Sofie Aandahl Børresen

Evaluating Modeling Approaches for State-Dependent Environmental Constraints in Medium-Term Hydropower Scheduling

Master's thesis in Energy and Environmental Engineering
Supervisor: Gro Klæboe
Co-supervisor: Linn Emelie Schäffer
June 2022

Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Electric Power Engineering

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Kunnskap for en bedre verden

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Abstract

As concerns of climate change and environmental degradation are becoming ever more prevalent in society today, power producers have a great responsibility to operate in an environmentally sustainable way. Many of the large reservoirs in Norway also are used for recreational activities and there are strict regulations on some reservoirs to ensure high enough water levels and avoid drought in popular recreational areas. These regulations are state-dependent, making them challenging to implement in the modeling framework used in medium-term hydropower scheduling today.

This master's thesis addresses the inclusion of state-dependent environmental constraints in medium-term scheduling of hydropower plants with reservoirs. An exact restriction formulation is compared, through a case study, to linear approximations; one complete relaxation and one tighter relaxation with a lower auxiliary reservoir bound. The three approaches are benchmarked against a base case method.

Results from the case study showed similar improvement for the exact formulation and the tighter linear approximation of the state-dependent constraints. The financial results indicate an earning potential, but the overall reservoir level did not increase substantially. Still, the model is very price sensitive, and a different price profile could lead to a more significant impact. There was no significant difference between the complete relaxation and the base case method, indicating poor performance. The tighter linear approximation method can be used in today's industry approaches and is a good alternative for including state-dependent environmental constraints in medium-term hydropower scheduling.

Sammendrag

Ettersom frykten for klimaendringer stadig blir mer utbredt i samfunnet i dag, har kraftprodusenter et stort ansvar for å produsere på en mest mulig bærekraftig måte. Mange av de store vannkraftmagasinene i Norge brukes også til formål som friluftsliv og rekreasjon, og derfor er det i noen tilfeller svært strenge reguleringer knyttet til magasinfylling. Disse lovene og reglene er tilstandsavhengige, noe som gjør de vanskelig å inkludere i modelleringsrammeverkene som brukes til vannkraftplanlegging i dag.

Denne masteroppgaven tar for seg inkluderingen av tilstandsavhengige restriksjoner i vannkraftplanlegging. En eksakt formulering av restriksjonen sammenlignes gjennom en case-studie med to lineære approksimasjoner; en fullstendig relaksering og en strammere relaksering som har en kunstig nedre magasingrense. Disse tre formuleringsmetodene er sett opp mot et base case.

Resultater fra case-studien viste at det er tilnærmet lik forbedring ved bruk av den eksakte formuleringen som med den strammere lineære relakseringen. De økonomiske resultatene indikerer at det er et inntjeningspotensial, men vannmengden i magasinet økte ikke. Modellen er svært prissensitiv, og en annen prisprofil vil kunne føre til en større innvirkning. Det var ingen signifikant forskjell mellom den fullstendige relakseringen og base caset, som indikerer at det er lite hensiktsmessig å bruke denne metoden. Den strammere relakseringsmetoden kan brukes i dagens vannkraftplanleggingsverktøy og er en god metode for å inkludere tilstandsavhengige miljørestriksjoner.

Preface

This master's thesis concludes my master's degree within Energy and Environmental Engineering at the Norwegian university of Science and Technology (NTNU), and marks the ending of five exciting years as a student in Trondheim. The thesis is a collaboration between NTNU and TrønderEnergi, and the work is closely related to SINTEF's project HydroCen.

I would like to express gratitude to my supervisor Gro Klæboe and co-supervisor Linn Emelie Schäffer. Our frequent meetings have helped structure this thesis and communicate the work carried out. I would also like to extend my thanks to TrønderEnergi for their help in offering valuable data and introducing this exciting research topic. A great motivation of the work has been the close industry collaboration and the access to actual data.

Finally, I would like to thank my dear family and friends. Thanks, to my fellow students for supportive conversations during coffee breaks and for keeping me company on long working days.

Trondheim, June 2022
Sofie Aandahl Børresen

Abbreviations

DP	Dynamic Programmin
EMPS	Multi-area Power-market Simulator
IP	Integer Programming
LP	Linear Programming
NVE	the Norwegian Water Resources and Energy Directorate
SDP	Stochastic Dynamic Programming
SDDiP	Stochastic Dynamic Dual integer Programming
SDDP	Stochastic Dynamic Dual Programming
SOS2	Special Ordered Set of Type Two

Nomenclature

Index Sets

$\mathcal{S}$ Set of scenarios (inflow and price)

$\mathcal{T}$ Set of stages (weeks)

$\mathcal{V}^0$ Set of states (discretized initial reservoir levels)

Parameters

$\alpha_t^{marginal}$ Marginal value of profit in stage t

$\bar{U}$ Maximum discharge

$\bar{V}$ Maximum reservoir volume

λ_t^s Power price in stage t, given scenario s

$\tilde{V}_t$ Environmental limit on reservoir volume in stage t

$\underline{V}^*$ Auxiliary lower limit on reservoir volume in stage t

e Energy conversion factor

$F_{v_{t+1}}$ Future profit function of v_t

i_t^s Inflow (Mm3/week) in stage t, given scenario s

V^0 Initial reservoir used in parallel simulations

v_t^0 Initial reservoir level in stage t (Mm3)

Variables

α_{t+1} Future expected profit

α_t Expected profit

$\alpha_t^{v_t^0}$ Expected profit for initial reservoir level v_t^0

q_t Plant outflow in stage t (Mm3/week)

s_t Spilled outflow in stage t (Mm3/week)

u_t Plant output (MWh)

v_t Reservoir level at end of period (Mm3)

v_t^+ Slack variable for v_t

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Chapter 1

Introduction

Climate change and environmental degradation are existential threats to Europe and the world. Power producers are encouraged to operate in an environmentally sustainable way, especially in recent years, as the unprecedented situation in European energy markets has led to a decisive involvement of public consumers. High electricity prices and low water levels in the Norwegian hydro reservoirs have put even greater pressure on hydropower producers. As many of the large reservoirs in Norway are also used for recreational activities, strict regulations have been imposed on the minimum level of some reservoirs. The environmental constraints aim to avoid drought in popular recreational areas, as it leads to great dissatisfaction among the local population. It has become more common to formulate environmental rules and regulations as state-dependent in recent years[1]. State-dependent restrictions balance economic interests and environmental considerations but have the disadvantage of being mathematically challenging to model[2].

1.1 Scope of the Thesis

This master's thesis aims to evaluate how different modeling approaches for state-dependent environmental constraints affect medium-term hydropower scheduling. More specifically, the thesis aims to answer the following research questions:

- How are economic aspects and reservoir distribution affected by state-dependent environmental restrictions?
- Is it possible to create a hydropower scheduling method that includes state-dependent environmental constraints, which today's industry can use?

Medium-term hydropower scheduling models currently used in the hydropower industry do not include accurate representations of state-dependent constraints as they often lead to nonconvexities and the need for logical conditions. State-of-the-art solution methods for hydropower scheduling, using stochastic dual dynamic programming (SDDP) [3], require a convex model formulation and rely on linear approximations of such constraints. Using another modeling framework, e.g., stochastic dynamic programming (SDP) [4], will enable the possibility of including nonconvexities and logical conditions. However, the SDP method is suitable only for small systems.

The main research objectives of this thesis summarized below.

- **Background and Theory:** Present an introduction to hydropower scheduling and look into relevant optimization techniques. Furthermore, an overview of existing research on state-dependent environmental constraints is provided.
- **Methodology:** Develop a medium-term hydropower scheduling model for local reservoir management, including four different modeling formulations. The model is then applied to a Norwegian case study.
- **Results and Discussions:** Observe and interpret results from the case study to investigate how the different modeling formulations affect solution quality and discuss sensitivities and weaknesses of the model.

1.2 Contribution

There exists research that considers accurate representations of state-dependent environmental constraints using stochastic dual dynamic integer programming (SDDiP) [3] and SDP [5] and linear approximations in SDDP[6]. Still, to the best of the author's knowledge, there is no material comparing the different approaches.

By implementing the different restriction formulations in an SDP model framework, both linear- and exact formulations may be evaluated without additional noise in the comparison. This master's thesis can therefore compare linear formulations that can be used in SDDP-based models and more accurate representations that cannot be included in SDDP due to nonconvexities.

The thesis is written in collaboration with TrønderEnergi, in addition to being affiliated with HydroCen, a Norwegian Research Centre for Hydropower Technology. The work is of relevance to research areas within hydropower and energy modeling. In addition to writing this master's thesis, the author has written an article for the European Energy Market Conference and an abstract for the International Conference on Hydropower Scheduling in Competitive Electricity Markets. These articles are attached in the Appendix A and B, and they are primarily based on results and insights from the work of this master's thesis.

Chapter 2

Background and Theory

Section 2.1 and the beginning of 2.3 are adapted from Section 1.1 and Section 2 in [7].

2.1 Introduction to Hydropower Scheduling

Hydropower scheduling can be defined as "utilizing available generation resources in such a way that the optimal result is obtained, and all relevant constraints are satisfied"[8, p.1]. After the deregulation of the Nordic power market in the 1990s, obtaining the optimal result is equivalent to maximizing the profit, given a price forecast. Before the deregulation, the optimal result was rather to minimize costs, given a demand forecast. These two objectives are equivalent from a global view and therefore many of the same methods and tools can be used in both cases. The definition also requires all relevant constraints to be satisfied. These constraints are typically considered to be restrictions on generation, transmission capacity, demand, and environmental constraints[8, p.2].

In hydropower scheduling an opportunity cost is used for valuing hydro storage as an energy resource. Similar to other renewable energy sources, the marginal cost of producing hydropower is close to zero, but in addition to this there is also an opportunity cost associated with the hydro storage[8, p.2]. The opportunity cost comes from the possibility to store water in a reservoir and utilize the resource at a later time. As the amount of water available is limited and uncertain, producing 1kWh of hydropower now deprives the opportunity to produce this water in the future. This is an evaluation that the power producers need to consider every week, every day and every hour. The possibility space of this consideration is large and complex, but is at its simplest form illustrated in Figure 2.1. A complicated aspect of the decision tree in the figure, is to find an appropriate value for the stored water, i.e. determine the opportunity cost. The value of the opportunity cost is challenging to calculate as there are many uncertainties to consider and the need for good hydropower scheduling is crucial to optimize revenue.

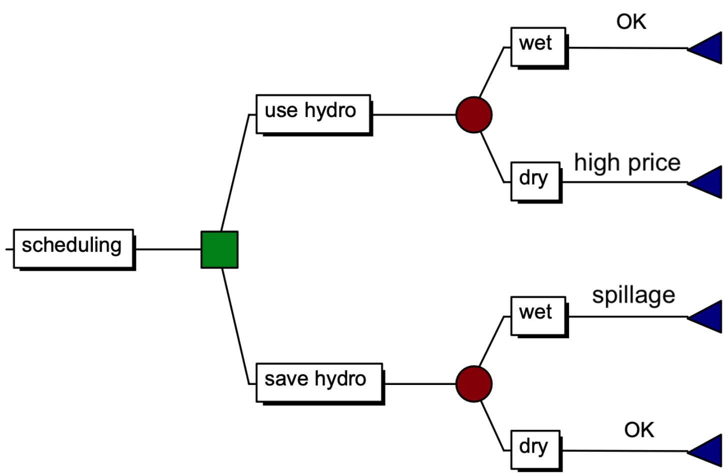


Figure 2.1: Illustration of the decision process for hydropower scheduling, adapted from [9, p.6].

Furthermore, the amount of inflow is negatively correlated with the demand. From Figure 2.2, which shows the average inflow and demand in Norway, it is clear that the inflow is lowest in the winter when the demand is highest and vice versa in the summer. This discordance signifies the crucial importance of hydro reservoir handling.

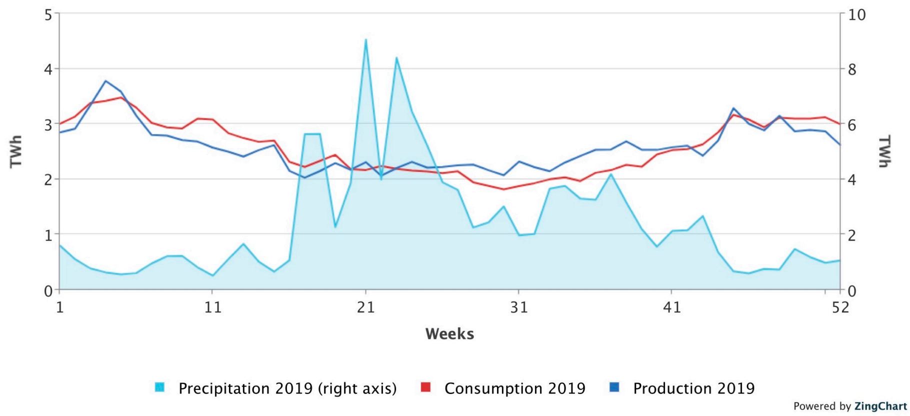


Figure 2.2: Precipitation, consumption and production of electricity in Norway in 2019, obtained from [10].

The time horizon in hydropower scheduling can be from a few hours to 5 years. Ideally, the optimal solution results from one single optimization process that considers all decisions across the time horizons. However, because the problem is extensive and highly complex, the optimization process is divided into smaller problems with different time horizons and levels of detail. A descriptive illustration of the sub-problems, along with its solution methods and scheduling hierarchy, is illustrated in Figure 2.3. The figure shows the most common division of the hydropower scheduling process, with the four main steps: long term, seasonal, short term, and detailed simulations. A description of the solution methods in the figure can be found in [8, p.11].

This thesis deals with medium-term hydropower scheduling for local reservoir management. Hydropower scheduling can be carried out at the global or local level. Global hydropower scheduling analyses entire power systems to predict electricity prices, while local scheduling uses price forecasts as exogenous parameters and aims to determine optimal reservoir management.

The scheduling model in this thesis aims to optimize hydro resources with a period of analysis of one year. Based on Figure 2.3, the model is placed somewhere in between long-term and seasonal scheduling. The time horizon is considered suitable due to the

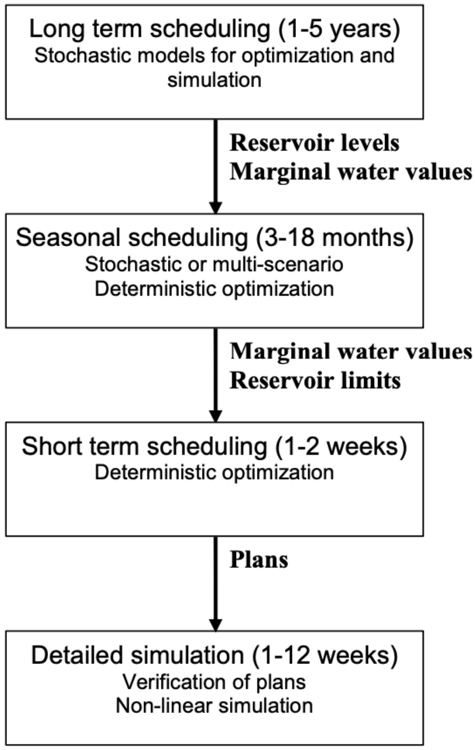


Figure 2.3: Scheduling hierarchy of operational decisions in hydropower scheduling, obtained from [8, p.30].

nature of the environmental constraints investigated in this thesis. The environmental constraints are closely linked to reservoir handling, a slow process that must be planned well in advance. Because the research question does not include any structural investments or expansions and only addresses local reservoir management, the long-term scheduling approach is unnecessary.

The hydropower scheduling problem is a large and complex problem with considerable financial resources involved. Medium-term hydropower scheduling can be solved with a weekly time step and a time horizon of up to several years, resulting in large problem sizes and many iterations. It is thus a clear need for, and a great opportunity in, good hydro reservoir planning and hydropower scheduling. However, there are many challenges in finding the optimal production schedule.

The modeling involves many uncertainties, particularly related to inflow (temperature, melting, precipitation) and electricity price (thermal fuel price, demand). Estimates and forecasts from global models play a significant role in local hydropower scheduling to deal with these uncertainties. The value of the water is, in reality, a function of future development depending on load, market prices, and inflow [8, p.39]. That is to say, some of the most influential factors for the producer's financial results are uncertain parameters. Uncertainty adds complexity to the model and is challenging from a production planning perspective. The complexity of the decision problem emphasizes the need for good decision support and hence a good hydropower scheduling model.

In addition to the fact that there are significant uncertainties associated with essential parameters, there are also physical constraints, rules, and guidelines that need to be fulfilled in each step. The state-dependent environmental constraints addressed in this master's thesis are examples of such rules. The constraints are thoroughly described in the following subsection.

2.2 Background to Environmental Constraints

As previously described, rules and guidelines are imposed on hydropower scheduling processes. One example of such regulations is environmental constraints. An environmental constraint is a term that broadly covers limits or boundaries that are put on the reservoir volumes and release plans for environmental considerations. Many of these are easy to include in hydropower scheduling processes, for example, static restrictions on reservoir levels or discharge, as modeling an absolute requirement is quite simple. When referring to environmental constraints in this thesis, these state-dependent environmental restrictions on the reservoir level are meant. State-dependent means that the restrictions depend on the situation or state of the hydropower system.

In Norway, many reservoirs are also used for recreational purposes. Hydropower production's reservoir handling and release plans can lead to drought in popular recreational areas, river sections and lakes, and impact fish mitigation and terrestrial ecosystems. Therefore, environmental constraints are imposed to facilitate synergies in reservoir usage and ensure high enough water levels. A photograph that illustrates the situation that follows at low reservoir levels is included in Figure 2.4.

Figure 2.4: Photograph of Gjevilvatnet reservoir at a low reservoir level. Foto: Gorm Kallestad / NTB

The environmental constraints handled in this model are state-dependent. The state-dependency in this situation means that they are contingent on a specific state of the reservoir level. State-dependent environmental constraints are imposed on the operation of several Norwegian hydropower plants and they may be imposed on more hydropower plants in the near future as a result of a revision of the concession terms of existing plants[1].

As these new considerations are imposed on the system, the scheduling models must adapt accordingly. On the one hand, state-dependent restrictions are often more economically efficient and can be better targeted in terms of environmental gains. On the other hand, they have the disadvantage of being mathematically challenging to model as they can make the problem formulation nonconvex [2]. This thesis aims to investigate how these mathematically challenging environmental constraints can be included in medium-term hydropower scheduling. The challenges and opportunities of environmental constraints will be further discussed in Chapter 3 through an in-depth literature review.

2.3 Mathematical Optimization of Hydropower Production

For decision-making in hydropower scheduling, there are several possible solution methods. The hydropower scheduling problem can be solved by simulations or optimization, and the optimization problem can be deterministic or stochastic. The choice of solution method is largely dependent on the time horizon and objective of the scheduling. As previously introduced in Section 2.1, the complexity of the hydropower scheduling problem requires smaller sub-problems with different solution methods. In order to find an optimal solution to the problem as a whole, a combination of optimization and simulation methods may be used.

Optimization methods are based on mathematical and numerical techniques and aim to find the single best solution among all possible outcomes[11, p.1]. A set of limitations or constraints defines the possible outcomes, and the best solution is determined by a defined objective, which typically maximizes profit or minimizes costs. All optimization techniques referred to in this thesis are exact optimization using mathematical programming. It is assumed that the reader has a good understanding of linear programming (LP) and integer programming(IP). For theory and mathematical background on mathematical programming, see [11, p.77] and [11, p.323].

To understand the optimization of hydropower scheduling, it is helpful to distinguish between deterministic and stochastic optimization. Deterministic optimization means that all parameters and conditions are known and given as inputs to the model. A deterministic approach in hydropower scheduling will assume parameters, for example, electricity price and inflow, to be known values. These are parameters that, in reality, cannot be known, and the predictability declines in pace with the time horizon. Therefore, a stochastic approach is better suited to optimize scheduling problems with a long analysis period. Stochastic optimization models take the uncertainty into account by including several realizations in each step of the process. These realizations may be described by a probability distribution, thereby considering the effects of extreme events. State-of-the-art solution methods for medium- to long-term hydropower scheduling in the Nordic are based on stochastic optimization[12] and is further explained in the following subsection.

2.3.1 Stochastic Dynamic Programming

The scope of the thesis is to evaluate different approaches for representing environmental constraints in medium-term hydropower scheduling models. In order to investigate the solution quality of the different representations of the constraint, a medium-term hydropower scheduling model based on stochastic dynamic programming (SDP) is developed. An SDP model framework is chosen due to its straightforward implementation and good opportunities for formulation flexibility. The same model framework is used for all approaches to avoid additional noise in the comparison. This subsection introduces the theory behind the SDP method.

Stochastic dynamic programming (SDP) is a stochastic optimization method utilizing a problem's dynamic structure to find the optimal solution. Problems have a dynamic structure if they can be divided into a number of sequential stages[11, p. 481]. The definition of a stage can depend on the problem, but it is usually defined as a time period. The solution strategy for dynamic programming problems is to find the optimal solution to a set of subproblems in each stage. The set of subproblems is defined by all possible states in that stage. Given the current state in one stage, the decision will give a new state in the next stage. In this way, a connection between the stages is obtained. The connection between the stages is used to compute the optimal solution to the whole problem. In relation to the hydropower scheduling problem, each state represents a possible reservoir level or power price, and each stage is a time step.

Each problem solved using dynamic programming (DP) can be described as the shortest path problem with a solution process based on Bellman's equations[11, p. 481]. Figure 2.5 illustrates how a network system can represent DP problems. Each arc represents a cost (or negative profit), and for each node in a given stage, we want to determine which arc to include in the shortest path. The cost on which each decision is based has two components. The first component is the arc cost, the cost of going from one node in the current stage to another node in the next stage. The second component is the total best cost to continue from the current node to the end node. The last stage computed provides the overall best objective function value.

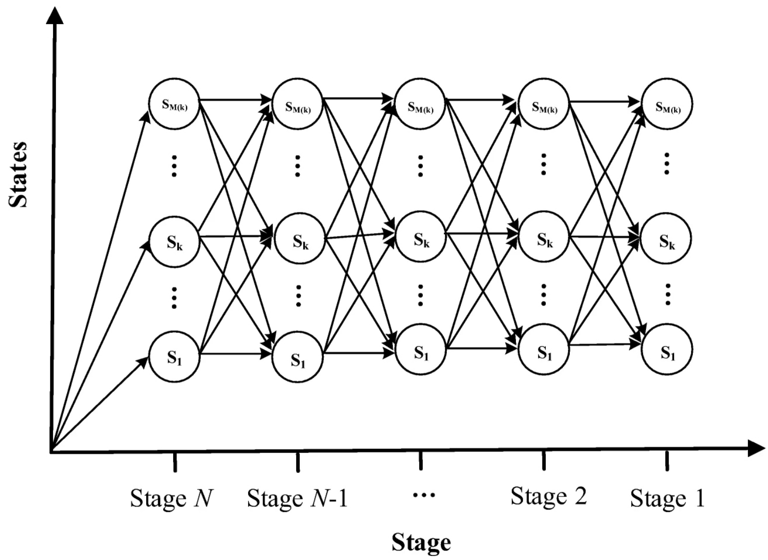


Figure 2.5: Illustration of the shortest path representation of a dynamic problem, obtained from [13].

One advantage of this solution method is that information about all arcs and nodes does not need to be stored explicitly. Bellman's equations can be formulated as *"Given the current state, the optimal decision for each of the remaining stages must not depend on previously reached states or previously chosen decisions."*[11, p.484] In other words, the decision made in each stage only depends on the current state and not on earlier states or decisions.

In relation to the hydropower scheduling problem, the connection between each stage is the reservoir level. The operational decisions in one step determine the reservoir level, affecting the decisions in the next step. The dynamic structure in the hydropower scheduling problem facilitates the ability to solve smaller problems for each time step independently and use the connection between time steps to establish the optimal solution for the whole problem.

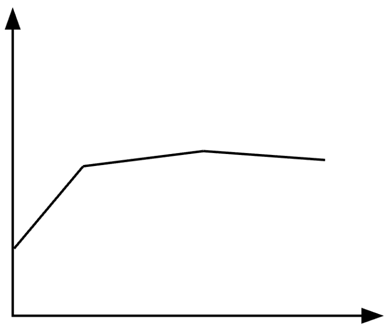
Another advantage of the SDP method is its straightforward implementation and good opportunities for formulation flexibility. The method allows for the inclusion of discrete variables, and it finds the optimal solution without requiring linearity or convexity [8, p.195]. Subsection 2.3.2 presents a thorough explanation of how nonlinearities and nonconvexities are handled in the mathematical programming framework.

A drawback of SDP in regard to hydropower scheduling is that the model cannot be scaled up to several reservoirs, as the discretization of state variables leads to an exponentially increasing problem size with the number of reservoirs [9, p.15]. Since the model developed in this project is based on a single reservoir, this is not an issue here. However, on larger hydro systems, the problem becomes too large. This is one of the reasons why the state-of-the-art medium to long-term hydropower scheduling models are based on the dual formulation, stochastic dual dynamic programming (SDDP). The SDDP scheme does not require discretization of state variables which reduces the solution time, but it cannot handle nonconvexities [9, p.15]. Chapter 3 includes a literature review regarding SDP and SDDP in hydropower scheduling.

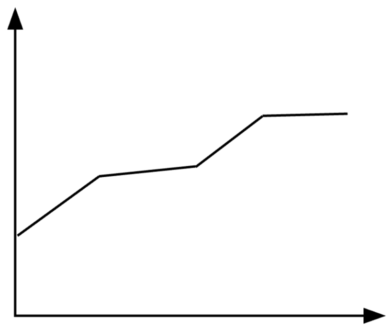
2.3.2 Modeling Non-linearity in Mathematical Programming Problems

A strength of the SDP framework introduced above is its possibility of including nonlinearities and nonconvexities. This, however, needs to be cautiously handled. The following subsection presents common ways of expressing nonlinearity in LP and IP problems. The difference between convex and nonconvex formulations and how these can be modeled will also be explained.

One possible way to handle the nonlinearities is through piecewise linear modeling. Modeling piecewise linear functions is useful when dealing with nonlinear, nonconvex, or noncontinuous interactions approximated as piecewise linear over a discrete set of points. In hydropower scheduling models based on SDP, the discretization of reservoir levels (states) leads to piecewise linearities. The modeling of piecewise linear functions will depend on whether or not the function is convex. A function is convex when the successive slopes of the piecewise linear approximation are nondecreasing and concave if these slopes are non-increasing [14, p.383]. A comparison of convex and nonconvex piecewise linear functions is included in Figure 2.6. A convex piecewise linear function can be modeled in an LP framework by representing the function by linear cuts or as convex combination of points. However, nonconvex piecewise linear functions are more challenging.



(a) Illustration of a piecewise linear convex(concave) function.



(b) Illustration of a piecewise linear nonconvex(nonconcave) function.

Figure 2.6: Comparison of convex and nonconvex piecewise linear functions.

When including nonconvex piecewise linear functions, one option is to include Special Ordered Sets of type 2 (SOS2). An SOS2 is a set of variables in which at most two can be non-zero. The two variables must be adjacent given the ordering of the set [15, p.178]. Hence, SOS2 is based on the same principles as a convex combination of points, except that the variables are sorted, and at most, two adjacent variables can be non-zero.

Chapter 3

Literature Review on State Dependent Environmental Constraints

This chapter provides an overview of existing research on state-dependent environmental constraints and aims to accumulate background knowledge for and contextualize the work in this master's thesis. The state-of-the-art solution methods for medium-term hydropower scheduling require a convex model formulation. Because state-dependent constraints often lead to nonconvexities and the need for logical conditions, accurate representations of state-dependent constraints are not included in the models currently used in the Nordic hydropower industry. To explore recent methodological advances, as well as place this thesis in the research field, previous research considering state-dependent environmental constraints using SDP [5], SDDiP [3], and linear approximations in SDDP [6] will be reviewed in this chapter.

3.1 Exact Formulation in SDP and SDDiP

There exist acknowledged research on environmental restrictions in hydropower in general. However, this subsection aims to present literature that betters comprehension of mathematical modeling of state-dependent restrictions. There is no standard way of dealing with state-dependent environmental constraints in commercial hydropower scheduling software as they are not easily treated in the SDDP method. This section explores previous research regarding the inclusion of environmental constraints in other modeling frameworks than SDDP, specifically SDP and SDDiP.

The research paper *"A Stochastic Dynamic Programming Model for Hydropower Scheduling with State-dependent Maximum Discharge Constraints"* [5], describes how environmental constraints can be formulated precisely. Using an SDP framework enables the modeling of nonconvexities, allowing for an exact formulation of the constraint in the scheduling model. The developed model is then applied to a case study of a Norwegian hydropower system with multiple reservoirs and the results indicate that environmental constraints significantly impact water values and the simulated hydropower operation. Though, it is worth noting that the methods used in this article cannot be transferred to other modeling frameworks that require a nonconvex formulation. In addition, using the SDP modeling framework on large scale systems is not beneficial because the discretization, which allows nonconvexities, leads to exponential growth in problem size and solution time. The results, therefore, serve more as an important benchmark in further work to linearize nonconvex environmental constraints than a solution to the problem.

Another research paper exploring the possibilities of including an exact formulation of environmental constraints is [3]. The paper *"Nonconvex Environmental Constraints in Hydropower Scheduling, "* describes how the stochastic dual dynamic integer programming (SDDiP) method can include nonconvex environmental constraints. SDDiP is a newly developed, advanced SDDP method that allows for handling nonconvexities by using integer variables. The authors present a mathematical SDDiP model for medium- to long-term hydropower scheduling, then tested on a multi-reservoir case study. The results of this study indicate the same as [5]; that there is potential for improving hydropower scheduling by a good approximation of environmental constraints. Despite favorable case study results, the SDDiP method is too immature to be scaled and used in commercial software today. Limitations include convergence challenges and extensive solving time.

3.2 Linear Approximation in SDDP

There are challenges regarding the inclusion of environmental constraints in the SDDP framework, and as previously mentioned, there is no common commercial way of dealing with them in hydropower scheduling software. Despite this, there exists research regarding the inclusion of environmental constraints in SDDP, which will be explored further in this section.

HydroCen has carried out research work related to the future renewable energy system in Norway. The 12th HydroCen Report[16] addresses state-dependent environmental constraints in seasonal hydropower scheduling. The authors surveyed the need for improved modeling of environmental and technical constraints related to operational hydropower scheduling software using SDDP. Based on the survey results, two types of constraints were selected as most relevant to explore further; volume-dependent discharge boundaries and inflow-dependent discharge boundaries, where the former resembles the constraints referred to in this master's thesis. The proposed solution method for volume-dependent discharge boundaries is a linear approximation. The HydroCen Report enlighted the need for modeling environmental restrictions in hydropower scheduling and proposed a possible solution method. However, an indication of the proposed solution method's optimality is not possible to provide as it has not been implemented and tested.

The most recent research regarding state-dependent environmental constraints [6] further addresses the implementation in hydropower scheduling. The authors propose a solution that combines constraint relaxation and time-dependent auxiliary lower bound on reservoir volume. The article highlights the trade-off between a tighter relaxation, using the auxiliary lower bound, and problem feasibility. Results from two different case studies indicate that adding an auxiliary lower bound on reservoir volume has significant potential for improved system operation. Because of the modeling challenges previously described, this research also does not include an exact formulation of the environmental constraint. To conclude whether or not the proposed approximations are accurate enough for practical use, the next step in the research could be to implement and compare the constraint approximations against the exact formulation.

3.3 State-of-the-Art

This chapter has explored previous research and recent advances considering environmental constraints in medium- to long-term hydropower scheduling. Research regarding exact formulations of the constraint showed an opportunity for significantly improved water value calculations, but this can only be implemented in modeling frameworks that handle nonconvexities. In addition, there exists research on approximated formulations of environmental constraints. However, there is not found any research comparing the performance of approximated constraints to the exact formulations. This master's thesis contributes to the research field by evaluating and comparing the performance of several constraint formulations. The same model framework, SDP, is used for all implementations to avoid additional noise and get the best possible basis for comparison.

Chapter 4

Methodology - Model Description

This chapter presents the medium-term hydropower scheduling model for local reservoir management. The model takes the perspective of a power producer, and the objective is to maximize revenue while complying with all physical and regulatory constraints, including environmental constraints. The solution process consists of two main steps; a strategy part that calculates water values, and a simulation part, where production plans are calculated.

Both water value calculations and production plan simulations are based on the dynamic method described in Subsection 2.3.1. The dynamic structure enables the ability to independently solve smaller scheduling problems for each weekly stage and use the connection between the weekly stages to establish the optimal solution for the whole scheduling problem. The solution strategy of the water value calculations, which then are used to simulate production plans, is illustrated in Figure 4.1. Each node in the figure represents a smaller sub-problem. Thus, there exists one sub-problem for each stage (week) and each state (discretized reservoir level).

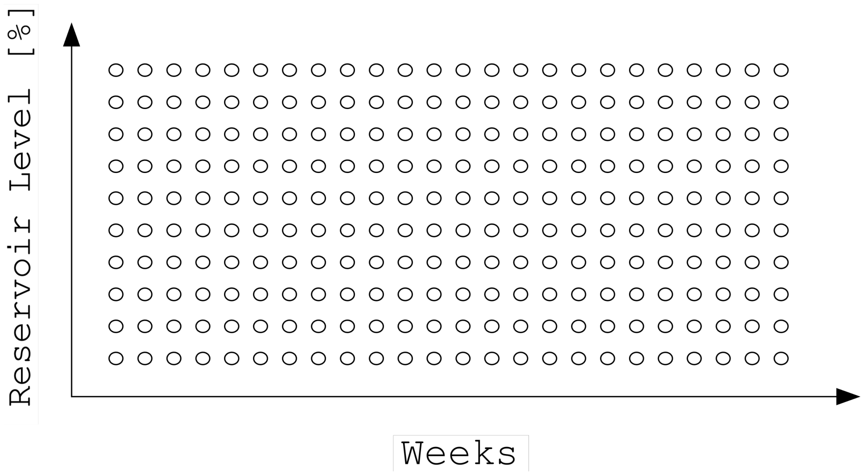


Figure 4.1: Illustration of the water value matrix.

In the strategy calculations, the sub-problems are stochastic, as inflow and price are uncertain parameters. All sub-problems are solved sequentially from $t = \mathcal{T}$ to $t = 1$. To calculate the water value, the model uses the stochastic power price and the profit from the week $t + 1$ evaluate whether the water is worth more by producing now or saving later. In that way the model can calculate the hydro storage's highest possible value.

In the production plan simulations, the sub-problems are deterministic. It is assumed that the inflow and price are known in each stage. To determine optimal production plans, the same sub-problem is solved in the reverse sequence, starting at $t = 1$ and ends at $t = \mathcal{T}$. The production plan simulations use water values from the strategy calculation to evaluate how much hydro to discharge in the current week and how much will be stored for later. One sub-problem is solved for each weekly stage, and the resulting reservoir level t becomes the initial reservoir in $t + 1$.

4.1 Modeling of System Components

The hydro system modeled is illustrated in Figure 4.2. The system consists of one reservoir and one power plant, and the physical components are represented in the weekly stage problem. The following section describes how basic system components are mathematically modeled in the hydropower production problem.

The material in Subsections 4.1.1 - 4.1.3 is a nearly verbatim adaptation of Section 3.1 of [7].

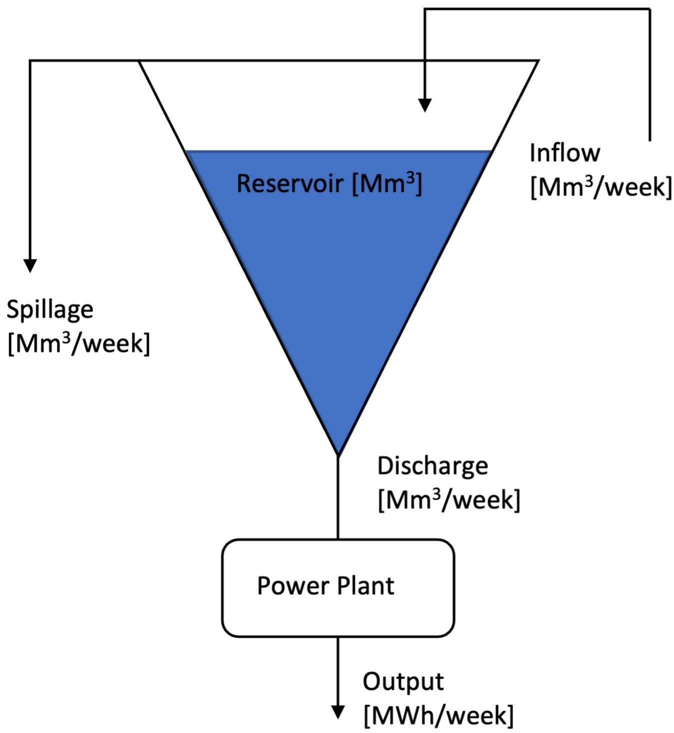


Figure 4.2: Illustration of the hydropower system, obtained from [7]

4.1.1 Water Balance

As illustrated in Figure 4.2 there is one waterway into the system, and two waterways leading the water out. The inflow i_t^s is water coming into the system and discharge u_t is the water going into power plant and converted to electricity. There is no bypass discharge in this system, which result in spillage when the inflow exceeds the reservoir space and the discharge capacity. Spillage water, s_t is wasted energy, because it cannot be used for electricity production. The reservoir level at the end of stage t, v_t is expressed in Equation 4.1 and this equation is used to model the reservoir balance. v_t^0 is the initial reservoir level in stage t.

$$v_t = v_t^0 - u_t - s_t + i_t^s \tag{4.1}$$

4.1.2 Energy Conversion

Energy conversion is the relation between discharge q_t and output u_t in hydropower production. This conversion is given in Equation 4.2, where e is the energy equivalent.

$$u_t = e \cdot q_t \cdot 10^3 \tag{4.2}$$

Energy equivalent determines how much energy is stored in each m^3 of water in the reservoir. Because the unit for e is [kWh/m^3], a factor of 10^3 is needed to get [MWh/Mm^3]. The energy equivalent is mainly determined by the efficiency and plant head, which is again dependent on the reservoir curve and backwater level. Because the variation in meters above sea level is assumed to be small compared to the plant head, the energy equivalent is modeled as a constant value. There is also assumed to be a minimal effect of backwater, and the variable turbine efficiency is disregarded. For a long term hydropower scheduling model a lower level of detail is needed, and therefore, a static energy equivalent is assumed.

4.1.3 Physical Constraints

There are physical constraints in the hydropower system in relation to plant discharge and reservoir level. The purpose of the physical constraints is to model the physical reality and ensure safe and legal operation of the power plant. Boundary constraints for reservoir volume $\bar{V}$ and discharge $\bar{U}$ are expressed in Equations 4.3 and 4.4, respectively.

$$0 \leq v_t \leq \bar{V} \tag{4.3}$$

$$0 \leq u_t \leq \bar{U} \tag{4.4}$$

The reservoir level is described by its volume given in Mm^3 and discharge is referred to as Mm^3/t. The upper boundary on output is assumed to be static as a consequence of the constant energy equivalent. The constraints on minimum reservoir volume and discharge are set to zero because the variables are assumed to only take positive values. In this formulation of discharge boundary the minimum run level is disregarded. This assumption can be made because a consequence of the static energy conversion factor is that the production will usually either be maximum or zero.

4.1.4 Future Profit

In order to determine the value of water in the reservoir, the future profit is a key parameter. The model represents the future profit as a continuous variable, constrained by a piecewise linear function. It is assumed that the future profit of a discrete set of end reservoir levels is known. From the set of discrete state variables (reservoir levels), it is possible to approximate a piecewise linear function, which acts as an upper bound of the future profit. This is illustrated in Figure 4.3.

To model the piecewise linearity in a mathematical programming framework, the SOS2 described in 2.3.2, are applied to the future profit function. In the typical hydropower scheduling formulation, the expected future profit is concave in terms of reservoir level.

Figure 4.3: Illustration of piecewise linear approximation of a discrete set of points.

Due to the risk of spillage and thereby lost revenue, the marginal profit of having one more unit of water in the reservoir consistently decreases with the increasing reservoir level. When the environmental constraints are included, the future cost function is no longer guaranteed to be concave. The nonconvexity make it necessary to model the piecewise linear constraint using SOS2. The following procedure does this:

Let $x_1, \ldots, x_n$ be the discrete set of end reservoir levels and $y_1, \ldots, y_n$ be the known profit of the discretized reservoir levels. Let $w_1, \ldots, w_n$ be a SOS2 of weights.

$$\forall i, w_i \in SOS2 \tag{4.5a}$$

$$\sum_{i=1}^{n} w_i = 1 \tag{4.5b}$$

$$\sum_{i=1}^{n} w_i \cdot x_i = v_t \tag{4.5c}$$

$$\sum_{i=1}^{n} w_i \cdot y_i = \alpha_{t+1} \tag{4.5d}$$

In most commercial solvers, built-in functions exist to take care of the inclusion of SOS2. For simplicity, the inclusion of future profit described in this subsection is further referred to by Equation 4.6.

$$\alpha_{t+1} \leq F_{\alpha_{t+1}}(v_t) \tag{4.6}$$

4.1.5 Environmental Constraint

In Section 4.1.3 the physical limits on reservoir level and release plans were described. In addition to these, there can also be environmental constraints on the reservoir level and release plans to ensure good conditions for surrounding nature and residents. As many of the large reservoirs in Norway also are used for recreational activities, the Norwegian government has imposed strict regulations on some reservoirs to facilitate synergies in reservoir usage and ensure high enough water levels.

The environmental constraints handled in this model are state-dependent, meaning that they are dependent on the reservoir level. The constraint imposes a lower reservoir limit $\tilde{V}_t$ that becomes active given that a specified condition is met. The state-dependency is modeled using binary variables. If the reservoir level is lower than the environmental threshold, $\tilde{V}_t$, the binary variable γ_t is set to zero, and the production has to stop. γ_t can be set to one when the reservoir level is higher than the threshold. Then the hydropower plant can produce power, but the resulting reservoir level has to be above the threshold. Equations (4.7) and (4.8) ensures that the environmental constraint is being complied with.

$$v_t \geq \gamma_t \cdot \tilde{V}_t \tag{4.7}$$

$$u_t \leq \gamma_t \cdot \bar{U} \tag{4.8}$$

4.2 Water Value Calculations

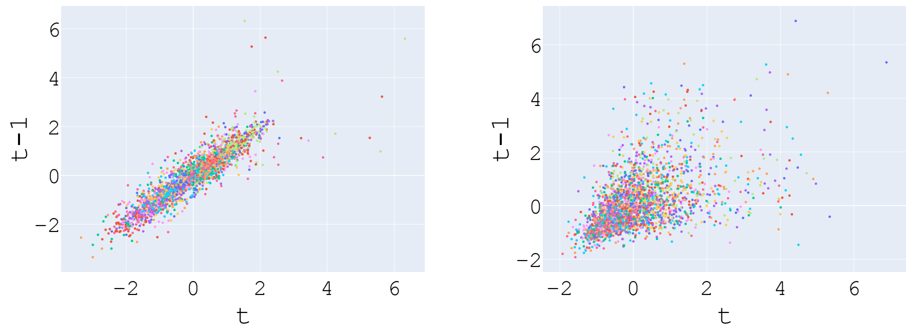
The first step of hydropower scheduling is to find optimal strategies for hydropower using the water value method. Water value is an expression for the expected marginal value of the energy stored in the reservoirs [8, p.39]. The water value is a helpful tool in production planning. Comparing the water value to the power price indicates whether it is profitable to produce water or wait until a later time. If the water value is lower than the power price, a producer will produce hydro. On the other hand, if the water value is higher than the power price, it is more profitable to wait and save the hydro. The water values are very complex to determine and are highly dependent on stochastic parameters, like the future development of market prices and future inflow. The stochastic values, with many uncertainties, are taken into account by calculating the expected profit of given scenarios or outcomes.

4.2.1 Modeling Uncertainties and Autocorrelation

The model developed in this thesis can handle uncertainty in both inflow and price. To include the uncertain parameters in the water value calculation, the model calculates the expected value of water values, given multiple possible values for inflow and price.

In [7], the expected value was calculated as an arithmetic mean with equally distributed probabilities for all data points. However, findings indicate that this simplification might not be the best way of handling the uncertainties. In a high price scenario, the model that did not consider autocorrelation anticipated lower prices in the weeks ahead. The production plan became exceedingly eager to use hydro without realizing that the price would likely be high in the coming weeks. The results in [7] suggest that autocorrelation affects the scheduling's optimality and that there is potential for improvement by modeling the uncertainties more realistically. Autocorrelation is a measure of non-randomness in data series [9, p. 8].

The correlation in price and inflow of each week is shown in Figures 4.4a and 4.4b. Figure 4.4a shows a very strong positive correlation. In practice, this means that if the price is higher than the median in week t-1, the price is more likely to be above average in week t, and vice versa for lower prices. From Figure 4.4b it can be read from the figure that there is a positive correlation for inflow as well, but it is not as strong as for the price series. Based on this information, it was deemed as interesting to look more closely at the inclusion of autocorrelation in the model.



(a) Correlation of Price Series.

(b) Correlation of Inflow Series.

Figure 4.4: Correlation of the Stochastic Data Series, obtained from [7].The slope of the scattered line is the autocorrelation factor.

There are several ways to include autocorrelation in the SDP framework for calculating water values, but common to all is that the problem size and complexity increase. The technical report "Application of Stochastic Dual DP and Extensions to Hydrothermal Scheduling[9]" addresses the inclusion of autocorrelation in inflow data series by modeling the inflow in the previous stage as a state variable. As previously mentioned, a weakness of SDP is that the model increases exponentially with the number of state variables. Hence, including autocorrelation increases the problem's complexity and solution time excessively. To assess solution time and complexity against benefit, an assessment was made of whether autocorrelation in the stochastic data series should be modeled explicitly. Based on the autocorrelation determined in the project thesis, displayed in Figure 4.4, it was evaluated as most critical to model autocorrelation in the price series as that resulted in a stronger correlation than the inflow series.

The uncertainty in inflow is represented using a Markov model with equally weighted probabilities, without regard to autocorrelation. In practice, this means that all inflow levels are equally as probable in week t, regardless of the inflow in the previous week $t-1$.

The autocorrelation in price is considered by modeling price as a state variable. The correlation from last week is represented by using the power price in the previous week $t-1$ as a state variable in week t. Even with autocorrelation modeled only in the price series, the problem is significantly larger. Therefore, as a measure to decrease the problem size, all data points were clustered into five scenarios.

Each sub-problem in the water value calculations is solved five times, i.e., for each price scenario. Thus, there are four water values per node in Figure 4.1.

4.2.2 Solution Algorithm

The algorithm used to calculate water values is described in this subsection. As previously mentioned, the dynamic structure enables the possibility of solving large and complex problems by solving a sequence of smaller sub-problems. These sub-problems are called "Weekly Stage Problems" and will be further described in Subsection 4.2.3. Each weekly stage problem is solved for all states, i.e., price scenarios and discrete reservoir levels, and time stages. After solving all the decision problems in each stage, the expected future profit is calculated and used when solving the previous stage ($t-1$). The solution algorithm for calculating expected profit is presented in Algorithm 1.

When the problem has been solved for all weeks, the algorithm re-solves the entire planning horizon, using the water values from the first stage as an end-value setting in the last stage. To avoid unwanted end-of-horizon effects, this continues until the algorithm converges, i.e., when the first week's water values equal the last week's water values. This process is described in Algorithm 2. When the SDP algorithm has converged, the calculated water values can be used for a final forward simulation in order to obtain production plans.

Algorithm 1 SDP algorithm for expected profit calculation

for $t = |\mathcal{T}|, |\mathcal{T}| - 1, ..., 0$ **do**
    for each discrete initial reservoir level **do**
        for each price scenario **do**
            for each inflow scenario **do**
                Solve one-stage problem with inputs $\lambda_t^s, i_t^s, v_t^0, F_{\alpha_{t+1}}(v_t)$,
                to obtain the objective value $\alpha_t^{v_t^0}$ for given inflow scenario,
                price scenario, reservoir level v_t^0, and week t
            end for
            Calculate expected profit for given price scenario:
            $\alpha_t^{v_t^0}$ = probability $\cdot \sum_{inflow} \alpha_t^{v_t^0}$
        end for
        Calculate expected profit for discrete initial reservoir level:
        $\alpha_t^{v_t^0}$ = probability $\cdot \sum_{price} \alpha_t^{v_t^0}$
    end for
    Save discrete profit values for future profit function
end for

Algorithm 2 End-of-horizon convergence

Set the marginal value of profit at end-of-horizon to 0
while convergence is not reached **do**
    Solve Algorithm 1 with $\alpha_{|\mathcal{T}+1|} = \alpha_0$
    if $\alpha_0^{marginal} == \alpha_{|\mathcal{T}+1|}^{marginal} + / - 1$ **then**
        Convergence reached
    end if
end while

After solving the algorithms, the result is a matrix of expected profits for each price scenario in each discrete reservoir level in each time step. The water value is the marginal value of the expected profit.

4.2.3 Weekly Stage Problem

The objective of medium-term hydropower scheduling is to find the dispatch strategy that maximizes profit for the hydropower producer [8, p.1]. A weekly decision problem is solved iteratively, as described in Algorithm 1, to calculate the optimal release strategy.

The weekly decision problem determines how much of the stored water is to be converted into electricity every week. If hydro energy is produced today, the opportunity to produce electricity at a later time decreases as the total amount of water is reduced. The optimal decision in each weekly stage is dependent on the initial reservoir level, amount of inflow, electricity price, and expected future profit of the stored hydro. The weekly stage problem is deterministic, meaning that all dependencies are known. We thus assume that the initial reservoir, electricity price, inflow, and expected future profit of stored hydro are known in each step.

This thesis aims to enlighten how different modeling approaches to include state-dependent environmental constraints in water value calculations affect water values and production plans. In order to compare the different approaches of modeling the state-dependent environmental constraint, production plans are simulated using four different sets of calculated water values. This subsection includes a description of three different modeling approaches for including the state-dependent environmental constraint; one exact representation and two linear approximations. The three approaches are compared towards a base situation, where these constraints are not considered in the planning. All formulations can be used in methods that do not require a convex model formulation, such as SDP. In models based on SDDP, a convex model formulation is required, and a linear approximation is necessary.

The solution algorithm developed and presented in Algorithm 1 is equal for all formulations of the environmental constraint. The differences in the methods arise in the weekly problem. The mathematical formulations of four different ways of including the environmental constraint into the water value calculations are presented below. The features previously described in Section 4.1 are reflected in the Weekly Stage Problems as constraints.

Exact Formulation

The exact formulation presented in this section uses binary logic to express the state dependencies in the constraint. Binary logic is possible for the modeling framework in this thesis, SDP, as it can handle nonconvexities. Binary logic is not applicable for SDDP. The purpose of including the exact formulation, even though it cannot be implemented into SDDP, is to have results to benchmark against the other approaches. The weekly decision problem for the exact formulation is formulated with (4.9a)-(4.9i).

$$\max \alpha_t = \lambda_t^s \cdot u_t + \alpha_{t+1} \tag{4.9a}$$

$$v_t = v_t^0 - u_t - s_t + i_t^s \tag{4.9b}$$

$$\alpha_{t+1} \leq F_{\alpha_{t+1}}(v_t) \tag{4.9c}$$

$$u_t = E \cdot q_t \tag{4.9d}$$

$$v_t \geq \gamma_t \cdot \tilde{V}_t \tag{4.9e}$$

$$u_t \leq \gamma_t \cdot \bar{U} \tag{4.9f}$$

$$v_t \leq \bar{V} \tag{4.9g}$$

$$u_t, v_t, \alpha_{t+1}, q_t, s_t \geq 0 \tag{4.9h}$$

$$\gamma_t \in \{0, 1\} \tag{4.9i}$$

The objective of the weekly stage problem (4.9a) is to maximize revenue from the current week, as well as the future revenue of remaining reservoir volume. The resulting reservoir level of each week is determined by (4.9b) and the future revenue is set by (4.9c). The energy conversion is described in (4.9d) and is modeled as a constant relation. Equations (4.9e) and (4.9f) ensures that the environmental constraint is being complied with. If the reservoir level is lower than the environmental threshold, $\tilde{V}_t$, the binary variable γ_t is set to zero and the production has to stop. γ_t can be set to one when the reservoir level is higher than the threshold. Then the hydropower plant can produce power, but the resulting reservoir level has to be above the threshold. Equation (4.9g) ensures reservoir level within the physical boundaries.

Linear Approximation

State-of-the-art solution methods for medium- to long-term hydropower scheduling in the Nordic are based on SDDP [12], which requires a convex model formulation. The exact formulation presented above is nonconvex and uses binary logic. To avoid this, a linear relaxation is imposed, setting γ_t to a continuous variable between 0 and 1 for all stages. The weekly decision problem for the linear approximation formulation is (4.9a) - (4.9h), and in addition to setting γ_t to continuous, the equation below is added to ensure values between 0 and 1.

$$0 \leq \gamma_t \leq 1 \tag{4.10}$$

Tighter Linear Approximation

In many practical situations, the reservoir level is far below $\tilde{V}_t$ at the beginning of the restriction period, and the complete relaxation presented previously may be too facile. To tighten the linear relaxation, a solution using an auxiliary lower reservoir bound is proposed. The weekly decision problem for the tighter linear approximation formulation is (4.9a) - (4.9h), setting γ_t to continuous and adding (4.10) to ensure values between 0 and 1. Finally, (4.9a) and (4.9e) is replaced with, (4.11a) and (4.11b), respectively.

$$\max \alpha_t = \lambda_t^s \cdot u_t + \alpha_{t+1} - C \cdot v_t^+ \tag{4.11a}$$

$$v_t + v_t^+ - \gamma_t \cdot (\tilde{V}_t - \underline{V}^*) \geq \underline{V}^* \tag{4.11b}$$

The auxiliary lower bound $\underline{V}^*$ is determined by the lowest possible accumulated inflow during the restriction period. The discretization of reservoir bounds in the SDP algorithm makes it necessary to include a slack variable v_t^+. In this way, water value calculations for discrete reservoir levels lower than $\underline{V}^*$ will be feasible, but as it is heavily punished in the objective function, never optimal.

Base Method

Calculating water values without including environmental constraints is often used in commercial Nordic hydropower scheduling as there are no good enough alternatives. The base method is useful for the research in this thesis as it provides a benchmark to other the approaches and highlights the opportunities of modeling environmental constraint at all levels of the hydropower scheduling. The base method, excludes environmental constraints in the hydropower strategy calculations.

The base method uses the mathematical formulation (4.9a) - (4.9h) and sets γ_t to 1 in (4.4) and γ_t to 0 in (4.9e).

4.3 Production Plan Simulations

Simulating production plans using water values is similar to the procedure of calculating water values. The main difference is that the algorithm uses forward recursion with deterministic parameters to imitate how the operation could be in reality. By forward recursion, it is meant that the sequence of time steps is reversed.

In the forward simulation, nonconvexities and binary logic are allowed. Therefore, to simulate production plans, the weekly stage problem with the exact environmental constraint formulations is solved in a sequence of steps. In relation to the four formulation methods described in 4.2.3, this means that the same production plan algorithm solves the same problem four times using the results from the four methods of calculating water values as input. The water value method calculates the expected profit of a discrete set of reservoir levels, and values from this computation are retrieved in the production plan simulations to estimate future profit. Already calculated water values, as well as deterministic parameters, lead to weekly decisions for production, illustrated in Figure 4.5. Instead of using a discrete set of initial reservoirs, the resulting reservoir level in one iteration becomes the initial reservoir in the next.

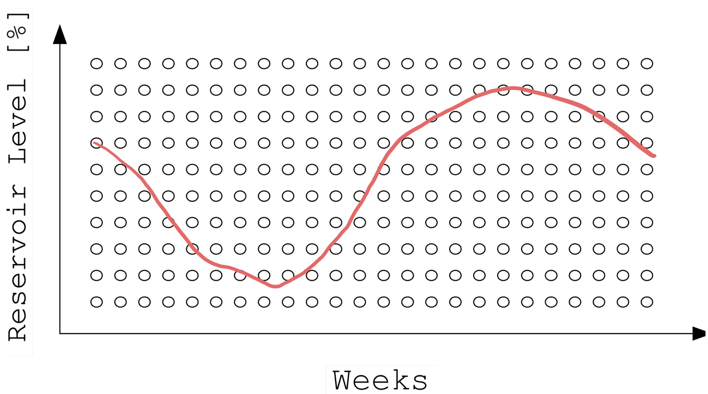


Figure 4.5: Illustration of production plans simulated using the water value matrix in Figure 4.1.

The algorithm for simulating production plans is described below, in Algorithm 3. The final simulations are conducted as parallel simulations, i.e., assuming a fixed start-reservoir level in week 1 for all simulated weather and price scenarios. Parallel simulation differs from series simulations, where the weather years are simulated consecutively, and the initial reservoir level in each year is set equal to the resulting reservoir in the last year. Parallel simulation is the selected approach because this resembles the industrial process of production planning in TrønderEnergi.

Algorithm 3 Algorithm for hydro power production planning

for each simulated weather year **do**
    $v_{-1}^{0} = V^{0}$
    for $t \in \mathcal{T}$ **do**
        if $t == |\mathcal{T}|$ **then**
            $F_{\alpha_{t+1}}(v_t) = F_{\alpha_0}(v_t)$
        end if
        Solve one-stage problem with inputs $\lambda_t^s, i_t^s, v_t^0 = v_{t-1}, F_{\alpha_{t+1}}(v_t)$,
        to obtain the production in given week. Store all decision
        variables from the one-stage problem
    end for
    Store yearly production plan
end for

Chapter 5

Case Study

In this section, the model from Chapter 4 is applied to a case study in Norway. First, the case study will be described in detail, and all input data is presented and explained. Then, useful results from water value calculations and production plan simulations is presented. Finally, the results will be interpreted and discussed, in addition to an analysis of plausible sensitivities and limitations.

5.1 Case Study Description

The model described in Chapter 4 is applied to a single-reservoir hydropower plant case study. The case study described in this section is the production planning of Driva power plant, with Gjevilvatnet as the main reservoir. Driva power plant is located in Møre and Romsdal county and Gjevilvatnet is located in Trøndelag county, both in Central Norway. TrønderEnergi, the Norwegian energy company that operates the power plant, initiated the study by request due to existing challenges regarding the inclusion of environmental constraints in their production planning process. Gjevilvatnet is, in addition to being a hydropower reservoir, an assembly point for recreational activities as seen in the picture in Figure 5.1. Every summer, many people come from surrounding cities to this area to spend their vacation fishing, swimming, and boating in Gjevilvatnet. Therefore, it is of great interest that the reservoir level is kept high enough to ensure that visitors can do these activities. The case study is a compelling case as there is a lot of pressure from the local population and the authorities that the reservoir level must be high in the summer. A main motivation of the work has been the close industry collaboration and the access to actual data from TrønderEnergi.

Figure 5.1: Photograph of Gjevilvatnet reservoir at a low reservoir level. Foto: Gorm Kallestad / NTB

The following subsections describe the case study in terms of relevant physical structures, imposed environmental regulations and stochastic input data. Parts of the section is taken from the case study description of the specialization project [7], specifically from Subsection 4.1 ”Data Handling”.

5.1.1 Static Data Inputs

This subsection is taken from section Static Data in project thesis. The Driva hydropower system consists of one reservoir, Gjevilvatnet, which has a maximum volume of 280 Mm^3. There are two generators with a combined maximum capacity of 150 MW. A rule of thumb for the energy equivalent used in energy conversion is 1.4 kWh/m^3. These values are included in the model by setting the input parameters below to their respective value.

$\bar{U}$ = 150 MW · 168h = 25 200 MWh

$\bar{V}$ = 280 Mm^3 = 100 %

e = 1.4 kWh/m^3

In addition, a reservoir curve is given in Table 5.1 for conversion between meters above sea level (masl) and volume (Mm^3).

Table 5.1: Gjevilvatnet Reservoir Curve.

Mm^3	0	11.2	19.4	44.9	53.6	116.6	125.8	192.3	202	232	242.2	280
masl	645.8	646.5	647	648.5	649	652.5	653	656.5	657	658.5	659	660.8
	Min											Max

Environmental Constraint from NVE

The environmental constraint set by the Norwegian Water Resources and Energy Directorate (NVE) is presented in Table 5.2. The table displays the state-dependent minimum restriction imposed on the system. If the reservoir level in the beginning of the week, is lower than the limit, the production has to stop. If the initial reservoir level is higher than the limit, the hydropower plant can produce power, but the resulting reservoir level has to be above the limit.

The restriction defined by NVE applies to stipulated dates. Because the SDP model is solved for weekly time steps, these stipulated dates need to be converted into week numbers. To ensure that the restriction is complied with at all times, the week containing the start date of each tightening is used. In addition to this the reservoir limit has to be converted to volume. This is done by interpolation using values from the reservoir curve in Table 5.1.

Table 5.2: Table of the imposed environmental constraint on reservoir level for each week.

Date	Week	Restriction (masl)	Restriction (Mm3)
	0-20	645.80	0.00
1st - 14th of June	21-22	656.80	198.12
15th - 30th of June	23-24	657.80	218.00
1st - 14th of July	25-26	658.80	238.12
15th July- 15th October	27-41	659.80	259.00
	42-51	645.80	0.00

5.1.2 Stochastic Data Inputs

All input data is provided from TrønderEnergi. The inflow scenarios are based on historical data, and the price scenarios are simulated from a fundamental model (EMPS)[17] that uses historical weather years as the stochastic input.

Price Data

The electricity price estimations used in this case study are predictions used for hydropower scheduling, by TrønderEnergi in 2018. The price predictions are gathered from the EMPS model [17] and adjusted to match the forward market curve as of 2018. The data is provided for the years 1958 to 2015, representing 57 unique weather years. Each year is defined to consist of 52 weeks, with 12 price segments for each week. In order to use the price forecasts from TrønderEnergi as price scenarios in the model, the forecasts are converted from weekly segments to a mean weekly price. The price scenarios are presented in Figure 5.2, with emphasis on the maximum, minimum and median value of each week.

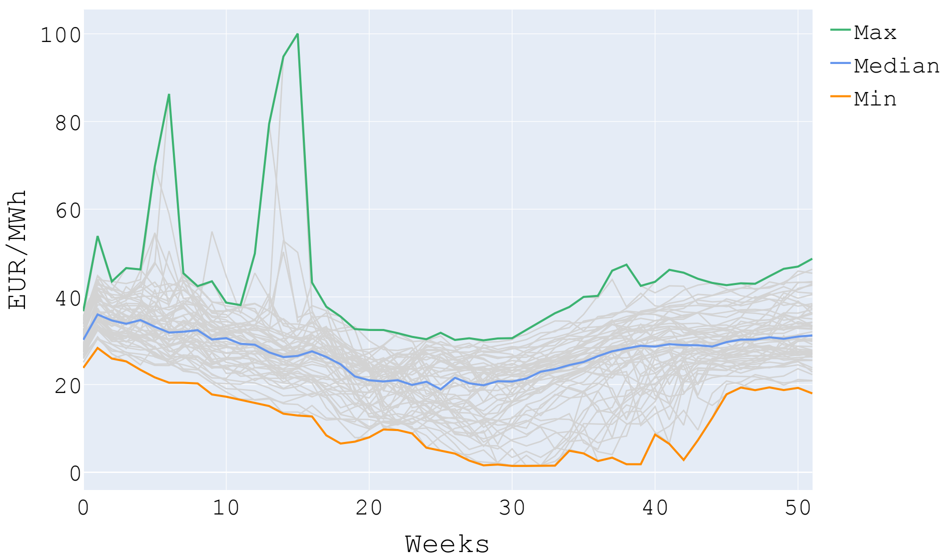


Figure 5.2: Input data for price scenarios.

In this model, the yearly price data series are clustered by k-means clustering into five price states, or five price scenarios. The transfer probabilites are determined by a Markov model with autocorrelation, as described in Subsection 4.2.1.

Inflow Data

Inflow scenarios are accumulated from historical data. Inflow has been measured from the start of the plant's lifetime and earlier data are based on NVE watermark measurements calibrated to measured inflow to Driva. The inflow data is given as a daily volumetric flow rate with the unit m^3/s. In order for the inflow data to correspond with the scenario format, some adjustments had to be made. Firstly, the data is converted to Mm3/day by multiplying the inflow with $60 \cdot 60 \cdot 24 \cdot 1/10^6$. Then, the daily volume is summed up over for each week. Finally, the yearly scenarios have to be altered according to the structure of price estimates. In order to impose equal sizes of all scenarios, the years with 53 weeks are adjusted by dropping the inflow of the last week. This will result in slightly less inflow, but as the 53rd week of the year usually has a very small amount of inflow, this assumed to be negligible. The inflow scenarios are presented in Figure 5.3, with emphasis on the maximum, minimum and median value of each week.

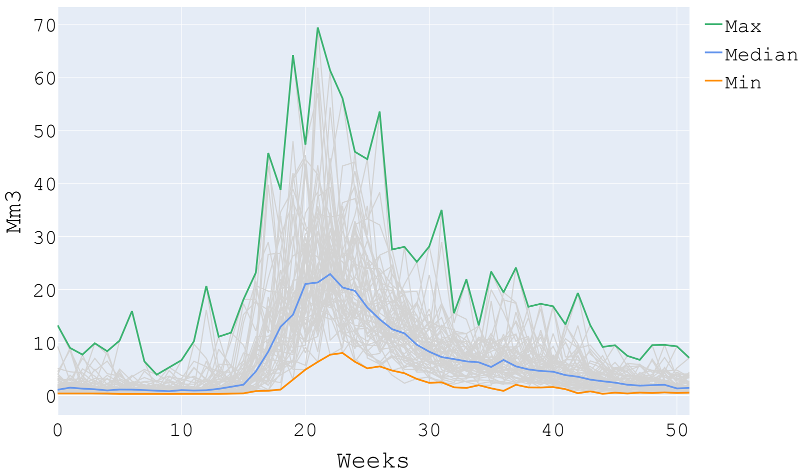


Figure 5.3: Input data for inflow scenarios.

To model inflow efficiently, the yearly inflow data series are clustered by k-means clustering into five scenarios. The transfer probabilities of scenarios are independent of state and determined by a Markov model without any autocorrelation, as described in Subsection 4.2.1.

5.2 Case Study Results and Discussion

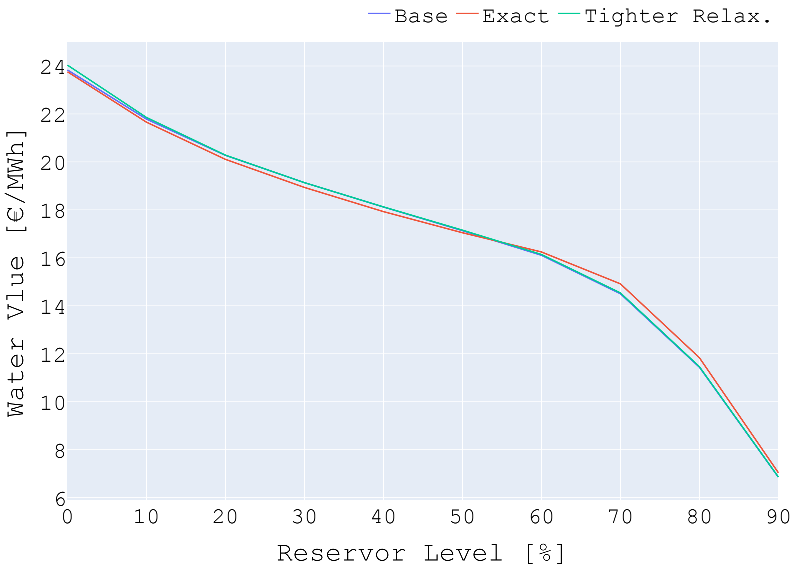
The four approaches described in 4.2.3 are used with the case described in Section 5.1 to calculate water values, which is then used to simulate production plans. The results of the water value calculations and production plan simulations are presented and compared in this section.

5.2.1 Comparison of Calculated Water Values

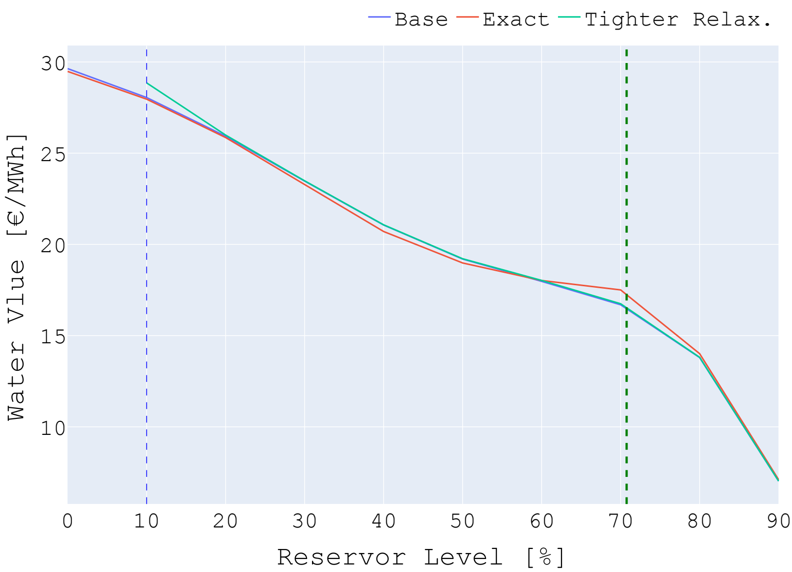
Applying the water value calculations in 4.2 on the case study in 5.1 resulted in 52 weekly water values. For each of the four restriction formulations presented in Subsection 4.2.3, weekly water values were obtained for 10 discretized reservoir levels, for 5 different price clusters. Essential post-processings of the water values include using the results to simulate production plans, which will be further presented in Subsection 5.2.2. In addition, some selected water values are presented in this subsection.

For illustrative purposes, the water values of the five different price levels were aggregated, using its associated probability weighting, to one value per reservoir level for each week. After the aggregation, weekly values for each reservoir level, and each of the four different methods, can be presented. The thesis aims to investigate how planning tools in hydropower take into account condition-dependent environmental restrictions when they are modeled in different ways in the model. Therefore, two weeks have been selected, one before the restriction and one at the very beginning of the restriction period. These water values are presented in Figure 5.4.

Moreover, the results revealed that the water values for the base case and the linear relaxation formulation were approximately equal. Therefore, the water values from the linear relaxation are not presented separately.



(a) week 17



(b) week 22

Figure 5.4: Water values of selected weeks. The color of the line distinguishes the different restriction formulations. The base formulation is blue, the exact formulation is red, while the tighter linear approximation is green. The two vertical dashed lines represent the auxiliary lower reservoir bound and environmental reservoir threshold.

Figures 5.4a and 5.4b display the water values before the environmental constraint is activated and the first week into the restriction period. In both weeks, the exact formulation's water values are lower than the base case and the tighter relaxed formulation up to a certain point. Then, the exact water values become higher than the base case and the tighter relaxed formulation. Finally, as the reservoir approaches 90%, the water values are equal in all formulations. A lower water value signifies a greater incentive to produce electricity this week. On the other hand, higher water values indicate a greater incentive to save water. At a reservoir level of 100%, any additional unit of water will be spillage and is therefore worth €0.

The exact formulation has lower water values than the base case up to a particular reservoir volume. This point signifies that the reservoir level is high enough to reach the environmental restriction, shifting according to how many weeks are left to store hydro before the constraint is activated. For lower reservoir volumes, it is unlikely to reach the restriction for a very long time. As production has to stop until the restriction is met, the possibility of profit from producing during the restriction period is lost. Comparatively, the tighter relaxation method follows a reversed path. The water values are higher than the base case and exact formulation for low reservoir levels. For higher reservoir levels, it is equal to the base case. The turning point occurs at lower reservoir volumes than the exact formulation because the lower auxiliary reservoir bound anticipated is significantly lower than the environmental constraint considered in the exact formulation.

The presence of lower reservoir bounds, illustrated with dashed vertical lines in Figure 5.4b, causes increased water values around the intersections for both the exact and tighter relaxed formulation. The water values are higher as being allowed to production in the current week grants the option to either produce for immediate income or save for more profitable weeks. This trend can be seen as early as week 13.

The curve for tighter relaxation is cropped for reservoir levels below 10 % because the auxiliary lower limit, modeled with strict punishment in the objective function, leads to artificially high water values for having an empty reservoir level. Because the auxiliary lower limit is determined by the lowest possible value, violating this is impossible and will not affect production plans or water values in other weeks. Hence, this is only a modeling measure.

5.2.2 Comparison of Simulated Production Plans

Water values from the four modeling approaches described in 4.2.3 are used to simulate production plans using parallel simulation. Although there were minimal differences in the water values of the base case of linear approximated formulation, all the water values were used to simulate production plans. Presented production plans are discussed and compared against each other and benchmarked against the base case. A necessary remark is that the aspects discussed in this section are the same as those presented in Subsection 5.2.1. One is simply a consequence of the other; higher water values result in higher reservoir levels and the other way around.

The simulated production plans show the recommended reservoir level each week for historical inflow and price prognosis from 57 years and calculated water values from each of the three approaches described in 4.2.3. The average simulated reservoir levels of each week from the simulations are provided in Figure 5.5.

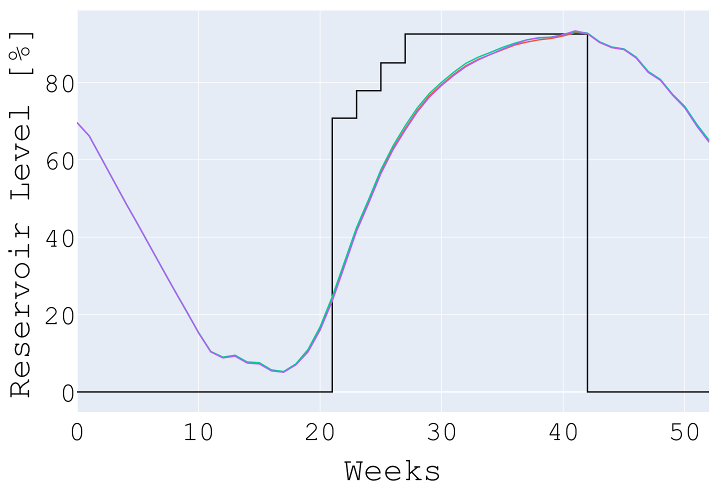


Figure 5.5: Average reservoir level of simulations from all four constraint formulations.

The resulting production plans follow a traditional, seasonal curve for reservoir management, with low reservoir levels prior to the spring flooding and higher reservoir levels for autumn and winter. The model plans in advance to avoid spillage and make room for a large amount of expected inflow to be stored in the reservoir. There is no apparent difference in average reservoir levels between the different model formulations. The production plans from simulations with different water values are equal for most simulated scenarios. With water values from the near exact formulation, 65% of the simulated production plans were identical to the plans without consideration of the restriction. With water values from the linearly approximated formulations, the complete linear relaxation and the tighter relaxation, respectively 93% and 75% of the simulated production plans, were equal to the plans simulated with water values that did not include the restriction.

Average yearly revenue for the base case, without the restriction in water value calculations, was 17.1M€. The average change in profit of all simulations is presented in Table 5.3. The economic results in Table 5.3 are calculated considering the change in yearly revenue from power production and the difference in the value of the reservoir level at the end of the analysis period.

Table 5.3: Economical Improvement from Base Case

	Formulation Method		
	Linear Approx.	***Tighter Linear Approx.***	***Exact Formulation***
Absolute average	2300 EUR/yr	43 000 EUR/yr	41 000 EUR/yr
Relative average	0.01%	0.25 %	0.24%

The average change in profit from Table 5.3 shows a variance between the different approaches. The water values from the stricter linear relaxation result in production plans that achieve 0.01 % better economic gain than the exact formulation. This can be explained by the fact that the methods make decisions based on different water values. The lower auxiliary bound is significantly lower than the environmental constraint, which causes the production to change during extreme weather years. The exact formulation method would not increase the reservoir levels in these scenarios as it is highly unlikely for the reservoir level to reach the actual restriction. Due to improbable occasions, with high prices and high inflow, there are some years of high financial gain for the tighter formulation. In addition, the end-of-horizon valuation will be of great importance. The end-of-horizon valuation is partly inaccurate because the models use their unique final valuation to calculate the optimal production plan. Hence, they become more difficult to compare at the end of the analysis period.

Although there was a slight difference between the exact and tighter linear formulation, both methods' profit gains are still relatively low. The low economic gains in the exact formulation and tighter linear method may be due to numerous simulations resulting in equal production plans for each approach. Therefore, the identical scenarios were filtered out to analyze differences caused by including the restriction in the water value calculations. In addition, the complete relaxed linearized formulation is not included in the following results due to the lack of change from the base case, neither in water values nor production plans. The average economic results from scenarios that deviate from the base method are presented in Table 5.4.

Table 5.4: Economical Improvement from Base Case of Filtered Simulations[a]

	Formulation Method	
	Tighter Linear Approx.	***Exact Formulation***
Best Improvement	1.87M EUR/yr	1.6M EUR/yr
Worst Deterioration	19 000 EUR/yr	1.3M EUR/yr
Absolute average	176 000 EUR/yr	117 000 EUR/yr
Relative average	1.03%	0.67%
% of simulations that differed from the base case	25%	35%

[a]Simulations that resulted in unequal production plans.

Average weekly reservoir levels filtered scenarios are presented in Figures 5.6 and 5.8, including base case formulation and, respectively, the exact formulation method and tighter linear relaxation method.

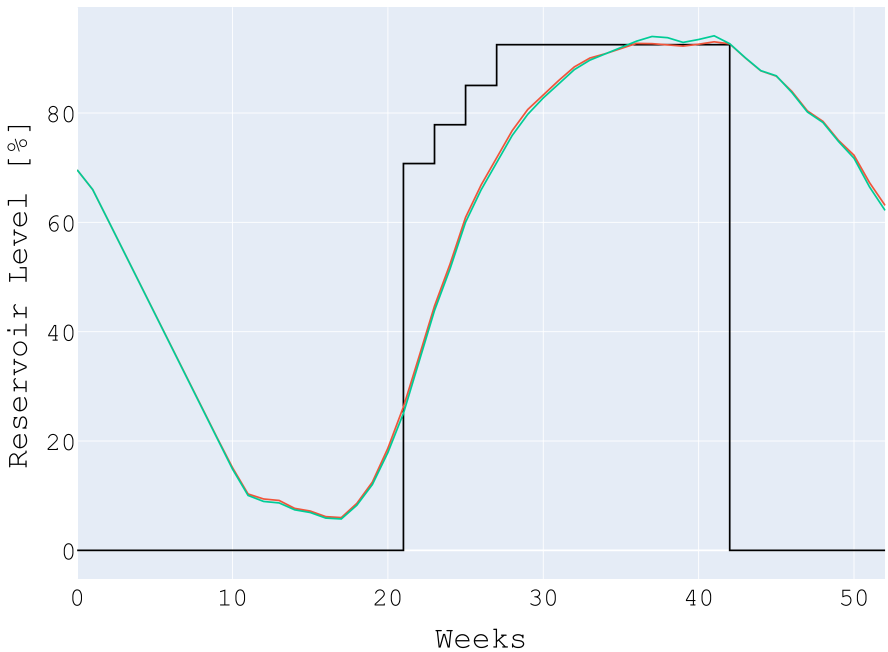


Figure 5.6: Average reservoir levels of scenarios where the exact formulation differed from base case. Red line is the base case simulations and green line is the exact formulation simulations.

The production plans in Figure 5.6 appear similar, but there is an interesting difference during the restriction period at two particular points. At the beginning of the restriction period, the reservoir level is lower for the simulations that uses water values that consider the constraint. After a few weeks, this reverses, and during the last weeks of the restriction period, the reservoir level is higher. This reflects the lower water values that become higher after the restriction period is activated. The producer has no chance to govern differently until the reservoir level reaches the threshold in the restriction period, i.e., the turning point comes from how the individual scenarios that have already reached the limit are handled. The same reasoning also explains why the average reservoir level crosses the boundary in weeks 37 and 39. The turning point, where the average reservoir levels of the exact formulation exceed the base case, is further illustrated in Figure 5.7.

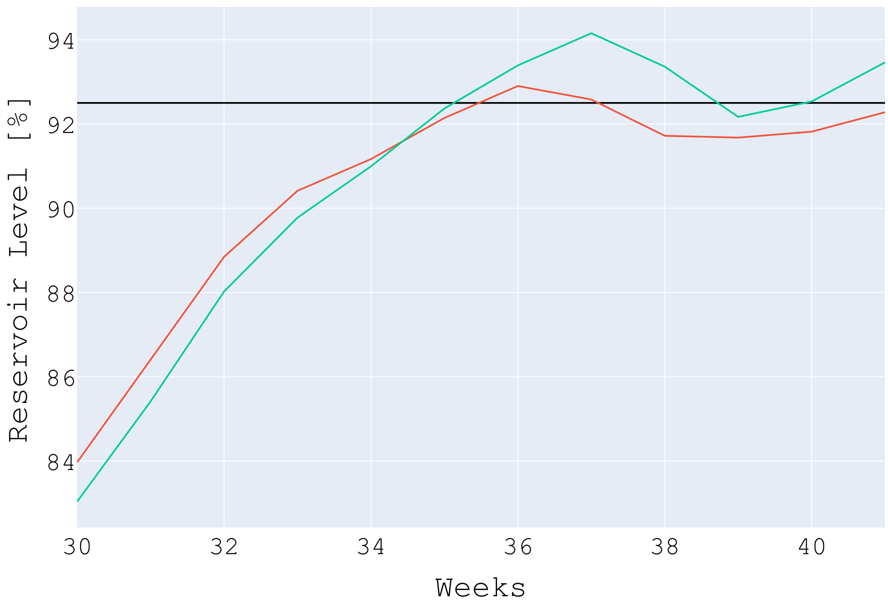


Figure 5.7: Excerpt from Figure 5.6. Red line is the base case simulations and green line is the exact formulation simulations.

An important remark to Figures 5.6 and 5.7 is that the average values do not fully reflect the spread in the curves, and for some scenarios, there are more significant differences. From the water values, we know that the water value is lower for small reservoir volumes, while the water value is higher for higher reservoir volumes. This is important for the production plans. In cases with low water levels in the reservoirs, the model does not believe in being able to reach the environmental restriction and therefore produces water more easily before this period. Moreover, at the same time, with high water levels, the model would choose to save water in the hope of producing towards the end of the restriction period. Taking the average of both higher and lower scenarios results in few visible changes.

The remark above does not apply to the same extent to the tighter relaxed restriction presented in Figure 5.8. As the auxiliary lower reservoir volume is set very low, there are no scenarios that cannot reach this limit. The production plans of the approximated formulation are generally higher than the base case during the restriction period.

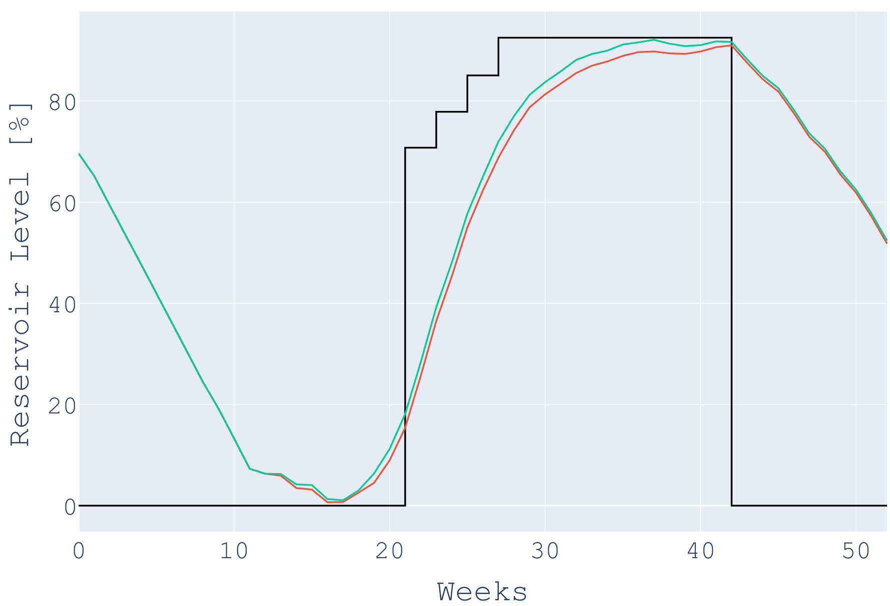
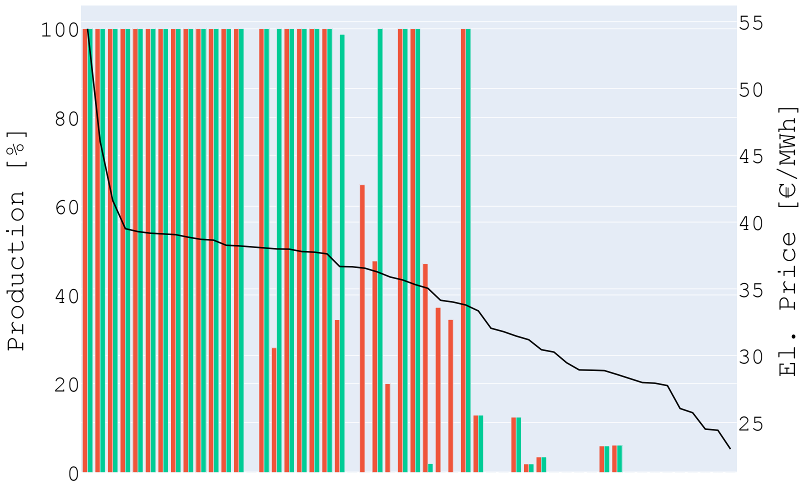
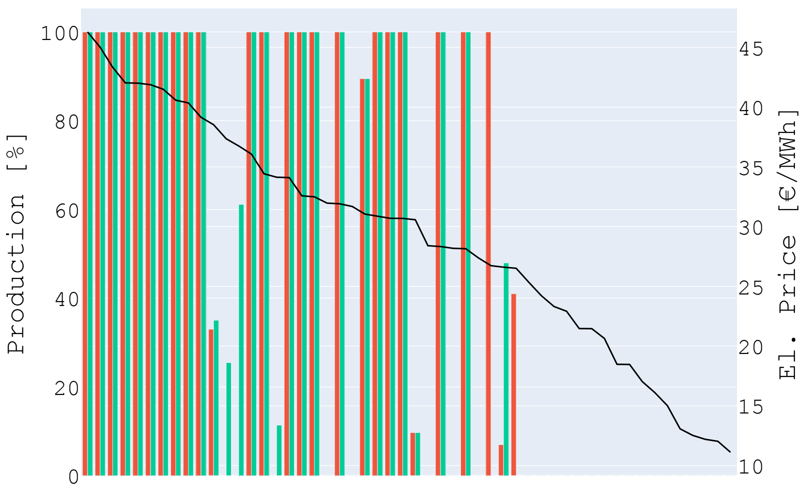


Figure 5.8: Average reservoir levels of scenarios where the tighter approximated formulation differed from base case.Red line is the base case simulations and green line is the tighter approximated formulation simulations.

Duration curves are valuable to understand better how the model produces new production plans, leading to improved economic results. The duration curves show weekly power production in a selected scenario for the water values with and without the restriction, sorted by descending price. The two scenarios selected, 5.9a and 5.9b, have been chosen on the basis that they illustrate well how the model can shift production to avoid having to produce in low price weeks. Here, the model moves production to weeks with a higher price and thus gets more profit from the water resource. The production is forced to stop whenever the reservoir level is lower than the threshold during the restriction period.



(a) Price duration curve of a selected simulation(1979). The bars show weekly production, sorted by descending weekly price. Red bars are the base case and green bars are the exact formulation approach.



(b) Price duration curve of a selected simulation(1975). The bars show weekly production, sorted by descending weekly price. Red bars are the base case and green bars are the tight linear approximation method.

Figure 5.9: Price duration curves for selected scenarios. The bars show weekly production, sorted by descending weekly price.

For most weeks, all model formulations are producing the same amount of power, with maximum discharge during the highest priced weeks, furthest to the left, and no production in the lowest priced weeks, furthest to the right. However, there are some exceptions, where the production plan differs. In Figure 5.9a the production at weeks around 35 €/ MWh are moved to the left. The same can be seen in Figure 5.9b where production at weeks with prices around 25 €/ MWh are moved to weeks with prices around 35 €/ MWh. In addition, some of the production have also been moved to another year.

5.3 Insights from Modeling Environmental Constraints

In the previous section, concrete results from the case study have been presented and discussed. This section addresses a more general discussion regarding the impacts of modeling environmental constraints, the industry application of the modeling approaches, and the limitations and sensitivities relevant to the case study.

5.3.1 Impact of Modeling Environmental Constraints

Section 5.2 identified various consequences following the introduction of environmental constraints in a medium-term hydropower scheduling case study. This subsection further discusses how the changes in reservoir distribution, as a result of the exact formulation of the constraint and the tighter linear approximated modeling approach, impact the intention and purpose of the policymakers.

The exact formulation method is the only out of the approaches that can foresee the environmental constraint in its actual characteristic. Ahead of the restriction period, there is a trade-off between either producing hydropower or storing hydro in hopes of reaching the environmental limit. For lower reservoir volumes, it is more profitable to use water now, as production is expected to stop for a long time to come. The possibility of profit from producing during the restriction period is lost, which leads to lower water values. The lower water values lead to increased discharge and lower reservoir levels during spring and the beginning of summer. However, for higher reservoir volumes, water values from the exact formulation are higher than the other formulation methods. This means that in some scenarios, there will be higher reservoir levels. In other words, there will be a larger gap in water values when the environmental restriction is included, but it is not straightforward to see as the average reservoir levels will be the same.

An essential reason for introducing this restriction, from NVE's point of view, is to make sure that there is enough water in the reservoir so that cabin owners and other visitors can fish, swim and drive a boat on the water, in addition to it being visually satisfying. Even though the case study resulted in a financial gain from including the constraint in the water value calculations, the threshold is not reached earlier in the restriction period. All simulated production plans comply with the regulations, but the restriction's purpose has been fulfilled to a lesser extent in some scenarios.

The trade-off previously discussed does not apply to the same extent to the tighter relaxed restriction, as the auxiliary lower reservoir volume is set very low. There will not be any scenarios that cannot reach this limit throughout the restriction period, and the higher water values led to an increased reservoir volume. As the tighter approximated formulation sees a different lower limit than the exact formulation, the increased water values occur at much lower reservoir levels. Despite being considerably lower, the auxiliary bound incentivizes the reservoir to stay above levels close to zero. Hence, the higher reservoir levels better achieve the purpose behind the environmental constraints in this case study.

Despite a rise in the average reservoir levels, the tighter relaxed formulation only altered the scenarios with the lowest reservoir volumes. Most scenarios have already reached the auxiliary lower bound and are therefore unchanged. The same argument can also explain why the completely relaxed formulation shows little to no change in water values. With a complete relaxation of the binary variable, the lower reservoir bound becomes close to zero in weeks with low production. Hence, there is no rigid lower reservoir that the model is rewarded for obeying. Consequently, the approximated models are not a good measure of the trade-off evaluation essential for planning well for the condition-dependent restriction. It does not see the production stop waiting ahead for most scenarios. A consequence of this is that the model believes it can govern production without limitations for all reservoir levels lower than the actual limit. Moving the auxiliary lower bound to a higher value may provide even better incentives, but infeasible solutions and convergence issues may occur.

Although there are varying degrees of achievement of the purpose behind the restriction, the hydropower schedules are impacted by the inclusion of environmental constraints. Both the tighter relaxation and exact formulation experienced higher water values due to the environmental constraint already in week 13, implying that the model plans for the restriction for many months before it arrives. Planning ahead of the restriction is crucial because, during the restriction period, the producers have no real chance to manage differently until the reservoir level reaches the threshold in the restriction period.

5.3.2 Industry Applications

One of the goals of the thesis was to investigate whether there is a way to include state-dependent environmental constraints that could be used in industry today. The exact formulation leads to nonconvexities and can therefore not be used in the SDDP planning tools that the industry uses. However, the two approximate formulations as well as the base case are possible to include in commercial software today.

All constraint formulations performed better than the base case, which excluded the constraints in the water value calculations. The economic improvement was less than 0.5% for all restriction formulations, but the least improvement was with the complete linear approximation, with only 0.01% change. The water values were almost identical to the base case, leading only to minimal differences in the production plan simulations. As the linear approximation approach did not change the water values and production plans of any economic significance, this indicates that it is not the most suitable method. The economic improvement for the tighter relaxation in this case study was approximately the same as for the exact formulation. The main challenge is many equal years, i.e., there have to be more extreme cases before the water values change. However, the simulated production plans show good financial gain and, to a greater extent, fulfill the purpose behind the restriction, which is to get a higher reservoir level through the summer. Therefore, the results from the case study indicate that the stricter linear approximation is a favorable alternative for including state-dependent environmental constraints in the SDDP algorithm used in industry today.

5.3.3 Generalization and Sensitivity

Insights from modeling environmental constraints include shifts in reservoir management and economic differences. The results presented are inevitably affected by case-specific sensitivities and sensitivities in the data input. This subsection addresses how sensitivity and uncertainty in stochastic parameters can affect the results to understand better which characteristics can be generalized and which are limited to this case study.

Despite the changes discussed previously, the reservoir levels in the case study do not change of any practical significance. The small changes in the reservoir levels may point to the case's price distribution, as the model is economically driven and governed by the earning potential in the period with the restriction. The power price data series show low summer prices during the summer, i.e., during the environmental restriction period, and high prices during the winter. Consequently, the model does not see an incentive to save water in the winter to reach a high enough level to be allowed to produce water earlier in the summer. This is also apparent in the duration curves, where most of the "no-production" weeks are further to the right, meaning that these weeks have a low price and it would not be beneficial to produce regardless of the restriction. Power production within the restriction period is already less beneficial than the rest of the year, which may lead to a dampening effect of the environmental constraint. In addition, it also further substantiates the observation that including environmental constraints in water value calculations does not necessarily lead to higher fulfillment of the purpose behind the restriction.

On the one hand, the case-specific price distribution is statistically typical, and the restriction will often lead to little change in optimal production plans. On the other hand, as seen in recent years, the price distribution may change, leading to higher prices in the summer. If higher prices in the summer are expected, saving water to produce in the summer weeks could be more favorable, making it more advantageous to plan for the restriction well in advance. While the price distribution in this case study is typical, some years may be abnormal, with higher summer prices. Years with this atypical price distribution predictions could incentivize planning for the restriction. The model can weigh the benefit of producing in the winter against the disadvantage of experiencing stop requirements in the summer; hence, the price distribution influences the model. In addition to price sensitivity, the results from the case study are also case-specific in terms of characteristics of the hydropower plant and the regulatory definition of the environmental constraint.

Chapter 6

Conclusion and Further Work

6.1 Conclusion

This master's thesis has evaluated formulation approaches for state-dependent environmental constraints in medium-term hydropower scheduling. The thesis aimed to contribute to the research field by implementing and comparing suggested methods of including environmental constraints. A case study was performed to compare an exact formulation to linear approximations; a complete relaxation and a tighter relaxation with a lower auxiliary reservoir bound. The three approaches were compared to a base case method, which excludes the restriction in water value calculations.

Findings from the case study showed performance improvement when including an exact formulation of the state-dependent constraints. The financial results indicate an earning potential, and the duration curve illustrated how planning ahead for the restriction could ensure production in higher priced weeks. On the other hand, the overall reservoir level did not increase substantially. Despite a financial gain, a higher fulfillment of the purpose behind the restriction, which is to get more water for recreational purposes, was not seen. Still, the model is very price sensitive, and it is expected that planning for the restriction could have a more significant impact with a different seasonal price profile.

The linear approximations of the environmental constraint impacted the hydropower scheduling to varying degrees. There was no significant difference between the complete relaxation and the base case method, indicating that a complete relaxation of the binary variables is not a suitable method. However, the tighter relaxation approach showed economic improvement very close to the exact method. In addition, the reservoir distribution led to higher reservoir levels in the weeks prior to and during the restriction period. This implies an improved fulfillment of the underlying purpose of the constraint, which is to get more water in the reservoirs. This method also has the advantage of not leading to nonconvexities and can therefore be used in the SDDP framework, which is the industry standard for medium-term hydropower scheduling. Hence, results from the case study indicate that the tighter linear approximation method is a good alternative to including state-dependent environmental constraints in medium-term hydropower scheduling.

6.2 Further Work

It was identified that the model is very price sensitive, as it is economically driven and governed by the earning potential. A possible extension of this thesis is to investigate how a different seasonal price profile would impact production planning. In recent years, there has been an extraordinary situation in the power market, with unusually high prices also during the summer. This situation has led to many concerns among both politicians and the civil population, and better and more accurate hydropower production planning will become more relevant and essential. Therefore, it is advantageous to better understand the effects of price changes by including more price data series in the case study.

Bibliography

[1] 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. DOI: `10.1080/10286608.2019.1615475`. eprint: `https://doi.org/10.1080/10286608.2019.1615475`. [Online]. Available: `https://doi.org/10.1080/10286608.2019.1615475`.

[2] 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)*, 2020, pp. 1–7. DOI: `10.1109/EEM49802.2020.9221918`.

[3] A. Helseth, B. Mo, and H. O. Hågenvik, "Nonconvex environmental constraints in hydropower scheduling," in *2020 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2020, pp. 1–6. DOI: `10.1109/PMAPS47429.2020.9183590`.

[4] R. Bellman, "Dynamic programming and stochastic control processes," *Information and Control*, vol. 1, no. 3, pp. 228–239, 1958, ISSN: 0019-9958. DOI: `https://doi.org/10.1016/S0019-9958(58)80003-0`. [Online]. Available: `https://www.sciencedirect.com/science/article/pii/S0019995858800030`.

[5] 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, ISSN: 0960-1481. DOI: `https://doi.org/10.1016/j.renene.2022.05.106`. [Online]. Available: `https://www.sciencedirect.com/science/article/pii/S0960148122007534`.

[6] A. Helseth, B. Mo, and L. E. Schäffer, "Hydropower scheduling with state-dependent discharge constraints – an sddp approach," in *Journal of Water Resources Planning and Management*, Unpublished, 2022.

[7] S. A. Børresen, "State-dependent environmental constraints in long term hydropower scheduling, specialization project," Unpublished, 2021.

[8] G. L. Doorman, "Course elk-15 hydro power scheduling."

[9] R. K. M. Pereira N. Campodónico, "Application of stochastic dual dp and extensions to hydrothermal scheduling," PSRI, Tech. Rep., 1999.

[10] M. o. P. EnergiFaktaNorge and Energy, *Electricity production*, `https://energifaktanorge.no/en/norsk-energiforsyning/kraftproduksjon/`.

[11] V. P. Lundgren J. Röhnqvist M., *Optimization*. Studentlitteratur, 2010.

[12] M. V. Pereira and L. M. Pinto, "Multi-stage stochastic optimization applied to energy planning," *Math. Program.*, vol. 52, no. 1–3, pp. 359–375, May 1991, ISSN: 0025-5610.

[13] Z. Li and T. Majozi, "Optimal synthesis of batch water networks using dynamic programming," *Process Integration and Optimization for Sustainability*, vol. 2, no. 4, pp. 391–412, Dec. 2018, ISSN: 2509-4246. DOI: `10.1007/s41660-018-0061-2`. [Online]. Available: `https://doi.org/10.1007/s41660-018-0061-2`.

[14] K. B. W. Fourer R. Gay D. M., "Ampl: A modeling language for mathematical programming," in 2nd ed. Boston: Cengage Learning, 2002, ch. 17.

[15] P. Williams, "Model building in mathematical programming," in 5th ed. New Jersey: Wiley & Sons, Ltd., Publication, 2013, ch. 9.

[16] A. Helseth, "Environmental constraints in seasonal hydropower scheduling - hydrocen report nr. 12," NTNU, SINTEF, NINA, Tech. Rep., 2019.

[17] 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, 11th Conference on Process Integration, Modelling and Optimisation for Energy Saving and Pollution Reduction, ISSN: 0360-5442. DOI: `https://doi.org/10.1016/j.energy.2009.07.025`. [Online]. Available: `https://www.sciencedirect.com/science/article/pii/S0360544209003119`.

Appendix A

Full Paper Submission: European Energy Market Conference

This paper was written for the European Energy Market Conference[kilde], with final review notification due in mid-July. The paper is based on the first results from the master thesis, not including the tighter linear approximated method.

Evaluating Modelling Approaches for State-Dependent Environmental Constraints in Medium-Term Hydropower Scheduling

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***Abstract*—This paper addresses the inclusion of state - dependent environmental constraints in medium-term scheduling of hydropower plants with reservoirs. The reservoir handling and release plans of hydropower production can lead to dry river sections and lakes, create barriers for fish mitigation and impact terrestrial ecosystems. In Norway, many reservoirs are also used for recreational purposes. Environmental constraints are imposed to facilitate synergies in reservoir usage and ensure high enough water levels. Some environmental constraints are challenging to mathematically include in hydropower scheduling models, due to nonconvex characteristics or binary logic. State-dependent constraints can make the problem formulation nonconvex, and are therefore not included in existing scheduling tools. This paper compare different approaches for representing such constraints in medium to long-term scheduling models and evaluate the difference in optimality.**

***Index Terms*—hydropower scheduling, environmental constraints, state-dependent constraints**

NOMENCLATURE

Index Sets

$\mathcal{T}$	Set of stages (weeks)
$\mathcal{S}$	Set of scenarios (inflow and price)

Parameters

λ_t^s	Power price in stage t, given scenario s, in $\frac{€}{MWh}$
i_t^s	Inflow in stage t, given scenario s, in Mm^3
v_t^0	Initial reservoir level in stage t, in Mm^3
E	Energy conversion factor, in $\frac{MWh}{Mm^3}$
$\bar{V}$	Maximum reservoir volume, in Mm^3
$\bar{U}$	Maximum discharge, in MW
$\tilde{V}_t$	Environmental limit on reservoir volume in stage t, in Mm^3
$F_{v_{t+1}}$	Future profit function of v_t

Variables

q_t	Plant outflow in stage t, in Mm^3
s_t	Spilled outflow in stage t, in Mm^3
u_t	Plant output in stage t, in MWh
v_t	Reservoir level at end of stage t, in Mm^3
α_{t+1}	Future expected profit in stage t, in €
α_t	Expected profit in stage t, in €
γ_t	Environmental binary variable for stopping production in stage t

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I. INTRODUCTION

Climate change and environmental degradation are existential threats to Europe and the world. To overcome these challenges, power producers are encouraged to operate in an environmentally sustainable way. The dominating energy source in Norway is hydropower, and to limit the ecological burden of hydropower production, the Norwegian government has imposed rules and regulations on the reservoir volume and release plans.

In Norway, many large reservoirs are also used for recreational activities such as fishing, boat trips, and swimming for the locals. There are strict regulations at the minimum reservoir level to keep these activities alive. The goal of the environmental constraint is to avoid low water levels in the reservoirs, which leads to great dissatisfaction among the local population. A picture that illustrates the situation that follows at low reservoir levels is included in 1.

Fig. 1. Example of low water level in a recreational area.

State-dependent environmental constraints are imposed on operation of several Norwegian hydropower plants, and may be imposed on more hydropower plants in near future as a result of revision of the concession terms of existing plants. State-dependent restrictions are often more economically efficient and can be better targeted in terms of environmental gains but have the disadvantage of being mathematically challenging to model.

Medium-term hydropower scheduling models currently used in the Nordic hydropower industry do not include accurate representations of state-dependent constraints as they often lead to nonconvexities and the need for logical conditions. State-of-the-art solution methods for medium- to long-term hydropower scheduling in the Nordic are based on stochastic dual dynamic programming (SDDP) [1], which require a convex model formulation. These models therefore rely on linear approximations of state-dependent environmental constraints. Using stochastic dynamic programming (SDP) [2] will enable the possibility to include nonconvexities and logical conditions but is suitable only for small systems. Previous research considers an accurate representation of state-dependent environmental constraints using SDDiP [3] and SDP [4], and linear approximations in SDDP, but there is, to the best of our knowledge, no material comparing the different approaches.

The research presented in this paper aims to enlighten how different modelling approaches of state-dependent environmental constraints in water value calculations affect water values and production plans. Our contribution includes a description of two different modelling approaches, an exact representation and a linear approximation of the environmental constraint. The two approaches are compared towards the current situation, where these constraints are not considered in the planning. The comparison is conducted for a case study of the Driva hydropower plant in mid-Norway, using data provided by the operator of the plant, TrønderEnergi. Both formulations can be used in methods that do not require a convex model formulation, such as SDP. In models based on SDDP, a convex model formulation is required and a linear approximation is necessary.

II. Model Description

A medium-term hydropower scheduling model based on SDP is used to investigate the solution quality of the different representations of the constraint. An SDP model framework is chosen due to its straightforward implementation and good opportunities for formulation flexibility, including nonconvexities and hereby state-dependent constraints. The same model framework is used for both implementations to avoid additional noise in the comparison.

The developed SDP-model takes the perspective of a power producer, and the objective is to maximize revenue while complying with all physical and regulatory constraints, including environmental constraints. The dynamic structure in the hydropower scheduling problem enables the ability to solve smaller scheduling problems for each weekly stage independently and use the connection between the weekly steps to establish the optimal solution for the whole scheduling problem. The connection between each weekly stage is the reservoir level and, due to strong autocorrelation, the level of the power price. The operational decisions in one step determines the reservoir level, affecting the decisions in the next step.

A. Modeling Uncertainties

Inflow and power price are considered uncertain and are represented in the model as stochastic variables. The uncertainty is represented using a Markov model with weighted probabilities. In addition, autocorrelation in price is considered by modeling price as a state variable. The correlation from last week is represented by using the power price in the previous week $t-1$ as a state variable in week t.

B. Weekly Stage Problem

The SDP-algorithm solves the decision problem for each weekly stage $t = 1, ..., \mathcal{T}$, for all discrete reservoir states and all stochastic states, see e.g. [5] for a description of a similar SDP-algorithm. The weekly decision problem is formulated with (1a)-(1i).

$$\max \alpha_t = \lambda_t^s \cdot u_t + \alpha_{t+1} \tag{1a}$$

$$v_t = v_t^0 - u_t - s_t + i_t^s \tag{1b}$$

$$\alpha_{t+1} \leq F_{\alpha_{t+1}}(v_t) \tag{1c}$$

$$u_t = E \cdot q_t \tag{1d}$$

$$v_t \geq \gamma_t \cdot \tilde{V}_t \tag{1e}$$

$$u_t \leq \gamma_t \cdot \bar{U} \tag{1f}$$

$$v_t \leq \bar{V} \tag{1g}$$

$$u_t, v_t, \alpha_{t+1}, q_t, s_t \geq 0 \tag{1h}$$

$$\gamma_t \in \{0, 1\} \tag{1i}$$

The objective of the weekly stage problem (1a) is to maximize revenue from the current week, as well as the future revenue of remaining reservoir volume. The resulting reservoir level of each week is determined by (1b) and the future revenue is set by (1c). The energy conversion is described in (1d) and is modeled as a constant relation. Equations (1e) and (1f) ensures that the environmental constraint is being complied with. If the reservoir level is lower than the environmental threshold, $\tilde{V}_t$, the binary variable γ_t is set to zero and the production has to stop. γ_t can be set to one when the reservoir level is higher than the threshold. Then the hydropower plant can produce power, but the resulting reservoir level has to be above the threshold. Equation (1g) ensures reservoir level within the physical boundaries.

After solving all the decision problems in each stage, the expected future profit is calculated and used when solving the previous stage $(t-1)$. When the problem has been solved for all weeks, the algorithm re-solves the entire planning horizon, using the water values from the first stage as end-value setting in the last stage. To avoid unwanted end of horizon-effects, this continues until the algorithm converges, i.e. when the water values in the first step equals the water values in the last step. When the SDP algorithm has converged, the calculated water values can be used for a final forward simulation in order to obtain production plans.

C. Solution Method

In order to compare the different approaches of modeling the state-dependent environmental constraint, production plans are simulated using three different sets of calculated water values. The three different approaches for calculating water values are presented below:

1) Without Environmental Constraint: To calculate water values without inclusion of environmental constraints is often the currently used method in commercial Nordic hydropower scheduling. In this case, the weekly stage problem presented in II-B is modified by excluding constraint (1e) and set γ_t to 1 for all stages.
2) Near Exact Formulation: To include the environmental constraint with a near exact formulation, the weekly stage problem presented in II-B is used to calculate water values.
3) Linear Approximation: The formulation in II-B is non-convex and uses binary logic. To avoid this, a linear relaxation is imposed, setting γ_t to a continuous variable between 0 and 1 for all stages.

The final simulations are conducted as parallel simulation, i.e. assuming a fixed start-reservoir level in week 1 for all simulated weather and price scenarios. This is the selected simulation approach because this resembles the industrial process of production planning in TrønderEnergi.

III. Case Study

Finally, the model is applied to a single-reservoir hydropower plant case study. The case study described in this section is the production planning of the Driva power plant, with Gjevilvatnet as the main reservoir, located in Norway. TrønderEnergi, the Norwegian energy company that operates the power plant, initiated the study by request due to existing challenges regarding the inclusion of environmental constraints in their production planning process. Gjevilvatnet is, in addition to being a hydropower reservoir, an assembly point for recreational activities. Every summer, many people come from surrounding cities to this area to spend their vacation fishing, swimming, and boating in Gjevilvatnet. Therefore, it is of great interest that the reservoir level is kept high enough to ensure that visitors can do these activities. The case study is a compelling case as there is a lot of pressure from the local population and the authorities that the reservoir level must be high in the summer. A main motivation of the work has been the close industry collaboration and the access to actual data from TrønderEnergi.

A. Price and Inflow Data Inputs

All input data is provided from TrønderEnergi. The inflow scenarios are based on historical data, and the price scenarios are simulated from a fundamental model (EMPS) that uses historical weather years as the stochastic input. The price and inflow scenarios are presented in Figures 3 and 2, respectively.

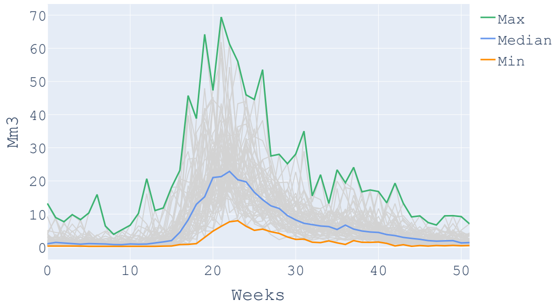

Fig. 2. Input data for inflow scenarios.

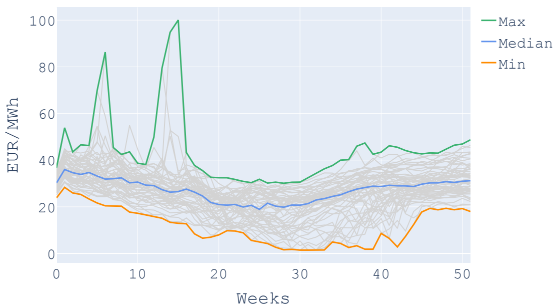

Fig. 3. Input data for price scenarios.

B. Results and Discussion

The three approaches described in II-C are used to calculate water values and simulate production plans using parallel simulation. The results of the simulations are presented in the following section.

To simulate production plans for the hydropower plant, historical inflow and price prognosis from 57 years are used together with calculated water values from each of the three approaches described in II-C. The resulting production plans follow a traditional, seasonal curve for reservoir management. This is reasonable considering that the assumed power price has a characteristic curve, with high prices in the winter and low in the summer. Comparing the results from simulations with different water values, we see that the production plans are equal between the three approaches for most of the simulated scenarios. With water values from the near exact formulation, 65% of the simulated production plans were identical to the plans without consideration of the restriction. With water values from the linearly approximated formulation, 93% of the simulated production plans were equal to the plans simulated with water values that did not include the restriction. The relatively low impact of considering the constraint can be explained by the assumed power price. Because of low prices during summer, power production within the restriction period is already less beneficial than the rest of the year, dampening the effect of the constraint.

Yearly revenue for the base case, without the restriction in water value calculations, was 17.1M€. The average change in profit of all simulations is presented in Table I. The economic results in Table I are calculated considering the change in yearly revenue from power production and the difference in the value of the reservoir level at the end of the analysis period.

TABLE I
ECONOMICAL IMPROVEMENT FROM BASE CASE

	Formulation Method	
	Linear Approximation	***Exact Formulation***
Absolute average	2333 EUR/yr	40 993 EUR/yr
Relative average	0.01%	0.24 %

The average change in profit from Table I shows a slight variance between the different approaches. The average difference is considerably more prominent for the exact formulation than for the linear approximated formulation but less than 0.5% in both cases. The low economic gains could be due to many weather years resulting in equal production plans for each approach.

The linear approximation approach did not change the production plans of any economic significance, indicating that it is not the most suitable method. Therefore, further studying results from the approximated constraint was seen as less valuable than the exact formulation to analyze how the new water values affect the production plans.

The following observations and discussions are comparing the exact constraint formulation to the base case method. The identical scenarios are filtered out to see what differences occur by including the restriction in the water value calculations. In other words, we only look at the 20 weather years that changed the production plan after introducing the exact restriction formulation. The average economic results in which the exact formulation deviates from the base method are presented in Table II. The scenario with the best improvement resulted in an economical gain of 1.6 M€, while the worst scenario gave a loss of 1.3M€. The average profit gain of all years with improvement was 460 000 €and the average profit loss of all years with deterioration was 302 000 €.

TABLE II
ECONOMICAL IMPROVEMENT FROM BASE CASE
OF FILTERED SIMULATIONS[a]

Absolute average	117 000 EUR/yr
Relative average	0.67 %

[a]Simulations that resulted in unequal production plans.

The average reservoir levels for each week are presented in Figure 4. An important remark is that the average values do not fully reflect the spread in the curves, and for some scenarios, there are greater differences. The production plans appear similar, but there is an interesting difference during the restriction period at two particular points. At the beginning of the restriction period, the reservoir level is lower for the water values that consider the constraint. After a few weeks, this reverses, and during the last weeks of the restriction period, the reservoir level is higher for the water values that consider the constraint.

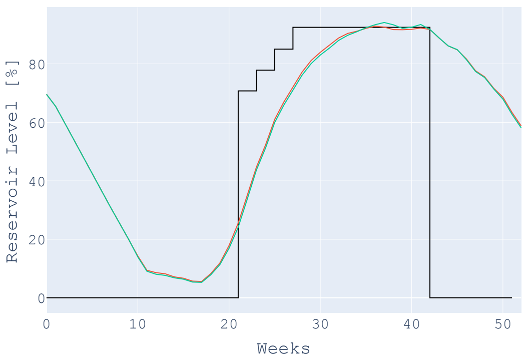

Fig. 4. Average reservoir level of simulations that resulted in unequal production plans. Red line is the base case simulations and green line is the exact formulation simulations.

The turning point, where the average reservoir levels of the exact formulation exceed the base case, is further illustrated in Figure 5. This means that the water values considering the environmental constraint are lower right before the restriction period and become higher during the following weeks. The producer has no chance to govern differently until the reservoir level reaches the threshold in the restriction period, i.e., the turning point comes from how the individual scenarios that have already reached the limit are handled. The same reasoning also explains why the average reservoir level crosses the boundary in weeks 37 and 39.

Despite the changes discussed previously, the reservoir levels in the case study do not change of any practical significance. The small changes in the reservoir levels may point to the case's price distribution, with lower prices in the summer and higher in the winter. The model does not see an incentive to save water in the winter to reach a high enough level to be allowed to produce water earlier in the summer.

The model is economically driven and therefore governed by the earning potential in the period with the restriction. Even though the case study resulted in a financial gain from including the constraint in the water value calculations, the threshold is not reached any earlier in the restriction period. The purpose behind the restriction is not better achieved, but the operation does not violate the terms of the restriction. A different price distribution will likely affect how the policy's purpose, which is to get more water, is met.

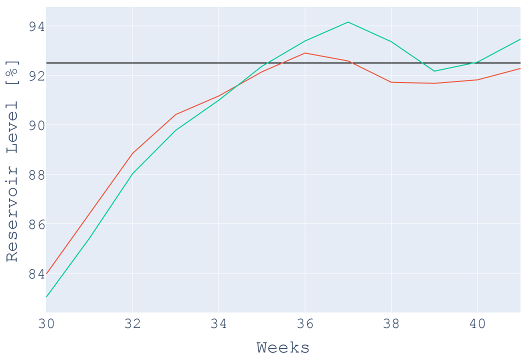

Fig. 5. Excerpt from Figure 4. Red line is the base case simulations and green line is the exact formulation simulations.

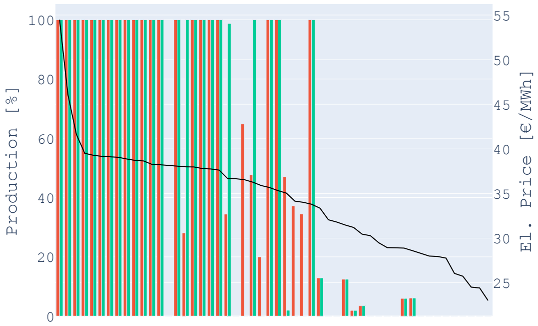

Fig. 6. Duration curve of a selected simulation. Red bars are the base case and green bars are the exact formulation approach.

The new water values, which take into account the environmental constraint, reflects a production halt in the weeks following activation of the restriction. By anticipating the restriction in advance, power producers can move production to weeks with higher prices. The shift in production is illustrated with the duration curve in Figure 6. The duration curve shows weekly power production in a selected scenario for the water values with and without the restriction, sorted by descending price. Here, the model manages to move production to weeks with a higher price and thus get more profit from the water resource.

The production is forced to stop whenever the reservoir level is lower than the threshold during the restriction period. From Figure 4 it is clear that there, on average, are a lot of simulations resulting in a no-production directive. From the duration curve in Figure 6 most of the ”no-production” weeks are further to the right, meaning that these weeks have a low price and it would not be beneficial to produce regardless of the restriction. This emphasizes what was seen from the production plans, that the reservoir level often does not change when the restriction is included in the water value calculations. In addition, it also further substantiates the observation that including environmental constraints in water value calculations does not necessarily lead to higher fulfillment of the purpose behind the restriction. Improved modeling of the constraint in the medium-term scheduling was not found to improve the fulfillment of the underlaying purpose of the constraint.

There may, however, be some years where this distribution does not occur. While the price distribution in this case study is typical, some years may be abnormal, with higher summer prices. Years with this atypical price distribution predictions could incentivize planning for the restriction. The model can weigh the benefit of producing in the winter against the disadvantage of experiencing stop requirements in the summer; hence, the price distribution influences the model. In addition to price sensitivity, the results from the case study are also case specific in terms of the characteristics of the hydropower plant where the constraint is imposed and the regulatory definition of the constraint.

IV. Conclusions

This research paper has investigated state-dependent environmental constraints in medium-term hydropower scheduling. The authors aimed to contribute to the research field by implementing and comparing suggested methods of including environmental constraints. A case study was performed to compare an exact formulation to a linear approximation. The two approaches were compared to the base case method, excluding the restriction in water value calculations.

The main findings from the case study showed performance improvement when including an exact formulation of the state-dependent constraints. The financial results indicate an earning potential, and the duration curve illustrated how planning ahead for the restriction could ensure production in higher priced weeks. On the other hand, the overall reservoir level did not increase substantially. Despite a financial gain, a higher fulfillment of the purpose behind the restriction, which is to get more water for recreational purposes, was not seen. Still, the model is very price sensitive, and it is expected that planning for the restriction could have a larger impact with a different seasonal price profile.

There was no significant difference between linear approximation and the base case method, indicating that a complete relaxation of the binary variables is not a suitable method. A possible extension of this study is to look at other tighter approximation methods.

Acknowledgment

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REFERENCES

[1] 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.

[2] R. Bellman, “Dynamic programming and stochastic control processes,” Information and Control, vol. 1, no. 3, pp. 228–239, 9 1958.

[3] 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

[4] L.E. Schäffer, A. Helseth, and M. Korpås, “A Stochastic Dynamic Programming Model for Hydropower Scheduling with State-dependent Maximum Discharge Constraints,” 2022, unpublished. [Online]. Available: https://ssrn.com/abstract=4042081

[5] M. Pereira, N. Campodonico, R.Kelman. ”Application of stochastic dual dp and extensions to hydrothermal scheduling”. Technical report, PSRI, 1999.

Appendix B

Abstract Submission: Hydropower Scheduling Conference

This abstract was written for the International Conference on Hydropower Scheduling in Competitive Electricity Markets[kilde]. The abstract is based on the work from this master's thesis but was written before the last results were obtained. The review is still pending.

Evaluating Modelling Approaches for State-Dependent Environmental Constraints in Medium-Term Hydropower Scheduling

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Abstract — **This paper aims to address the inclusion of state -dependent environmental constraints in medium-term scheduling of hydropower plants with reservoirs. Hydropower production's reservoir handling and release plans may cause ecological burdens, including dry river sections and lakes. In Norway, many reservoirs are also used for recreational purposes. Environmental constraints are imposed to facilitate synergies in reservoir usage and ensure high enough water levels. There are different possibilities to mathematically include these constraints in hydropower scheduling models, each with its advantages and disadvantages. This paper compares different approaches to evaluate the difference in optimality.**

Keywords — Hydropower Scheduling, Environmental Constraints, State-Dependent Constraints

I. Introduction

Climate change and environmental degradation are existential threats to Europe and the world. Power producers are encouraged to operate in an environmentally sustainable way to overcome ecological challenges. As many of the large reservoirs in Norway also are used for recreational activities, there are strict regulations on the minimum reservoir level. The goal of the environmental constraint is to avoid drought in popular recreational areas, which leads to great dissatisfaction among the local population. It has become more common to formulate environmental rules and regulations as state-dependent in recent years. State-dependent restrictions are often more economically efficient and better targeted in terms of environmental gains but have the disadvantage of being mathematically challenging to model.

Medium-term hydropower scheduling models currently used in the hydropower industry do not include accurate representations of state-dependent constraints as they often lead to non-convexities and the need for logical conditions. State-of-the-art solution methods for hydropower scheduling, using stochastic dual dynamic programming (SDDP) [1], require a convex model formulation and rely on linear approximations of such constraints. Using stochastic dynamic programming (SDP) [2] will enable the possibility of including non-convexities and logical conditions but is suitable only for small systems. There exists research that considers accurate representations of state-dependent environmental constraints using SDDiP [3] and SDP [4] and linear approximations in SDDP. Still, to the best of our knowledge, there is no material comparing the different approaches.

This paper aims to compare linear formulations that can be used in SDDP based models and more accurate representations that cannot be included in SDDP due to nonconvexities. The more accurate representations of state-dependent constraints can be used in methods that do not require a convex model formulation, such as SDP.

II. Methodology

The representations are implemented in an SDP model framework to investigate differences in solution quality. The same model framework is used for all the implementations to avoid additional noise in the comparison. An SDP model for medium-term hydropower scheduling of local reservoir management has been developed. The model takes the perspective of the power producer, and the objective is to maximize revenue while complying with all physical and regulatory constraints, including environmental constraints. It was of great interest to develop a process close to industrial production planning, as the study was initiated at the request of TrønderEnergi, a Norwegian energy company. TrønderEnergi has an existing problem they want to solve in Driva Power Station, a single reservoir hydropower plant in Norway.

In order to compare the different approaches to model the state-dependent environmental constraint, several formulations of the constraint are implemented in the model framework. The authors have implemented and studied one linear approximation and one accurate representation of the constraint. Further, this work will be continued by including a tighter linear approximation and a formulation closer to TrønderEnergi's industrial approach. Finally, the model is applied to the TrønderEnergi case study.

III. Results

The expected results are practical and financial consequences of including environmental constraints in the medium-term scheduling of reservoirs. Preliminary results show a considerable difference between the formulations implemented. The results indicate that a complete relaxation of the exact formulation is a poor linear approximation and suggest that other approximations could be more helpful. The final results will include an evaluation of the performance of two more constraint formulations, a tighter linear approximation and a hard stop-the-station constraint used by

TrønderEnergi today. The latter is an alternative approach since the actual constraint cannot be included in existing decision support tools.

References

[1] 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.

[2] R. Bellman, “Dynamic programming and stochastic control processes,” Information and Control, vol. 1, no. 3, pp. 228–239, 9 1958.

[3] 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

[4] L.E. Schäffer, A. Helseth, and M. Korpås, “A Stochastic Dynamic Programming Model for Hydropower Scheduling with State-dependent Maximum Discharge Constraints,” 2021, unpublished. [Online]. Available: https://doi.org/10.36227/techrxiv.15141885.v1

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