal{K}} F_k^H\Big(\lambda_k e_k + C^{ls} ls_k + C^r(s_k^{s+} + s_k^{s-} + s_k^{ns})\Big) + \sum_{k\in\mathcal{K}}\sum_{h\in\mathcal{H}} c_{k,h} + \alpha_{t+1}(v_{h\in\mathcal{H},k=K}, s_t^u)\Bigg\} \tag{1}$$

2.2.2 Approximation of the expected future cost function

The expected future cost function is approximated by a two-dimensional piece-wise linear and convex combination of the discrete expected future cost points ($\alpha_{t+1}(V_{n,m}, s_t^u)$) in Eq. (2). The future cost points are the expected objective function value, given the current stochastic state (s_t^u), calculated in the previous stage ($t+1$) for each reservoir state ($V_{n,m}$), where n, m denotes the combination of discrete reservoir fillings in the two reservoirs. The weighting variables ($\gamma_{n,m}$) are defined for all possible combinations of discrete reservoir fillings in the reservoirs and have to sum up to one as given in Eq. (3). The final reservoir fillings by the end of the stage (week) are connected to the weighting variables and the discrete reservoir states as given in Eqs. (4) and (5), respectively, where each reservoir is discretised into $n \in \mathcal{N}$ reservoir segments.

$$\alpha_{t+1}(v_{h\in\mathcal{H},k=K}, s_t^u) = \sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{N}} \gamma_{n,m}\alpha_{t+1}(V_{n,m}, s_t^u) \tag{2}$$

$$\sum_{n=1}^{N}\sum_{m=1}^{N} \gamma_{n,m} = 1 \tag{3}$$

$$v_{k,h} = \sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{N}} \gamma_{n,m} V_{h,n}^{seg} \qquad \forall \quad k = K, h = 1 \tag{4}$$

$$v_{k,h} = \sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{N}} \gamma_{n,m} V_{h,m}^{seg} \qquad \forall \quad k = K, h = 2 \tag{5}$$

Nonconvex future cost functions can be handled by introducing special ordered sets of type two (SOS-2). SOS-2 are ordered sets of non-negative variables where only 2 adjacent variables are allowed to take on non-zero values. This behaviour can be used to force the use of neighbouring weighting variables ($\gamma_{n,m}$) in the interpolation between future cost points, thereby capturing the nonconvex characteristics in the linear approximation of the future cost function. The implementation follows the approach for piecewise linear approximation of two-dimensional functions described in [41]. Special ordered sets are frequently applied in operational research and are included as functionality in many commercial solvers such as CPLEX. Note that the basic formulation of the decision problem in this study is linear, but that nonconvex expected future cost functions may occur when the state-dependent maximum discharge constraint is included, as described in section 3.3. If a nonconvex expected future cost function may occur, SOS-2 are added to the formulation through Eqs.(6)-(7), where $\theta_{l,h}$ is the sum of the weighting variables for each discrete reservoir segment l in reservoir h, as given in Eq.(6), and $\Theta_h = \{\theta_{l=1,h}, \theta_{l=2,h}, ..., \theta_{l=N,h}\}$.

$$\theta_{l,h} = \sum_{\{n,m\} \in \mathcal{N}_{l,h}^{comb}} \gamma_{n,m} \qquad \forall \quad l \in \mathcal{N}, h \in \mathcal{H} \tag{6}$$

$$\Theta_h \quad SOS-2 \qquad \forall \quad h \in \mathcal{H} \tag{7}$$

2.2.3 Hydropower constraints

The hydropower system is modelled as a cascade of connected hydropower plants with stations and reservoirs. The reservoir management is restricted by the water balance (Eq. (8)) and the reservoir regulation boundaries (Eq. (9)). Eq. (8) describes the balance of water entering and exiting the hydropower reservoirs for each plant h in each time step k. Water can exit from the reservoirs by release in the form of discharge to the turbines ($q_{k,h}$), bypass ($b_{k,h}$) or spillage ($f_{k,h}$) if the reservoir is full. Water may enter the reservoir as inflow (Z_h) or due to discharge from reservoirs higher up in the cascade ($\mathcal{H}_h^{up}$). The total weekly inflow is distributed to each time step by (ω_k^Z). Bypass and spillage are assumed to flow directly to sea level. The units are converted from flow ($\frac{m^3}{s}$) to volume (Mm^3) by a conversion factor (F^C).

$$v_{k,h} - v_{k-1,h} + F^C(q_{k,h} + b_{k,h} + f_{k,h}) - F^C \sum_{j \in \mathcal{H}_h^{up}} (q_{k,j}) = \omega_k^Z Z_h \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{8}$$

$$V_h^{min} \leq v_{k,h} \leq V_h^{max} \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{9}$$

The operation of the hydropower stations h for each time step k is constrained by Eq. (10)-(15). The unit commitment of each station is controlled by a variable indicating if the station is running ($u_{k,h}$). A linear approximation of unit commitment is used for computational purposes, i.e., the "running" variable ($u_{k,h}$) is a continuous variable between 0 and 1, as given by Eq. (10). Linear approximations of the power-discharge relationship (PQ-curve) normally provide good estimates when the hydropower stations are operated close to the best efficiency points of the units in the station, but overestimate the power generation when the station is running on low output. To reflect the reduced efficiency in "low operation" points, we include a minimum discharge (Q_h^{min}) and power output (P_h^{min}), following the approach described in [12].

The cost of start-up ($c_{k,h}$) is given by the cost C_h^{start} and change in running status as given in Eq. (11) and Eq. (12). The total discharge is described by Eq. (15) and the total power output as a function of the station discharge by Eq. (13). The modelling of the minimum operational point is based on the running variable ($u_{k,h}$). The power output for a station operating above the minimum generation level is described as a piecewise linear and concave function of $\mathcal{D}_h$ discharge segments, where the power output of each discharge segment d is given by the efficiency ($\eta_{h,d}$). The use of each segment ($q_{k,h,d}$) is restricted by a maximum limit ($Q_{h,d}^{max}$) in Eq. (14).

$$0 \leq u_{k,h} \leq 1 \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{10}$$

$$c_{k,h} \geq C_h^{start}(u_{k,h} - u_{k-1,h}) \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{11}$$

$$c_{k,h} \geq 0 \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{12}$$

$$p_{k,h} = u_{k,h} P_h^{min} + \sum_{d \in \mathcal{D}_h} \eta_{h,d} q_{k,h,d} \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{13}$$

$$0 \leq q_{k,h,d} \leq u_{k,h} Q_{h,d}^{max} \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H}, d \in \mathcal{D}_h \tag{14}$$

$$q_{k,h} \leq u_{k,h} Q_h^{min} + \sum_{d \in \mathcal{D}_\langle} q_{k,h,d} \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{15}$$

Eqs. (16)-(19) describe the amount of reserve capacity that can be provided by the hydropower plants. Provisions of upwards ($r_{k,h}^{s+}$) and downwards ($r_{k,h}^{s-}$) spinning reserves require that the hydropower plant is running, as given by Eqs. (16) and (18), respectively. Provision of upwards non-spinning reserves ($r_{k,h}^{ns+}$) is restricted by the total turbine capacity in Eq. (17) and the availability of water in the reservoirs. Eq. (19) provides an optimistic boundary for the required available water based on the maximum efficiency ($\frac{r_{k,h}^{ns+}}{\eta_h^{max}}$), where F^C converts the units from flow ($\frac{m^3}{s}$) to volume (Mm^3).

$$r_{k,h}^{s+} + p_{k,h} \leq u_{k,h} P_h^{max} \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{16}$$

$$r_{k,h}^{ns+} + r_{k,h}^{s+} + p_{k,h} \leq P_h^{max} \qquad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{17}$$

$$r_{k,h}^{s-} \leq p_{k,h} - u_{k,h} P_h^{min} \quad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{18}$$

$$F^C(\frac{r_{k,h}^{ns+}}{\eta_h^{max}}) \leq v_{k,h} \quad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{19}$$

The linearised unit commitment formulation does not guarantee operation above the minimum production point. To discourage operation below minimum output to occur for the purpose of delivering reserves, parameters σ_h^{up} and σ_h^{down} are introduced in Eqs. (20) and (21) respectively. Eq. (20) limits the delivery of upwards spinning reserves from hydropower plant h if operating below minimum output, where $\sigma_h^{up} = \frac{P_h^{min}}{R^{S+}}$ for $P_h^{min} \geq R^{S+}$ and 0 if $P_h^{min} < R^{S+}$. Similarly, Eq. (21) limits the delivery of downwards spinning for operations below minimum output, where $\sigma_h^{down} = \frac{P_h^{min}}{R^{S-}}$. The requirements for upwards and downwards spinning reserves are given by R^{S+} and R^{S-}, respectively. Note that Eqs. (20) and (21) only tighten the problem formulation if $P_h^{min} \geq R^{S+}$ and $P_h^{min} \geq R^{S-}$, accordingly. These constraints are therefore only useful in some special situations, for example, if a smaller amount of reserve capacity is required to be provided within a region or from a particular hydropower cascade, e.g., like the case study in [17].

$$\sigma_h^{up} r_{k,h}^{s+} \leq p_{k,h} \quad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{20}$$

$$(\sigma_h^{down} + 1) r_{k,h}^{s-} \leq p_{k,h} \quad \forall \quad k \in \mathcal{K}, h \in \mathcal{H} \tag{21}$$

2.2.4 Wind power constraints

The wind power generation (w_k) is restricted by the wind power potential (W) and the curtailment of wind power (w_k^c), as given in (22). The average weekly wind power potential is scaled to each time step by a weekly profile (ω_k^W).

$$w_k - w_k^c = \omega_k^W W \quad \forall \quad k \in \mathcal{K} \tag{22}$$

2.2.5 System constraints

The power balance, given by Eq. (23), ensures that the sum of the hydropower generation ($p_{k,h}$), wind power generation (w_k) and exchange of energy (e_k) equals the total demand in all time steps k. The total electricity demand is given by an industry demand (D_k^I), a household demand (D^C) and the option to ration demand (ls_k) at a high cost. The weekly average household demand is scaled to each time step by a weekly demand profile (ω_k^D). The utilisation of the transmission cable is limited by Eq. (24).

$$\sum_{h \in \mathcal{H}} p_{k,h} + w_k + e_k + ls_k = D_k^C + \omega_k^D D^I \quad \forall \quad k \in \mathcal{K} \tag{23}$$

$$-E \leq e_k \leq E \quad \forall \quad k \in \mathcal{K} \tag{24}$$

The requirements for reserve capacity can only be met by provision of spinning ($r^{s+}_{k,h}, r^{s-}_{k,h}$) and non-spinning ($r^{ns+}_{k,h}$) reserves by the hydropower plants in the system. Eq. (25)-(27) ensure that the requirements for upwards spinning reserves (R^{S+}), downwards spinning reserves (R^{S-}) and non-spinning reserves (R^{NS+}) are met. The reserve requirements in Eq. (25)-(27) can be relaxed by the use of slack variables (s^{s+}, s^{s-}, s^{ns+}) but are penalised at a high cost in the objective function.

$$\sum_{h \in \mathcal{H}} r^{s+}_{k,h} + s^{s+}_k \geq R^{S+} \qquad \forall \quad k \in \mathcal{K} \tag{25}$$

$$\sum_{h \in \mathcal{H}} r^{s-}_{k,h} + s^{s-}_k \geq R^{S-} \qquad \forall \quad k \in \mathcal{K} \tag{26}$$

$$\sum_{h \in \mathcal{H}} r^{ns+}_{k,h} + s^{ns+}_k \geq R^{NS+} \qquad \forall \quad k \in \mathcal{K} \tag{27}$$

2.3 Overview of the model framework

The solution framework is divided into two main parts: a strategy calculation (SDP model) and an operational forwards simulation (FS) as described in Fig. 1. The strategy calculation serves to compute the expected future cost functions (sometimes also referred to as the cost-to-go functions) that are used in the forwards simulation to represent the value of storing water.

In the strategy calculation, the SDP model is solved iteratively based on backward recursion. The algorithm iterates from the last stage T to the first stage. In each stage, the decision problem is solved for all combinations of discrete reservoir states (i.e., N^2 states) and the nodes in the Markov model (i.e., M nodes). The state variables comprise all the information passed from one decision stage to the next. We consider two state variables: the reservoir state (s^p) and the stochastic state (s^u_t). The reservoir states comprise information about the water levels in the reservoirs at the beginning of each stage, while the stochastic states comprise information about the stochastic variables. Three stochastic variables are considered in this work: the total weekly inflow to the reservoirs, average weekly wind power generation and the total weekly temperature-dependent electricity demand. The expected future costs are calculated by taking the expectation of the calculated future costs for each system state over all the stochastic states.

To account for end-of-horizon effects, the algorithm iterates until the water values in the first and last stages converge, as shown in Fig. 1. The water values are the marginal value of storing water in the reservoir (i.e., the marginal change in the expected future cost function). Convergence is achieved when the maximum difference between the water values in the last stage and the first stage is below a predefined error (ϵ). The water value matrix (Ψ) comprises the calculated expected water values for all reservoir states. If the convergence criterion has not been met, the water values from the first stage are used to calculate the expected future cost at the end of the planning horizon ($t =$

T) before a new iteration starts. The pseudocode of the implemented SDP algorithm is given in Appendix A. When convergence is achieved, the operation of the system is optimised for the weekly decision stages in a forwards sequence in the simulation. The forwards simulation is conducted for a set of S scenarios, using the calculated expected future costs to approximate the value of storing water in the weekly decision problem.

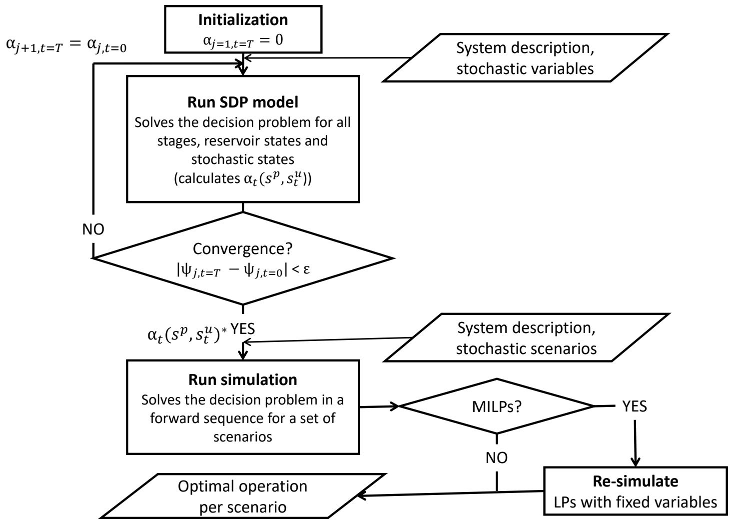


Fig. 1: Flow chart of the solution process with the strategy phase (SDP-model) and final simulation.

The weekly decision problem is solved in both the strategy calculation and the forward simulation. The basic formulation of the decision problem is given by Eqs. (1)-(5),(8)-(27) and is an LP, as described in section 2.2. All decision variables are defined as positive variables, except the expected future cost (α_{t+1}) and exchange (e_k), which may take non-positive values. Furthermore, the environmental constraints presented in section 3 may be added to the problem. If the environmental constraints make the problem nonconvex, Eqs. (6)-(7) are added to the formulation, turning the problem into a MILP. If the simulation comprises weekly decision problems that are MILPs, a second simulation may be conducted in order to obtain dual values from the solution. In the second simulation, the weighting variables ($\gamma_{n,m}$) that are used to represent the nonconvex expected future value curve (see section 2.2.1) are fixed to the optimal solution from the first round of simulations. The SOS-2 (Eqs. (6)-(7)) can then be removed from the decision problem, turning the problems into LPs before a second round of simulations is conducted.

3 Modelling of environmental constraints

Operation of hydropower plants can be restricted by a wide range of environmental constraints, often with the goal of controlling the water level in the reservoir or the flow downstream of the plant or in a side river (bypass section). The constraints aim to mitigate negative effects on surrounding ecosystems or facilitate other water uses (e.g., recreational use or irrigation). While some environmental constraints are designed for a specific purpose, and might therefore only be used for one particular hydropower plant or system, some types of environmental constraints are frequently recommended and more generic in type. Most commonly used are constraints to control the flow in certain parts of the river reach, i.e., minimum flow requirements or maximum ramping rates.

In the following, we present the three types of environmental constraints included in this study. We briefly describe the purpose of the constraints and the implications for operational flexibility, before we provide the mathematical formulation of the constraints as included in the weekly decision problem described in section 2.2. The environmental constraints can be imposed on all or a subset of the hydropower plants in the system ($\hat{\mathcal{H}} \subset \mathcal{H}$), for the entire planning horizon or a given period ($\bar{\mathcal{T}} \subset \mathcal{T}$). State-dependent constraints introduce non-convex characteristics to the problem and are therefore challenging to include in models based on linear programming [32].

3.1 Minimum flow constraints

Minimum flow constraints can be attributed either to the bypass section or to the river section downstream of the outlet of the hydropower plant. Minimum flow in the bypass section requires a constant discharge of water to be released from the reservoir past the turbines or intake, to maintain water flow in the original river bed. This results in a direct energy loss proportional to the amount of water released. The minimum discharge constraint targeted at the downstream section of the river also requires a minimum flow of water to be released from the reservoir, but in this case, the water can be released through the turbines, which implies that the water can still be used for power generation. Still, total power production can be reduced, as operations with sub-optimal efficiency may occur more frequently in order to meet the constraint. The minimum flow regimes are often defined as a constant flow throughout the year, sometimes diversified between seasons [42], but are usually only a small proportion of the original flow. In Norway, a few cases have more dynamic minimum flow regimes with the intention to mimic natural, hydrological variations.

Both for minimum flow requirements in the bypass sections and downstream sections, water must be stored and available to meet the constraint in all periods of the year, hence reducing the operational flexibility of the hydropower plant. Considering the minimum discharge downstream of the outlet, parts of the power generation may be moved from hours with high demand to hours with low demand to meet the constraint, thereby reducing the operational flexibility of the plant. In addition, the hydropower plant's capability to supply downwards reserves may be reduced, since the plant may be forced to stay in operation to deliver the required water flow.

Minimum flow requirements are normally straightforward to include in long-term scheduling models, even though more advanced requirements may introduce modelling complexities (e.g., flow regulations dependent on the stochastic state). The minimum release requirement, given in Eq. (28), ensures that the sum of discharge ($q_{k,h}$) and bypass ($b_{k,h}$) is above a minimum requirement ($\underline{Q}_h^{env}$). The amount of discharge allocated to meet the minimum release requirement is represented by a separate variable ($q_{k,h}^{min}$) and constrained by the total discharge (Eq. 29)). The parameter $\sigma_h^{min} = max\{\frac{Q_h^{min}}{\underline{Q}_h^{env}}, 1\}$ is introduced to discourage operation below minimum output. A slack variable penalised with a high cost in the objective function can be included in Eq.(28) to ensure feasibility in low water and inflow states or if negative inflows are considered.

$$q_{t,k,h}^{min} + b_{t,k,h} \geq \underline{Q}_{t,h}^{env} \qquad \forall \quad t \in \mathcal{T}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{28}$$

$$(\sigma_h^{min})q_{t,k,h}^{min} \leq q_{t,k,h} \qquad \forall \quad t \in \mathcal{T}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{29}$$

As discussed, minimum discharge obligations may limit the plants' ability to deliver downwards spinning reserves. By introducing $q_{k,h}^{min}$ as a separate variable, the minimum amount of turbine capacity allocated to meeting the minimum release requirement ($q_{k,h}^{min}\eta_h^{min}$) can be withdrawn from the capacity available for providing downwards reserves by updating Eq.(18) as shown in Eq. (30). The efficiency of operating at the minimum output is given by η_h^{min}. Furthermore, Eq. (21) is tightened as shown in Eq. (31).

$$r_{t,k,h}^{s-} \leq p_{t,k,h} - u_{t,k,h}P_h^{min} - q_{t,k,h}^{min}\eta_h^{min} \qquad \forall \quad t \in \mathcal{T}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{30}$$

$$(\sigma_h^{down} + 1)r_{t,k,h}^{s-} \leq p_{t,k,h} - q_{t,k,h}^{min}\eta_h^{min} \qquad \forall \quad t \in \mathcal{T}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{31}$$

3.2 Ramping constraints

Maximum ramping constraints limit the rate of change in discharge from the power plants. The aim of such restrictions is to reduce the environmental impacts of rapid and frequent fluctuations in flow, sometimes denoted as hydropeaking operations. A major concern related to hydropeaking operation is stranding of fish and other water-related organisms during down-ramping (because of de-watering of the downstream rivers), and flushing of organisms when the hydropower plants ramp up. In Norway, the majority of such restrictions have previously been expressed in qualitative terms. More quantitative constraints on ramping rates are expected to be defined in revisions of these types of terms, following new classification systems for environmentally acceptable hydropower operations [43].

Constraints on ramping rates do not have a direct energy loss but reduce the flexibility of the plant by shifting parts of the production between hours in the short-term (within a day). Furthermore, the plants' potential to supply up and/or down-regulating reserves is limited by the maximum allowed ramping rates. Ramping restrictions can be more challenging to model in long-term scheduling models, as such constraints couple decision variables in consecutive periods. Here we consider ramping rates within the weekly decision problem, as given in Eq. (32), and not between the stages. The maximum allowed ramping rates are given by δ_h^{env}.

$$-\delta_h^{env} \leq q_{t,k,h} - q_{t,k-1,h} \leq \delta_h^{env} \qquad \forall \quad t \in \mathcal{T}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{32}$$

Provision of upwards and downwards reserves is implicitly restricted by Eq. (32). The problem formulation is tightened further by adding Eq.(33) and Eq. (34). By including these constraints, the maximum allowed increase/decrease in power output per time step ($\eta_h^{max}\delta_h^{env}$) is scaled to an hourly limitation on provision of reserve capacity ($\frac{1}{F_k^H}$). For example, a ramping restriction of 15 MW per time step of three hours would give a maximum ramping of 5 MW per hour, if we assume even ramping within the time step, and the maximum reserve capacity that can be provided would therefore be 5 MW.

$$r_{t,k,h}^{ns+} + r_{t,k,h}^{s+} \leq \frac{1}{F_k^H}\eta_h^{max}\delta_h^{env} \qquad \forall \quad t \in \mathcal{T}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{33}$$

$$r_{t,k,h}^{s-} \leq \frac{1}{F_k^H}\eta_h^{max}\delta_h^{env} \qquad \forall \quad t \in \mathcal{T}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{34}$$

3.3 State-dependent maximum discharge constraints

State-dependent maximum discharge constraints (also known as soft reservoir constraints) are limitations on discharge imposed to achieve certain water levels in the reservoirs for given periods and are therefore categorised as a type of reservoir constraint. In Norway, reservoir constraints are divided into hard and soft reservoir constraints. Hard reservoir constraints define maximum and minimum allowed water levels for given periods. Minimum water levels may be imposed to ensure water supply (e.g., for ecological purposes, irrigation and drinking water) or to facilitate tourism and recreational activities, while maximum reservoir levels can be imposed to secure sufficient dampening of floods. State-dependent maximum discharge constraints (i.e., soft reservoir constraints) can be used when hard reservoir constraints are unsuitable because of seasonal variation in inflow, or if hard constraints are considered too strict. In Norway, state-dependent discharge constraints are used to incentivise high water levels in the summer season for recreational and landscape purposes, but these constraints can also be applied to ensure irrigation or drinking water supply [44].

Hard reservoir constraints, and especially minimum water levels, may have large flexibility implications. A minimum water level requirement for the summer season could potentially reduce the power production in winter and early spring, since water must be restrained in the reservoir to ensure that the minimum level can be met for all possible inflow realisations. Instead, power production is increased in the summer season (which typically has lower demand) and the probability of spillage increases. The plants' capability to provide reserve capacity is not considered to be reduced. On the contrary, state-dependent maximum discharge constraints do not require water to be restrained in the reservoir before the constraint becomes active, but the operation of the plant is strictly limited during the constraint period. As illustrated in Figure 2, power production can be restricted in parts of the period when the cc ıg re

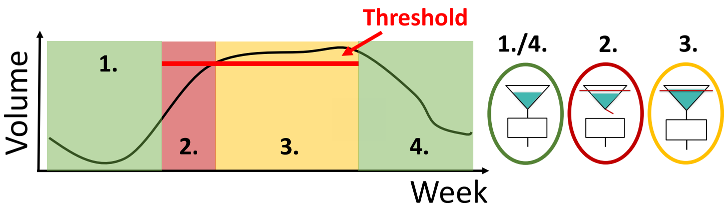


Fig. 2: Illustration of the state-dependent discharge constraint. The constraint is active in periods 2 and 3 (red and yellow shaded areas). When the water level is below the threshold, discharge from the reservoir is not permitted (i.e., red shaded area, period 2), but when the threshold is met, the constraint changes into a minimum water level constraint (i.e., yellow shaded area, period 3).

The constraint is defined mathematically as follows:

1. If the water level in the reservoir is below a given threshold V_h^{lim} for a given period $t \in \bar{\mathcal{T}}$, discharge from the reservoir is restricted to allow only environmental flow requirements by Eq. (35).

$$q_{t,k,h} \leq \underline{Q}_h^{env} \quad | \, v_{t-1,k=K,h} < V_h^{lim} \qquad \forall \quad t \in \bar{\mathcal{T}}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{35}$$

2. If the water level exceeds the threshold V_h^{lim} within the given period $\bar{\mathcal{T}}$, Eq. (35) is replaced by a minimum reservoir level constraint enforcing the water level to stay above the threshold for the remainder of period $\bar{\mathcal{T}}$ in Eq. (36).

$$v_{t,k,h} \geq V_h^{lim} \quad | \, v_{t-1,k=K,h} \geq V_h^{lim} \qquad \forall \quad t \in \bar{\mathcal{T}}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{36}$$

By constraining the discharge, the power production and provision of reserve capacity from the plant are also restricted. In practice, no provision of reserves is allowed when Eq. (35) is active, as given by Eq. (37). If the reservoir threshold is met (i.e., Eq. (35) is replaced by Eq. (36)), provision of reserves is possible, but Eq. (19) is replaced by Eq. (38).

$$\sum_{h \in \mathcal{H}} (r^{ns+}_{t,k,h} + r^{s+}_{t,k,h} + r^{s-}_{t,k,h}) \leq 0 \quad | \, v_{t-1,k=K,h} < V^{lim}_h \qquad \forall \quad t \in \bar{\mathcal{T}}, k \in \mathcal{K} \tag{37}$$

$$F^C(\frac{r^{ns+}_{t,k,h}}{\eta^{max}_h}) \leq v_{t,k,h} - V^{lim}_h \quad | \, v_{t-1,k=K,h} \geq V^{lim}_h \qquad \forall \quad t \in \bar{\mathcal{T}}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{38}$$

We also consider a relaxed version of the state-dependent maximum discharge constraint;

1. Even if the reservoir threshold is not met, production at the minimum discharge point and provision of spinning reserves are allowed, replacing Eq. (35) with Eq. (40) and Eq. (37) with Eq. (39).

$$\sum_{h \in \mathcal{H}} r^{ns+}_{t,k,h} \leq 0 \quad | \, v_{t-1,k=K,h} < V^{lim}_h \qquad \forall \quad t \in \bar{\mathcal{T}}, k \in \mathcal{K} \tag{39}$$

$$q_{t,k,h} \leq \underline{Q}^{min}_h \quad | \, v_{t-1,k=K,h} < V^{lim}_h \qquad \forall \quad t \in \bar{\mathcal{T}}, k \in \mathcal{K}, h \in \hat{\mathcal{H}} \tag{40}$$

The reservoir level dependent logical conditions described above are handled in the SDP algorithm. Within the constraint period ($t \in \bar{\mathcal{T}}$), the water level in the reservoir is checked at the beginning of each week (stage) before the decision problem is solved. If the water level is below the threshold, constraints (35) and (37) are added to the decision problem. For the relaxed version of the constraint, (40) and (39) are added instead of (35) and (37). If the water level is above the threshold, constraints (36) and (38) are added to the decision problem. In the backwards recursion, the decision problem is solved for a set of discrete reservoir states. The reservoir level at the beginning of the week is then given by the discrete value for the water level in each reservoir (given by $V_{n,m}$), instead of the end-reservoir filling in the previous week ($v_{t-1,k=K,h}$).

We avoid adding binary variables to the decision problem by handling the state-dependent logic directly in the SDP algorithm. However, due to the nonconvex characteristics of the regulation, the future expected cost function may become nonconvex. This is handled by including special ordered sets in the modelling of the expected future cost curve, i.e., adding Eqs.(6)-(7) to the decision problem as described in section 2.2.2, which turn the problem into a MILP.

4 Case study

This section describes the test case study of a regional, renewable-based power system based on real-life and simulated data from Norway. The test case is used to analyse the impact of different environmental constraints on the operation of the system, while also considering three different levels of reserve capacity requirements. The operational flexibility needed to meet net demand and the reserve capacity requirements has to be supplied by the hydropower plants. The system represents a realistic future situation in parts of the Nordic system where hydropower plants have to balance net load in systems with high shares of wind power generation, while delivering reserve capacity and respecting stricter environmental constraints. The case study design is highly relevant for the hydro-dominated Norwegian power system. Several hydropower cascades in the Nordic area are subject to environmental constraints and contain power plants that are crucial for security of supply. Moreover, several of these systems have limited access to the larger power system due to grid constraints.

The case study was conducted using the scheduling model described in section 2 including the different environmental constraints described in section 3. The model was implemented in Julia v1.5 using the JuMP package [45] and the CPLEX 12.10 solver [46]. For the MILP problems, the relative MIP gap is set to zero and the absolute MIP gap to 10^{-10} in the solver settings. The SDP model was solved for a convergence criterion of $\epsilon < 0.1 \frac{€}{Mm^3}$, where ϵ denotes the maximum difference in the water values from the previous iteration.

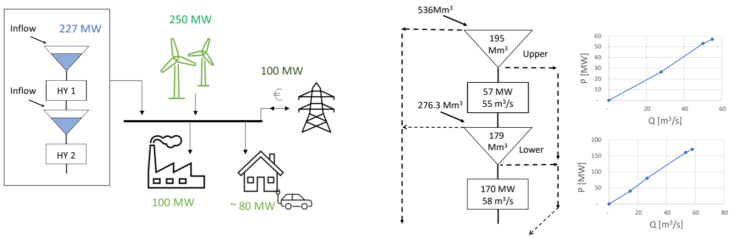
4.1 System description

An overview of the case study system is provided in Fig. 3a. The system consists of two hydropower plants in a cascade, wind power, household demand and industry demand. We assume that there are no grid limitations within the modelled area, but the system is connected to a larger power system through a transmission line with limited capacity. The transmission line can be used to trade towards a deterministic, exogenous power price (given in Appendix C). The transmission link can cover parts of the demand but is not sufficient to completely support the local system. The costs of curtailment of demand for energy and reserve capacity are set to 4,000 $\frac{€}{MWh}$ and 2,000 $\frac{€}{MW}$, respectively.

The hydropower system is set up to resemble a physical system, in order to represent the physical properties of the environmental constraints. The topology of the system is given in Fig. 3b together with an illustration of the PQ-curves of both stations. As discussed in section 2.2, a lower efficiency is assumed for operation at minimum output (or below). The efficiency at minimum output is set 20% lower than the best operational efficiency.

4.2 Markov model and scenarios sampling

As described in 2.1, three stochastic variables are considered in this work: weekly inflow to the reservoirs, average weekly wind power generation and



(a) The test case power system (b) Details of the hydropower system

Fig. 3: Illustration of the test case system.

average weekly household demand. The stochastic variables are represented by a Markov model in the SDP model and a set of scenarios in the simulation. Plots of the stochastic input data, the sampled scenarios and the Markov model are shown in Appendix B.

The Markov model was generated by the use of a vector auto-regressive model and clustering. Weekly time series from 58 weather years from the HydroCen Low Emission dataset for 2030 of Northern Europe [47] are used as input data for the stochastic variables. The dataset consists of weekly historical inflow series, simulated wind power generation and temperature-adjusted household demand for a region in mid-Norway. The data follow seasonal patterns. To subtract the seasonality from the time series, the data was first normalised by Eq. (41), where μ_t and σ_t are the mean and standard deviation of the series in week t.

$$\bar{X}_t = \frac{X_t - \mu_t}{\sigma_t} \tag{41}$$

To account for correlations in time and between the variables in the multivariate time series, a vector auto-regressive model of order one (VAR(1)) was fitted to the data, assuming the seasonally adjusted data to be weekly stationary. VAR models have been found to give improved descriptions of inflow in systems with correlations between inflow and wind [48]. A general VAR(p) model is given in Eq. (42), where $\boldsymbol{X}_t$ are vectors of variables, $\boldsymbol{B}_i$ are the coefficient matrices and $\boldsymbol{\epsilon}_t$ are noise vectors.

$$\boldsymbol{X}_t = \sum_{i=1}^{p} \boldsymbol{B}_i \boldsymbol{X}_{t-i} + \boldsymbol{y}_t \tag{42}$$

The SDP model requires a discrete representation of the stochastic variables. This was achieved by scenario generation and clustering [49]. To generate a larger sample of scenarios than provided in the original data, 10,000 scenarios consisting of successive, weekly realisations of the stochastic variables were sampled from the VAR(1) model. To obtain a manageable number of scenarios, a Markov chain with 10 nodes per stage (week) was generated from the sampled scenarios by the use of K-means clustering [50].

The Markov model was generated based on the sampled scenarios, rather than the original data, to have a larger sample (than the original 58 scenarios). If a small sample is used for clustering, some nodes may only be visited by a few scenarios, which could lead to very low transition probabilities and numeric issues in the SDP algorithm. The centre points of the clusters are used as nodes (stochastic states) in the Markov model and the probability of transitioning between the nodes (stochastic states) from one week to the next was determined by counting the share of trajectories transitioning between the clusters. Note that each stochastic state comprises a value for each of the three stochastic variables. The generation of the Markov model is illustrated in Fig. 4. An alternative approach to clustering could be to use a scenario reduction method like in [51].

A weakness of the applied method is that the nodes in the Markov model may not represent the most extreme outcomes of each stochastic variable adequately. Extreme realisations of the stochastic variables are essential for the scheduling of the hydropower plants [52]. If low and high inflow years are not satisfactorily represented in the stochastic model, the cost of running out of water or spilling water may be undervalued. To account for this, the representation of extreme inflow scenarios in the Markov model is adjusted by adding an additional high and low inflow node for each week, similar to the approach in [52]. The extreme nodes are set equal to the highest and lowest inflow values for each week in the original input data. Finally, the transition probabilities are adjusted by allocating the scenarios closest to the extreme values to the new nodes.

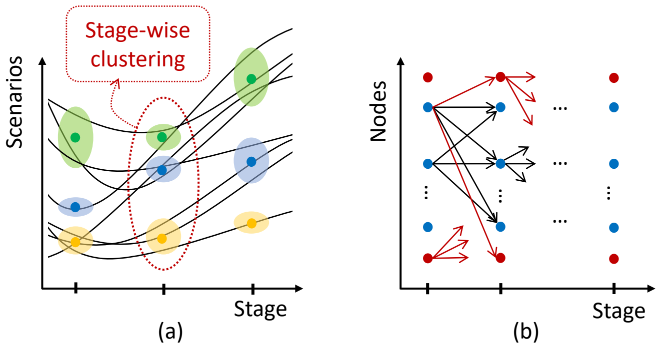


Fig. 4: Illustration of the generation of a Markov model by clustering. For each stage (week), the scenario trajectories are clustered together, as illustrated by the coloured areas in (a). Each cluster is represented by the centre point of the cluster. The centre points are used as nodes (representative stochastic states) for each stage in the Markov chain, illustrated in (b). Finally, the Markov chain is expanded by adding two extreme nodes in each stage, as represented by red in (b).

The stochastic variables (scenarios and Markov model) are de-normalized reversing the process in Eq. 41 before being applied in the case study. The forward simulation was conducted for 1,000 of the 10,000 sampled scenarios. The scenarios were drawn randomly from the sample, and the same scenarios were used for all the cases in the case study.

4.3 Intra-week variability

Inter-weekly variations in the stochastic variables are modelled by weekly profiles which are used to distribute the weekly values to the three-hour time steps. Household demand is represented by a generic weekly profile with a three-hourly resolution. For wind power generation and inflow, flat weekly profiles are used in the SDP calculation, as the real weekly variations cannot be well described by a single generic profile. In the forwards simulation, a set of weekly profiles for variability in wind power generation are used. The weekly wind profiles are from the original input data and matched to the weekly scenario values based on the average weekly wind power generation. The deterministic industry demand is assumed to be constant in all time steps, while the deterministic, exogenous power price is given for a three-hour resolution. The deterministic exogenous power price, the average seasonal profiles for inflow, wind power and household demand, and the weekly profiles for demand and wind power generation are given in Appendix C.

4.4 Environmental constraints

Three environmental constraints are considered for the lower hydropower plant (HY 2): state-dependent maximum discharge, ramping on discharge and minimum release. An overview of the environmental constraints is presented in Table 1. The environmental constraints are considered in each case by adding the associated equations (given in section 3) to the decision problem.

Table 1: Overview of environmental constraints

Case	**Constraint name**	**Active period**	**Level**
E0	None	None	None
E1	State-dependent maximum discharge	Week 18-35	$q \leq 0$ if $v < 85\%$ of reservoir capacity
E1*	Relaxed state-dependent maximum discharge	Week 18-35	$q \leq \underline{Q}^{min}$ if $v < 85\%$ of reservoir capacity
E2	Ramping on discharge	All weeks	15 $\frac{m^3}{s}$ per time step up and down
E3	Minimum release	Week 1-17 and 44-52 (winter), 18-43 (summer)	Winter: 6.95 $\frac{m^3}{s}$, Summer: 20.07 $\frac{m^3}{s}$

The state-dependent maximum discharge constraint (E1) states that from week 18, no discharge is permitted from the reservoir before a target level of 85% of the reservoir capacity is reached. After the wanted water level is reached, the water level has to stay above the target level until week 35. The relaxed version of the constraint (E1*) is active for the same period but allows for operation at minimum output when the water level is below the thresholds in the constraint period. The ramping constraint limits the maximum permitted change in discharge from one time step to the next (up and down). This type of constraint is only considered within the week and not included as a state variable connecting the subproblems in the SDP-model. The maximum ramping level corresponds to a ramp-up period of approximately 12 hours to ramp up from 0 to maximum capacity, while the minimum output point can be reached in three hours (one time step). Finally, the required minimum release is defined for the summer and winter seasons specifically. For the summer season, the minimum release requirement is set to 35% of maximum turbine discharge, while the requirement is set to 12% in the winter. This is a relatively high flow requirement, but in line with emerging best-designed mitigation measures in the range of 25–30% of the max turbine flow capacities [9].

4.5 Reserve capacity requirements

We consider two different levels of required reserve capacities, in addition to the Level 0 (L0) case without reserve capacity requirements, as presented in Table 2 and Fig. 5. The spinning reserve requirement in Level 1 (L1) is approximately 10% of the average variable demand, while the requirement in Level 2 (L2) is dimensioned to 10% of the wind power generation in the 10% hours with the highest wind power potential for the summer and winter seasons, respectively. In Level 1, the non-spinning reserve requirement is defined for the winter season and dimensioned to cover approximately 25% of the average household demand. In Level 2, a constant amount of non-spinning reserves dimensioned to cover approximately 30% of the average household demand is required throughout the year.

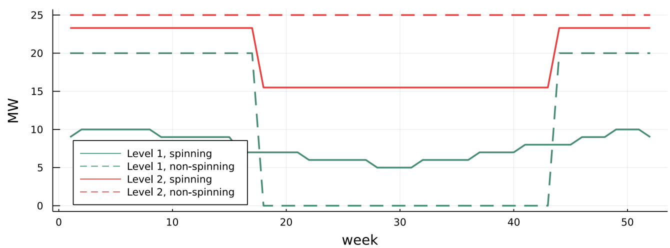


Fig. 5: Illustration of the spinning (solid lines) and non-spinning (dashed lines) reserve requirements for Level 1 (green) and Level 2 (red).

Table 2: Overview of the reserve capacity levels.

Case	Spinning Reserve Requirements	Non-spinning Reserve Requirements
Level 0	0 MW	0 MW
Level 1	5-10 MW	0-20 MW
Level 2	15.5-23.3 MW	25 MW

4.6 Overview of case runs

The model is solved for a range of different cases, combining the different environmental considerations and reserve capacity requirements as given in Table 3. Note that the E1+L2 case is solved using the modified state-dependent maximum discharge constraint (see E1* in Table 1). An additional set of simulations are conducted for the cases that include environmental constraints (E1-3) to evaluate the importance of consistency in the strategy and simulation part, i.e., the importance of including the environmental constraints in the strategy calculation as well as the simulation. This is done by simulating the cases with the constraints (E1-3) using inconsistent future cost functions (IC), namely expected future cost functions calculated without the constraints (E0). Furthermore, a small sensitivity study of the characteristics of the lower hydropower plant is outlined in Section 5.5.

Table 3: Overview of case runs (X), simulations with inconsistent future cost functions (IC) and cases included in the sensitivity study (S).

	E0	**E1**	**E2**	**E3**
Level 0	X	X, IC	X, IC	X, IC
Level 1	X	X, IC	X, IC	X, IC
Level 2	X, S	X[1], IC[2], S[2]	X, IC	X, IC, S

5 Results and discussion

This section describes the results from the case study. We first discuss some overall operational results. This is done for the three different types of environmental constraints considering the different levels of reserve capacity requirements. Secondly, we discuss the capability of the system to meet the demand for electricity and the requirements for reserve capacity. Thirdly, the value of considering the environmental constraints in the strategy calculation (i.e., the SDP model) is assessed, before we finish with a sensitivity study of the design of the lower hydropower plant.

5.1 Average total results (yearly)

This part describes the overall results given in Table 4 and discusses the development when including the different environmental constraints and reserve capacity requirements. Total curtailments of demand for energy and reserves (i.e., unmet demand and reserve capacity requirements) are only briefly mentioned here and discussed further in sections 5.2 and 5.3.

For reference, we first consider the cases without environmental constraints (E0+L0, E0+L1 and E0+L2). The overall operational costs are negative, due to the export of energy out of the area. The cost of operation increases (i.e., the profit is reduced from 12 M€ to around 8 M€) when reserve capacity requirements are included (E0+L1 and E0+L2 compared to E0+L0). The average total hydropower generation is maintained with increasing levels of reserve capacity requirements, but the average wind power generation is reduced (down 2-5%), resulting in a lower net export of energy. Minor amounts of energy and reserve capacity demand are curtailed. There is a higher curtailment of demand in the E0+L1 case and higher curtailment of demand for reserves in the E0+L2 case (compared to E0+L0). The rest of this section discusses the implications of the environmental constraints (E1-3 compared to

[1] Uses E1* in Table 3.

E0) considering different levels of reserve capacity requirements (L0-2). In general, larger impacts of the environmental constraints are seen for high reserve capacity requirements (L2). This is logical, as this is the most constrained system setup, where larger parts of the generation capacity are used to provide reserves.

When the state-dependent maximum discharge constraint is included (E1 compared to E0), there is an increase in spillage for all the levels of reserve capacity requirements (L0-2), resulting in a slight reduction in hydropower generation and net export. Only small changes in wind power generation are found when E1 is imposed. Compared to without the constraint (E0), curtailment of demand increases in the E1+L0 case but slightly decreases in the E1+L1 and E1+L2 cases. There is a slight increase in curtailed demand for reserves in the E1+L1 case and a higher increase in the E1+L2 case. The costs of operation increase in all cases with the constraint (E1 compared to E0), and especially for the E1+L2 case compared to E0+L2, due to the penalty of curtailed demand for reserves.

The ramping constraint (E2) has small to no impact (<1%) on the average hydropower generation, wind power generation and net export for all the levels of reserve capacity requirements (L0-2), compared to without the constraint (E0+L0-2). Curtailment of demand is slightly reduced in the E2+L1 case and more so for the E2+L2 case, while spillage increases by around 2-6% for the two cases, compared to the E0+L1 and E0+L2 cases. A small amount of demand for reserves has to be curtailed in the E2+L1 case, while there is a considerable increase in the E2+L2 case (6.37 MW/h on average compared to a 0.1 MW/h average in the E0+L2 case). Compared to without the ramping constraint (E0+L0-2), the cost of operation is slightly increased for the E2+L0 and E2+L1 cases, while there is a high-cost increase for the E2+L2 case due to a large amount of curtailed demand for reserves.

Table 4: Average total results from all the case runs.

Case		**Operational costs** [M€/yr]	**Hydropower** [GWh/yr]	**Wind power** [GWh/yr]	**Net export** [GWh/yr]	**Curtailment of demand** [GWh/yr]	**Spillage** [GWh/yr][2]	**Curtailment of wind** [GWh/yr]	**Curtailed demand for reserves**[3] [MW/h]
L0	**E0**	-12.68	844.61	726.10	254.90	0.12	2.08	1.77	na
L0	**E1**	-11.79	841.15	725.88	251.36	0.27	3.88	1.99	na
L0	**E2**	-12.37	845.51	725.95	255.64	0.12	2.30	1.92	na
L0	**E3**	-9.84	818.41	726.12	228.77	0.18	0.95	1.75	na
L1	**E0**	-8.43	846.15	708.12	238.77	0.43	1.85	19.75	0.08
L1	**E1**	-8.09	842.32	707.84	234.64	0.42	3.78	20.03	0.09
L1	**E2**	-8.37	846.83	707.57	238.82	0.35	1.91	20.29	0.09
L1	**E3**	1.66	813.40	704.62	202.76	0.67	0.83	23.24	0.43
L2	**E0**	-7.87	844.78	692.38	221.39	0.17	2.32	35.49	0.10
L2	**E1**	-0.93	842.64	691.85	218.69	0.14	3.54	36.02	0.50
L2	**E2**	101.01	844.77	694.19	223.06	0.03	2.48	33.68	6.37
L2	**E3**	24.76	800.58	684.75	169.87	0.48	1.10	43.11	1.69

[2]The energy loss from spillage is estimated assuming operation at best point
[3]Average curtailed demand for reserve capacity over all time steps

For the minimum release constraint (E3), reductions in hydropower generation (of about 3-5%) and net export (of about 10-23%) are seen for all cases and increase with the level of reserve capacity requirements. Spillage is about halved when the minimum release constraint is included. Reductions in both hydropower generation and spillage imply that the hydropower plants are operated at lower efficiency. Wind power generation is slightly reduced when reserve capacity requirements are included (L1 and L2 cases). Higher curtailments in demand for energy and reserve capacity are observed for all cases and increase with the level of reserve capacity requirements.

5.2 Impacts on operational flexibility

The curtailment of demand and the dual value of the power balance can be interpreted as measures of the available operational flexibility in the system. The results in Table 4 show that the minimum release constraint (E3) leads to the highest curtailment of demand of the considered environmental constraints. This increase is due to water being used to meet the minimum release requirement, which reduces the amount of water available for seasonal shifting. The consequence is an increased probability of low water levels (and in the worst case, running out of water) in low-inflow years. Fig. 6 shows the average total reservoir filling and curtailment of demand with and without the minimum release constraint for the L1 reserve capacity requirement (E3+L1 compared to E0+L1). An increase in average curtailment is found for many of the weeks when including this constraint, even though curtailment of demand only happens in the most extreme scenarios. A similar development was apparent for all the assessed reserve capacity levels when adding the minimum release constraint (E3). For the state-dependent maximum discharge constraint (E1), the total curtailment of demand increases in the E1+L0 case and decreases for the E1+L1 and E1+L2 cases. The ramping constraint (E2) gives equal or lower amounts of curtailment of demand for all the reserve capacity levels.

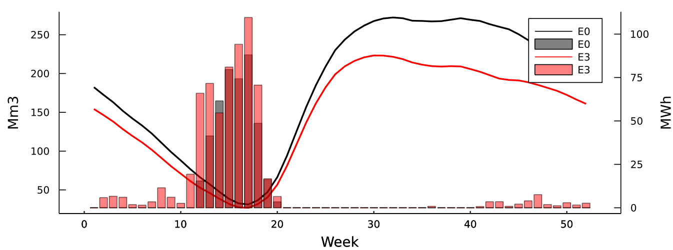
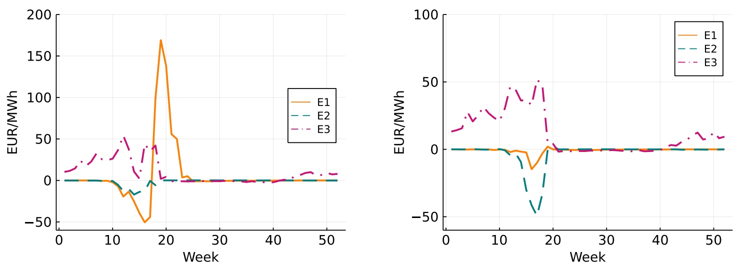


Fig. 6: The average total reservoir level (solid lines) and curtailment of demand (bars) with and without the minimum release constraint (plotted in red and black respectively) for the Level 1 reserve capacity requirements (E0+L1 compared to E3+L1). The dark red areas are where the grey and red bars overlap.

Fig. 7 plots the change in the average dual value of the power balance (Eq.(23)), when including the environmental constraints (E1-E3) compared to without (E0). The dual value of the power balance can be interpreted as the marginal cost of meeting demand. For the minimum discharge constraint (E3), an increase in the marginal cost of meeting demand is observed for a large part of the year. The ramping constraint (E2), reduces the marginal cost in the period before the snow melting starts (i.e., the end of the winter period) for both the levels of reserve capacity requirements (L1 and L2), but especially for L2. This is because the reservoir filling is kept slightly higher when the ramping constraint is included, resulting in lower average curtailment of demand in the winter period, but also slightly higher system costs due to more spillage and curtailment of wind power. For the state-dependent maximum discharge



(a) Reserve requirement level 1 (b) Reserve requirement level 2

Fig. 7: Change in the average marginal cost of meeting demand (over all the simulated scenarios) when including different environmental constraints (i.e., the difference compared to the E0+L1 and E0+L2 cases).

constraint (E1), there is first a decrease in the marginal cost around week 16, before there is a larger increase around week 18-20 in the E1+L1 case. This is due to a slightly higher reservoir filling in the late winter, resulting in reduced curtailment of demand in this period. The increase in the marginal cost right after is caused by the environmental constraint limiting discharge from the lower hydropower plant before the target reservoir level is reached, as shown in Fig. 8. In the E1+L2 case, the state-dependent maximum discharge constraint has a smaller impact. This is because a less strict version of the constraint is used, allowing production at minimum output within the constraint period. Even though the constraint still imposes a large reduction in the operational flexibility in this period, the impact on the marginal cost of meeting demand is more or less removed. There is still a small reduction in the marginal cost around week 16, demonstrating that the constraint has an impact on the reservoir filling coming into the constraint period (i.e., there is a slightly higher reservoir filling by the end of the winter period).

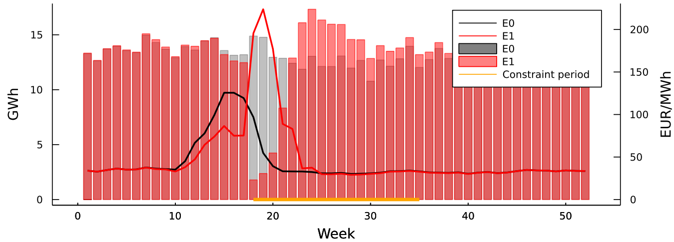
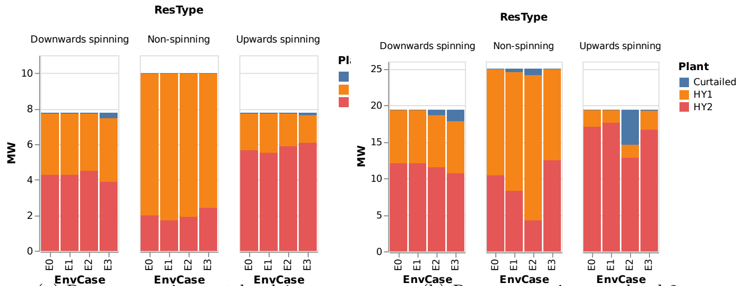


Fig. 8: The average dual value of the power balance constraint (solid lines) and the average power production (bars) for the lower hydropower plant with and without the state-dependent maximum discharge constraint (plotted in red and black, respectively) for the Level 1 reserve capacity case. The dark red areas are where the grey and red bars overlap.

5.3 Provision of reserve capacity

Fig. 9 displays the average provision of each type of reserve capacity in several of the cases. We see that the lower hydropower plant (HY 2) delivers less downwards spinning reserves when the minimum release constraint is imposed (E3 compared to E0) but more upwards spinning and non-spinning reserves. As a result, the amount of curtailed demand for downwards reserves increases considerably. When the state-dependent maximum discharge constraint is included (E1 compared to E0), there is a slight decrease in the provision of upwards and non-spinning reserves by HY 2 for the case with level 1 reserve requirements. For the high reserve capacity requirements case (L2), there is a higher decrease in non-spinning reserves and a small increase in upwards-spinning reserves. When the ramping constraint is imposed (E2 compared to E0), HY 2 delivers more upwards and downwards reserves when a medium-high level of reserve capacity is required (L1). However, for higher reserve capacity requirements (L2), a large decrease in the provision of upwards spinning and non-spinning reserves from HY 2 is observed when imposing the ramping constraint. We observe that the high reserve capacity requirements (L2) are not always possible to meet, especially when the ramping constraint is imposed.

The dual value of the requirements for upwards and downwards spinning reserve capacity (Eqs. (25) and (26)) represent the marginal cost of providing one more unit of each type of reserve capacity, or in other words, the marginal cost of meeting the reserve capacity requirements. The changes in the dual values when the environmental constraints are imposed (E1-3 compared to the E0 case) are plotted in Fig. 10. For the Level 1 reserve capacity requirements, the state-dependent discharge constraint (E1) has a similar impact on the marginal cost of meeting the upwards and downwards spinning reserve requirements as seen for the marginal cost of meeting demand in Fig. 7. The marginal cost decreases around week 16 and then increases in weeks 18-20 when the discharge limitation becomes active. When the minimum discharge constraint is imposed



(a) Reserve requirement level 1 (b) Reserve requirement level 2

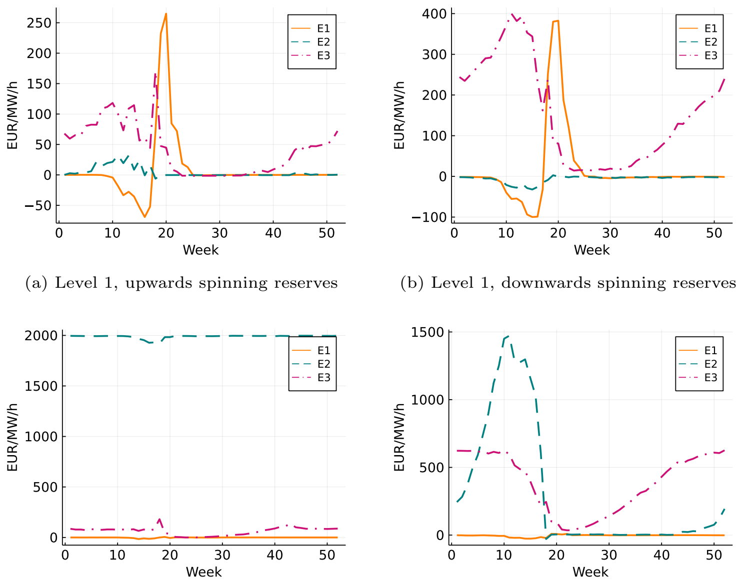
Fig. 9: Average provision of reserves by the upper (HY1) and lower (HY2) hydropower plant for each type of reserves in the Level 1 and Level 2 reserve capacity requirement cases.

(E3), the marginal costs of meeting both the upwards and downwards spinning reserve requirements increase in all weeks of the year except the summer weeks. Particularly, the marginal cost of providing downwards reserves increases. Similar impacts, only larger in magnitude, are found for higher reserve capacity requirements (L2) when imposing the minimum release requirement. On the contrary, smaller impacts are seen in the E1+L2 case because of the relaxation of the state-dependent maximum discharge limitation, as previously discussed.

For the level 1 reserve capacity requirements, the ramping constraint induces a slight increase in the marginal cost of providing upwards reserves and a slight reduction for the downwards spinning reserves (E2 compared to E0). On the other hand, for higher reserve capacity requirements (L2), the average marginal cost of upwards reserve capacity rises drastically when the ramping constraint is included, implying that the upwards reserve requirement (in combination with the non-spinning requirement) cannot be met. There is also a high increase in the marginal costs of providing downwards reserve capacity in the winter period.

5.4 Importance of strategy

So far we have discussed the overall operational results, the implications for operational flexibility and the changes in the provision of reserve capacity due to imposing the different environmental constraints. Another aspect is the importance of considering the environmental constraints in the calculation of the expected future cost functions (consistent strategy), compared to when the environmental constraints are **not** considered in the calculation of the expected future cost functions (inconsistent strategy). Fig. 11 shows the difference in costs of the simulated operation using consistent versus inconsistent strategies.



(a) Level 1, upwards spinning reserves (b) Level 1, downwards spinning reserves

(c) Level 2, upwards spinning reserves (d) Level 2, downwards spinning reserves

Fig. 10: Change in the marginal cost of meeting the upwards and downwards spinning reserve requirements when including different environmental constraints (i.e., the difference compared to the E0 cases).

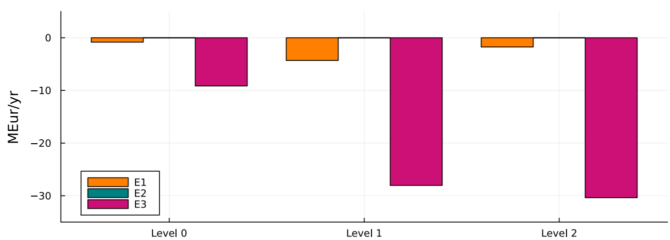


Fig. 11: Reduction in the operational costs of using consistent strategies in the forwards simulation compared to using inconsistent strategies (i.e., expected future cost functions calculated considering the environmental constraints versus expected future cost functions not considering the constraints).

We see that there is a reduction in operational costs for the state-dependent maximum discharge constraint (E1) and the minimum release constraint (E3). A larger reduction in costs is observed for higher levels of reserve capacity requirements for both constraints. For the E1 case, the economic improvement is lower for the highest level of reserve capacity requirements (Level 2 compared to Level 1), but this is likely due to a less strict version of the constraint being used in the E1+L2 case. The cost savings are mainly a result of avoiding curtailment of demand for energy and reserve capacity. For the minimum release constraint (E3), the amount of water available for seasonal shifting is overestimated when the constraint is not included in the calculation of the expected future cost functions, resulting in less efficient management of the reservoir. For the state-dependent maximum release constraint (E3), the reservoir management is adjusted to mitigate the implications of the constraint when a consistent strategy is used. This is achieved by increasing the water level in the reservoir and thereby meeting the reservoir threshold earlier in some of the scenarios. We do not find an economic improvement resulting from including the ramping restriction in the calculation of the expected future cost functions. This is partly logical, as the reservoir level cannot actively be used to mitigate the constraint (like for E1), nor does the constraint directly restricts the amount of water (i.e., energy) that can be regulated (like for E3). However, the low impact of including this constraint in the strategy calculation may also partly be a result of the level of detail in the study, such as the ramping constraint only being active within the week, the underestimation of the intra-week variation in the SDP model (backwards recursion) and the coarse temporal resolution (3h). This result also aligns with previous studies when considering Nordic conditions [31].

5.5 Sensitivity of hydropower plant flexibility

A sensitivity study of the operational flexibility of the lower hydropower plant was conducted for the E0-3+L2 cases. The capacity factor (CF) and the degree of regulation (DR) of the plant were changed by adjusting the maximum turbine capacity and reservoir size. The sensitivity cases are described in Table 5, where V, Q and P give the reservoir size, maximum discharge and maximum power output for the lower reservoir, respectively. The estimated DR for the total hydropower system and the estimated CF of the lower power plant are also given. The “Base” case in the sensitivity study refers to the design as described in Fig. 3b.

Table 5: Description of sensitivity cases.

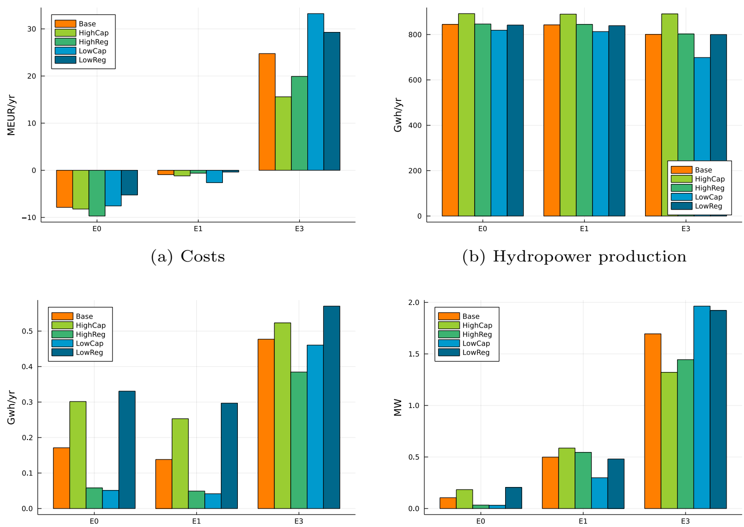
Sensitivity	**Description**
Base	$V = 179\ Mm^3$, $Q = 58.0 \frac{m^3}{s}$, $P = 170.0\ MW$ $(DR = 0.46,\ CF = 0.45)$
HighReg	$V = 239\ Mm^3$, $Q = 58.0 \frac{m^3}{s}$, $P = 170.0\ MW$ $(DR = 0.53,\ CF = 0.45)$
LowReg	$V = 119\ Mm^3$, $Q = 58.0 \frac{m^3}{s}$, $P = 170.0\ MW$ $(DR = 0.39,\ CF = 0.45)$
HighCap	$V = 179\ Mm^3$, $Q = 75.5 \frac{m^3}{s}$, $P = 233.1\ MW$ $(DR = 0.46,\ CF = 0.34)$
LowCap	$V = 179\ Mm^3$, $Q = 40.5 \frac{m^3}{s}$, $P = 114.9\ MW$ $(DR = 0.46,\ CF = 0.64)$

The average operational costs, hydropower production, curtailment of demand and curtailment of reserve capacity of including the state-dependent discharge (E1) and the minimum release (E3) for different configurations of the hydropower system are shown in Fig. 12. In general, similar trends were seen for the solutions based on the different hydropower plant configurations when imposing the two environmental constraints. For the state-dependent discharge case (E1), we did not find a consistent change in how the constraint impacts the operation depending on the configuration of the power plant. For the minimum release constraint (E3), the induced cost of imposing the constraint was found to be lower for more flexible system configurations and higher for less flexible system configurations. Without the environmental constraints (E0), the degree of regulation has a larger cost impact than the capacity factor. However, when including the minimum release constraint (E3), the largest span in average costs is seen for the different capacity factors. In other words, the impact on the operational cost of the minimum release constraint is found to be sensitive to the capacity factor of the plant. Furthermore, the total hydropower production is reduced relatively more for lower turbine capacities when the minimum release constraint is included (E3 compared to E0). The curtailment of demand for energy and reserve capacity increases considerably when the minimum release constraint is included (compared to E0), but the relative increases are higher for lower turbine capacities and for higher degrees of regulation. We have omitted the results considering the ramping constraint (E2) since the requirements for reserve capacity cannot be met for this case (E2+L2).

6 Conclusion

The impacts of environmental constraints on the operation of hydropower plants and the provision of spinning and non-spinning reserve capacity in a wind- and hydropower-dominated region of a congested power system, like the Norwegian, have been assessed using a stochastic, long-term scheduling model. Three types of environmental constraints on hydropower discharge are considered: reservoir-level dependent maximum discharge (i.e., state-dependent), maximum ramping of discharge and minimum release. The representative Norwegian case study demonstrates the economic value of including the state-dependent maximum discharge constraint and the minimum release constraint in the long-term strategic scheduling, i.e., the calculation of the expected future cost functions. This value was found to increase with the level of reserve capacity requirements. In general, the operational costs increase with the level of reserve capacity requirements and when environmental constraints are imposed. The highest cost increases were found for the cases with the minimum release constraint and when a ramping constraint was imposed in combination with high reserve capacity requirements.

The operational flexibility of the hydropower plant and the plant's capability to provide reserve capacity were found to depend on the type of



(a) Costs (b) Hydropower production

(c) Curtailment of demand (d) Curtailment of demand for reserves

Fig. 12: Average operational costs (a), hydropower production (b), curtailment of demand for energy (c) and curtailment of demand for reserve capacity (d) solving without the environmental constraints (E0), with the state-dependent discharge constraint (E1) and the minimum release constraint (E3) for different configurations of the hydropower system.

environmental constraint being imposed. The minimum release and ramping constraints are active throughout the entire year, and the largest flexibility impacts of these constraints are observed in the most energy-restrained periods of the year. On the other hand, the state-dependent discharge constraint is only active for a limited period, mainly resulting in increased marginal costs of meeting demand and reserve capacity requirements at the beginning of this period. The ramping constraint was mostly found to have very small operational consequences, besides reducing the rate of change in discharge. However, high requirements for reserve capacity could not be met when the ramping constraint was imposed. Similarly, the minimum release constraint was found to limit the provision of downwards reserves.

The magnitude of the implications of the environmental constraints was found to be sensitive to the reserve capacity requirements but is also likely to depend on the strictness of the environmental regulation. A slightly relaxed version of the state-dependent maximum discharge constraint was used in some of the cases, showing considerably lower impacts on the marginal cost of meeting the demand for energy and reserve capacity. Alternative formulations of environmental constraints could be investigated further to assess the change in operational flexibility towards the effectiveness of meeting environmental targets.

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References

[1] IEA. Net Zero by 2050. Paris; 2021. Available from: https://www.iea.org/reports/net-zero-by-2050.

[2] Holttinen H, Kiviluoma J, Helistö N, Levy T, Menemenlis N, Jun L, et al. Design and operation of energy systems with large amounts of variable generation: Final summary report, IEA Wind TCP Task 25; 2021. Available from: https://cris.vtt.fi/en/publications/design-and-operation-of-energy-systems-with-large-amounts-of-vari.

[3] IEA. Hydropower Special Market Report. Paris: IEA; 2021. Available from: https://www.iea.org/reports/hydropower-special-market-report.

[4] Brondizio ES, Settele J, Díaz S, Ngo HT, (editors). Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Bonn, Germany: IPBES; 2019. Available from: https://zenodo.org/record/6417333.

[5] Richter BD, Baumgartner JV, Powell J, Braun DP. A Method for Assessing Hydrologic Alteration within Ecosystems. Conservation Biology. 1996 8;10(4):1163–1174. https://doi.org/10.1046/J.1523-1739.1996.10041163.X.

[6] Poff NL, Allan JD, Bain MB, Karr JR, Prestegaard KL, Richter BD, et al. The Natural Flow Regime. BioScience. 1997;47(11):769–784. https://doi.org/10.2307/1313099.

[7] Grill G, Lehner B, Thieme M, Geenen B, Tickner D, Antonelli F, et al. Mapping the world's free-flowing rivers. Nature 2019 569:7755. 2019 5;569(7755):215–221. https://doi.org/10.1038/s41586-019-1111-9.

[8] The European Parliament.: European Water Framework Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy. Available from: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32000L0060.

[9] Halleraker JH, Kenawi MS, L'Abée-Lund JH, Bakken TH, Alfredsen K. Assessment of flow ramping in water bodies impacted by hydropower operation in Norway – Is hydropower with environmental restrictions more sustainable? Science of The Total Environment. 2022 8;832:154776. https://doi.org/10.1016/J.SCITOTENV.2022.154776.

[10] Halleraker JH, Bjørnhaug M, Langåker RM, Selboe OK, Sørensen J, Brodtkorb E, et al. Vannkraftkonsesjoner som kan revideres innen 2022. NVE; 2013. Available from: https://www.miljodirektoratet.no/publikasjoner/2013/oktober-2013/vannkraftkonsesjoner-som-kan-revideres-innen-2022/.

[11] Statnett. Verdien av regulerbar vannkraft - Betydning for kraftsystemet i dag og i fremtiden; 2021. Available from: https://www.statnett.no/contentassets/b82dcf206acc4762b2abcc3182e5bc52/verdien-av-regulerbar-vannkraft-statnett-mars-2021.pdf.

[12] Helseth A, Haugen M, Farahmand H, Mo B, Jaehnert S, Stenkløv I. Assessing the benefits of exchanging spinning reserve capacity within the hydro-Dominated nordic market. Electric Power Systems Research. 2021 10;199:107393. https://doi.org/10.1016/J.EPSR.2021.107393.

[13] Moreira C, Castro M, Vasconcelos M, Silva B, Vagnoni E, Nicolet C, et al. D2.1 Flexibility, technologies and scenarios for hydro power. The Hydropower Extending Power System Flexibility project (XFLEX HYDRO); 2020. Available from: https://www.xflexhydro.com/knowledge/flexibility-technologies-and-scenarios-for-hydropower-report.

[14] Khodadadi A, Herre L, Shinde P, Eriksson R, Soder L, Amelin M. Nordic Balancing Markets: Overview of Market Rules. International Conference on the European Energy Market, EEM. 2020 9;2020-September. https://doi.org/10.1109/EEM49802.2020.9221992.

[15] Farahmand H, Doorman GL. Balancing market integration in the Northern European continent. Applied Energy. 2012 8;96:316–326. https://doi.org/10.1016/J.APENERGY.2011.11.041.

[16] Jaehnert S, Doorman GL. Assessing the benefits of regulating power market integration in Northern Europe. International Journal of Electrical Power & Energy Systems. 2012 12;43(1):70–79. https://doi.org/10.1016/J.IJEPES.2012.05.010.

[17] Helseth A, Fodstad M, Mo B. Optimal Medium-Term Hydropower Scheduling Considering Energy and Reserve Capacity Markets. IEEE Transactions on Sustainable Energy. 2016 7;7(3):934–942. https://doi.org/10.1109/TSTE.2015.2509447.

[18] Abgottspon H, Njalsson K, Bucher MA, Andersson G. Risk-averse medium-term hydro optimization considering provision of spinning reserves. 2014 International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2014 - Conference Proceedings. 2014 11;https://doi.org/10.1109/PMAPS.2014.6960657.

[19] Pérez-Díaz JI, Guisández I, Chazarra M, Helseth A. Medium-term scheduling of a hydropower plant participating as a price-maker in the automatic frequency restoration reserve market. Electric Power Systems Research. 2020 8;185:106399. https://doi.org/10.1016/J.EPSR.2020.106399.

[20] Hjelmeland MN, Helseth A, Korpås M. A Case Study on Medium-Term Hydropower Scheduling with Sales of Capacity. Energy Procedia. 2016 1;87:124–131. https://doi.org/10.1016/J.EGYPRO.2015.12.341.

[21] van Ackooij W, Danti Lopez I, Frangioni A, Lacalandra F, Tahanan M. Large-scale unit commitment under uncertainty: an updated literature survey. Annals of Operations Research. 2018;271(1):11–85. https://doi.org/10.1007/s10479-018-3003-z.

[22] Sørensen B. A combined wind and hydro power system. Energy Policy. 1981 3;9(1):51–55. https://doi.org/10.1016/0301-4215(81)90207-X.

[23] Kan X, Hedenus F, Reichenberg L. The cost of a future low-carbon electricity system without nuclear power – the case of Sweden. Energy. 2020 3;195:117015. https://doi.org/10.1016/J.ENERGY.2020.117015.

[24] Tande JO, Korpås M, Uhlen K. Planning and Operation of Large Offshore Wind Farms in Areas with Limited Power Transfer Capacity. Wind Engineering. 2012;36(1):2012–69. https://doi.org/10.1260/0309-524X.36.1.69.

[25] Matevosyan J, Olsson M, Söder L. Hydropower planning coordinated with wind power in areas with congestion problems for trading on the spot and the regulating market. Electric Power Systems Research. 2009 1;79(1):39–48. https://doi.org/10.1016/J.EPSR.2008.05.019.

[26] Chazarra M, García-González J, Pérez-Díaz JI, Arteseros M. Stochastic optimization model for the weekly scheduling of a hydropower system in day-ahead and secondary regulation reserve markets. Electric Power Systems Research. 2016 1;130:67–77. https://doi.org/10.1016/J.EPSR.

2015.08.014.

[27] Guisández I, Pérez-Díaz JI, Wilhelmi JR. Approximate formulae for the assessment of the long-term economic impact of environmental constraints on hydropeaking. Energy. 2016 10;112:629–641. https://doi.org/10.1016/J.ENERGY.2016.06.076.

[28] Huuki H, Karhinen S, Ashraf FB, Haghighi AT, Marttila H. The economic cost of hydropower environmental constraints under decreasing price volatility. River Research and Applications. 2022;https://doi.org/10.1002/RRA.4049.

[29] Niu S, Insley M. On the economics of ramping rate restrictions at hydro power plants: Balancing profitability and environmental costs. Energy Economics. 2013;39:39–52. https://doi.org/10.1016/j.eneco.2013.04.002.

[30] Guisández I, Pérez-Díaz JI, Wilhelmi JR. The influence of environmental constraints on the water value. Energies. 2016;9(6). https://doi.org/10.3390/en9060446.

[31] Guisández I, Pérez-Díaz JI, Nowak W, Haas J. Should environmental constraints be considered in linear programming based water value calculators? International Journal of Electrical Power and Energy Systems. 2020;117. https://doi.org/10.1016/j.ijepes.2019.105662.

[32] Schäffer LE, Adeva-Bustos A, Bakken TH, Helseth A, Korpås M. Modelling of Environmental Constraints for Hydropower Optimization Problems – a Review. In: 2020 17th International Conference on the European Energy Market (EEM). IEEE; 2020. p. 1–7. Available from: https://ieeexplore.ieee.org/document/9221918/.

[33] Schäffer LE, Helseth A, Korpås M. A stochastic dynamic programming model for hydropower scheduling with state-dependent maximum discharge constraints. Renewable Energy. 2022 7;194:571–581. https://doi.org/10.1016/J.RENENE.2022.05.106.

[34] Helseth A, Mo B, Hågenvik HO. Nonconvex Environmental Constraints in Hydropower Scheduling. In: International Conference on Probabilistic Methods Applied to Power Systems (PMAPS); 2020. p. 1–6.

[35] Helseth A, Mo B, Hans, Hågenvik O, Schäffer LE. Hydropower Scheduling with State-Dependent Discharge Constraints: An SDDP Approach. Journal of Water Resources Planning and Management. 2022 9;148(11):04022061. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001609.

[36] Bellman R. Dynamic programming and stochastic control processes. Information and Control. 1958 9;1(3):228–239. https://doi.org/10.1016/S0019-9958(58)80003-0.

[37] Labadie JW. Optimal Operation of Multireservoir Systems: State-of-the-Art Review. Journal of Water Resources Planning and Management. 2004 3;130(2):93–111. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:2(93).

[38] Gjerden KS, Helseth A, Mo B, Warland G. Hydrothermal scheduling in Norway using stochastic dual dynamic programming; A large-scale case study. 2015 IEEE Eindhoven PowerTech, PowerTech 2015. 2015 8;https://doi.org/10.1109/PTC.2015.7232278.

[39] Mathisen S. Improved Inflow Modelling. Trondheim: HydroCen rapport 30. Norwegian Research Centre for Hydropower Technology; 2022. Available from: https://hydrocen.nina.no/english/Publications/HydroCen-Report-series.

[40] Nandalal KDW, Bogardi JJ. Dynamic programming based operation of reservoirs: Applicability and limits. Cambridge University Press; 2007. Available from: https://www.cambridge.org/core/books/dynamic-programming-based-operation-of-reservoirs/95F0B8768ADCD261343E1A21F59F7C3F.

[41] Misener R, Floudas CA. Piecewise-Linear Approximations of Multidimensional Functions. J Optim Theory Appl. 2010;145:120–147. https://doi.org/10.1007/s10957-009-9626-0.

[42] Bakken TH, Zinke P, Melcher A, Sundt H, Vehanen T, Jorde K, et al. Setting environmental flows in regulated rivers. Trondheim: SINTEF; 2012. Available from: https://www.researchgate.net/publication/334162598_Setting_environmental_flows_in_regulated_rivers.

[43] Bakken TH, Harby A, Forseth T, Ugedal O, Sauterleute JF, Halleraker JH, et al. Classification of hydropeaking impacts on Atlantic salmon populations in regulated rivers. River Research and Applications. 2021;https://doi.org/10.1002/RRA.3917.

[44] Pereira-Bonvallet E, Püschel-Løvengreen S, Matus M, Moreno R. Optimizing Hydrothermal Scheduling with Non-Convex Irrigation Constraints: Case on the Chilean Electricity System. In: Energy Procedia. vol. 87. Elsevier Ltd; 2016. p. 132–140.

[45] Dunning I, Huchette J, Lubin M. JuMP: A Modeling Language for Mathematical Optimization. SIAM Review. 2015;59(2):295–320. https://doi.org/10.1137/15M1020575.

[46] IBM.: CPLEX optimizer. Last accessed 01.07.2021. http://www-01.ibm.com/software/.

[47] Schäffer LE, Mo B, Graabak I. Electricity Prices and Value of Flexible Generation in Northern Europe in 2030. In: International Conference on the European Energy Market, EEM; 2019. .

[48] Larsen CT, Doorman G, Mo B. Joint Modelling of Wind Power and Hydro Inflow for Power System Scheduling. Energy Procedia. 2016;87:189–196. https://doi.org/10.1016/J.EGYPRO.2015.12.350.

[49] Jardim DLDD, MacEira MEP, Falcão DM. Stochastic streamflow model for hydroelectric systems using clustering techniques. 2001 IEEE Porto Power Tech Proceedings. 2001;3:244–249. https://doi.org/10.1109/PTC.2001.964916.

[50] Lloyd SP. Least Squares Quantization in PCM. IEEE Transactions on Information Theory. 1982;28(2):129–137. https://doi.org/10.1109/TIT.1982.1056489.

[51] Hjelmeland MN, Larsen CT, Korpas M, Helseth A. Provision of rotating reserves from wind power in a hydro-dominated power system. 2016 International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2016 - Proceedings. 2016 12;https://doi.org/10.1109/PMAPS.2016.7764206.

[52] Mo B, Gjelsvik A, Grundt A, Kåresen K. Optimisation of hydropower operation in a liberalised market with focus on price modelling. 2001 IEEE Porto Power Tech Proceedings. 2001;1:228–233. https://doi.org/10.1109/PTC.2001.964603.

Appendix A SDP Algorithm

Algorithm 1: SDP Algorithm

1 $j \leftarrow 0, \Delta \leftarrow \infty, \alpha_{t=T}(...) \leftarrow 0$
2 **while** $\Delta > \epsilon$ *or* $j < J$ **do**
3     $j \leftarrow j + 1$
4   **for** t = *T:-1:1* **do**
5   **for** $s^p \in \mathcal{S}^p$ **do**
6   **for** $s_t^u \in \mathcal{S}_t^u$ **do**
7                 $\{\hat{Z}_t, D_t^C, W_t\} \leftarrow stochVar(s_t^u)$
8   **for** $h \in \mathcal{H}$ **do**
9                     $V_h \leftarrow resVolume(s^p, h)$
10                     $Z_h \leftarrow \omega_h \times \hat{Z}_{t,s_t^u}$
11   **end**
12                 $\alpha_{t+1}(s^p, s_t^u) \leftarrow \Phi_{j,t}(\{1, ..., P\}, s_t^u)$
13                 $\alpha_t(s^p, s_t^u) \leftarrow solveProblem(t, s^p, s_t^u)$
14   **end**
15   **for** $s_{t-1}^u \in \mathcal{S}^u$ **do**
16                 $\Phi_{j,t-1}(s^p, s_{t-1}^u) \leftarrow \sum_{s_t^u \in \mathcal{S}_t^u} Pr(s_t^u \mid s_{t-1}^u)\alpha_t(s^p, s_t^u)$
17   **if** $s^p > 1$ **then**
18                     $\Psi_{j,t-1}^{h \in \mathcal{H}}(s^p - 1, s_{t-1}^u) \leftarrow$
                      $getWV(\Phi_{j,t-1}(\{1, ..., s^p\}, s_{t-1}^u))$
19   **end**
20   **end**
21   **end**
22   **end**
23     $\Delta \leftarrow \mid \Psi_{j,t=T}^h(s^p, s_t^u) - \Psi_{j,t=0}^h(s^p, s_t^u) \mid, \quad s^p \in \mathcal{S}^p, s_t^u \in \mathcal{S}^p, h \in \mathcal{H}$
24   **if** $\Delta > \epsilon$ **then**
25         $\Psi_{j+1,t=T}^h(s^p, s_t^u) \leftarrow \Psi_{j,t=0}^h(s^p, s_t^u), \quad s^p \in \mathcal{S}^p,\ s_t^u \in \mathcal{S}, h \in \mathcal{H}$
26         $\Phi_{j+1,t=T}(s^p, s_t^u) \leftarrow \Phi_{j,t=0}(s^p, s_t^u), \quad s^p \in \mathcal{S}^p,\ s_t^u \in \mathcal{S}^u$
27   **end**
28 **end**

The SDP algorithm is described in Algorithm 1. The algorithm is based on backwards recursion and solves the decision problem for each stage and state of the system for a planning horizon of one year. The algorithm iterates over all stages (T), all reservoir states ($\mathcal{S}^p$) and all stochastic states ($\mathcal{S}^u$) in lines 4-6. The reservoir state ($\mathcal{S}^p$) comprises all combinations of discrete storage volumes for the reservoirs in the system. The stochastic variables are updated in line 7 and reservoir-specific data is updated in lines 8-11. The expected future costs of all end reservoir states are updated in line 12, before the decision problem is solved in line 13. The solution of the optimisation problem for all stochastic states s_t^u is used to calculate the expected future cost in line 16. The expected future cost for each reservoir state is stored in matrix Φ. The water values are calculated and stored to the water value matrix Ψ in line 18. Convergence is determined at the end of each iteration in line 23, by comparing the calculated water values in the last and first stages. If the algorithm has not converged, the water value matrix and the expected future cost matrix for the last stage T are updated with the values from the first stage in the last completed iteration before the next iteration, see lines 25 and 26.

Appendix B Stochastic variables

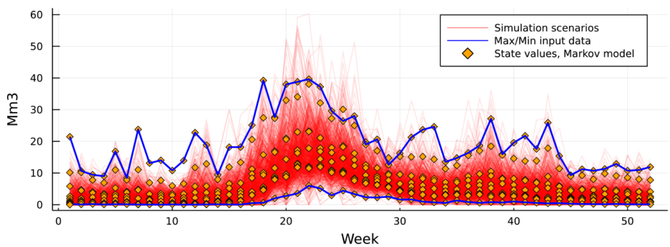

Fig. B1: Plot of the stochastic inflow states used in the Markov model (orange diamonds), the simulation scenarios (red) and the minimum and maximum of the input data (marked by blue lines).

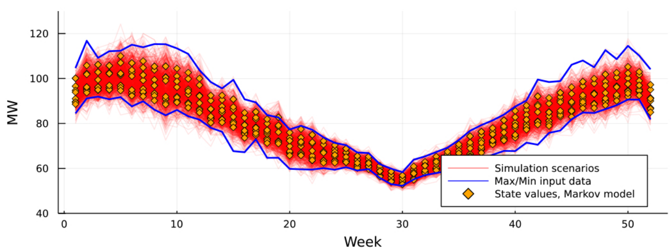

Fig. B2: Plot of the stochastic household demand states used in the Markov model (orange diamonds), the simulation scenarios (red) and the minimum and maximum of the input data (marked by blue lines).

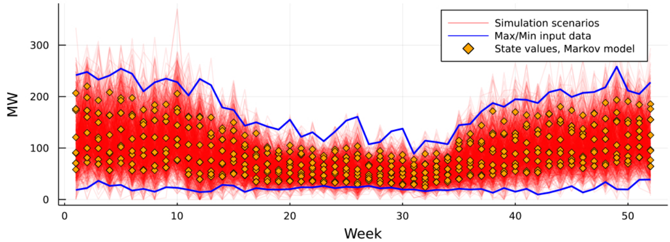

Fig. B3: Plot of the stochastic wind power generation states used in the Markov model (orange diamonds), the simulation scenarios (red) and the minimum and maximum of the input data (marked by blue lines).

Appendix C Additional input data

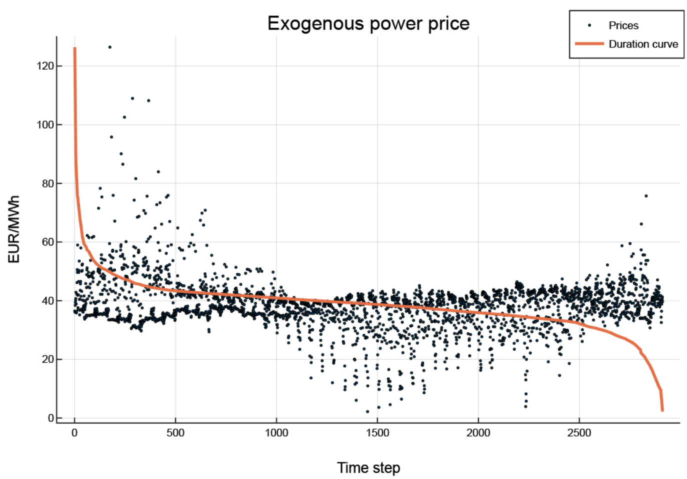

Fig. C4: Illustration of the deterministic price series with three-hour resolution used for exchange/trade towards the larger power system.

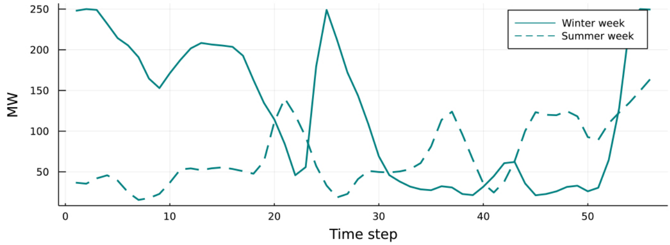

Fig. C5: Wind power generation for two random weeks (examples) with a three-hour resolution, as represented in the simulation. A flat (average) profile is used in the SDP model, but the total wind power generation varies from week to week.

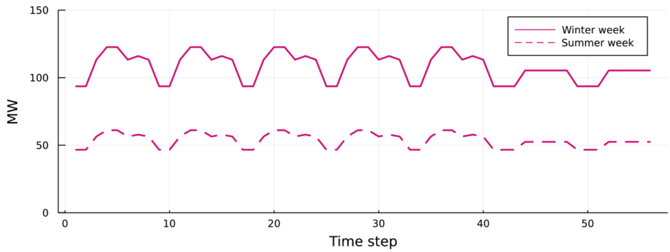

Fig. C6: Illustration of the weekly profile for the household demand (three-hour resolution). The same profile is assumed for all weeks in the SDP model and the final simulations, but the total demand varies from week to week.

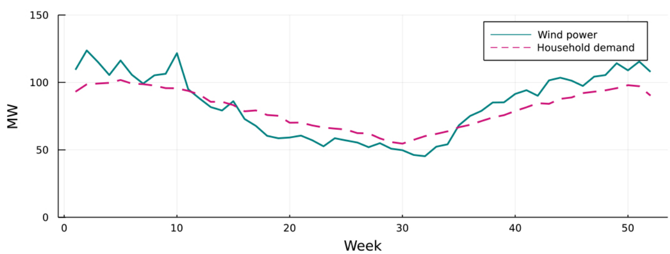

Fig. C7: Illustration of the average yearly profile for the household demand and wind power generation.

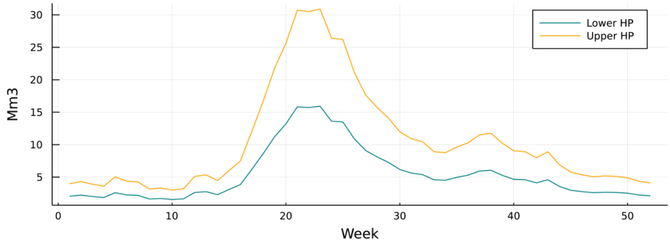

Fig. C8: Illustration of the average yearly inflow to each of the hydropower plants.

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