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Analysis of the impact of demand response on the Norwegian energy system

Mohammadreza Ahang[1] · **Pernille Merethe Sire Seljom**[2] · **Asgeir Tomasgard**[1]

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Abstract

European CO_2 reduction goals have led to an increase in variable energy sources such as wind and solar, and consequently to an energy system that will need more flexibility in the future. In Norway, the hydropower reservoirs will enable the country to play a crucial role in European electrification by delivering flexibility to countries in Northern Europe. A further source of flexibility is demand response (DR) accumulated in residential, commercial, and industrial sectors. The paper discusses DR, load shifting, and load shedding based on the application of a stochastic TIMES model and it evaluates the role of DR in the Norwegian energy system towards 2050. The analysis shows that cost-efficient DR operation primarily comes from space heating in residential buildings. The use of DR, which is season-dependent, increases the volume of electricity trade, including electricity export and import to neighboring countries, and it smooths electricity prices. The implementation of DR in Norway leads to decreases in expected electricity price and total system cost by exporting flexible electricity and importing low price electricity. Additionally, it affects hydropower and reservoir management.

Keywords Demand response · Stochastic optimization · Energy system · Hydropower · TIMES model

1 Introduction

Based on EU Reference Scenario 2016 it is projected that from 2020, electricity demand will experience a 0.7% growth rate every 5 years [1]. Norway's climate target for 2030, aiming to achieve a more than 40% reduction in greenhouse gas

✉ Mohammadreza Ahang
mohammadreza.ahang@ntnu.no

Asgeir Tomasgard
Asgeir.tomasgard@ntnu.no

1 Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology, Trondheim, Norway

2 Department of Renewable Energy Systems, Institute for Energy Technology, Kjeller, Norway

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(GHG) emissions compared to the reference year 1990, sets the foundation for its long-term goals. Looking ahead, the country's commitment will continue to strengthen, with the target progressively increasing towards an ambitious 80–95% reduction in GHG emissions by 2050 [2]. At the same time, high shares of non-dispatchable renewable energy sources, such as solar and wind energy, will create an increasing need for flexibility in European the energy system to mitigate reliability issues [3].

Demand response (DR) can be a tool to keep demand and supply in balance, and it can smooth price spikes and protect against system contingencies in energy systems with a high share of renewables [4]. Stochastic supply and demand variations may have a negative influence on prices and supply security if they are not managed. DR, alongside other sources of flexibility such as hydropower, batteries, fossil power plants with carbon capture and sequestration (CCS), and transmission, is crucial to ensure the stability of the energy system. Flexible generators can address the problem of intermittency by providing fast ramp-up and ramp-down, and by operating at low-capacity levels. Transmission can tackle local imbalances but may be limited by grid bottlenecks [5]. Flexible demand-side resources can help to balance the power system by responding to market needs, such as those triggered by system operator requests (direct) and price signals (indirect) [6]. Demand response allows a utility to increase flexibility by persuading consumers either to decrease or shift their consumption during peak load time by responding to price signals or predefined agreements with the utilities. A DR program can increase the system's reliability and reduce the prices of ancillary services [7].

This paper is based on the application of a version of the TIMES model used by Seljom et al. [8], with a stochastic programming approach that includes intermittent production. In addition, the model is extended to include demand response (DR). The paper makes two main contributions. First, it analyzes the impact of DR on the Norwegian energy system by considering stochastic programming in a TIMES model. Second, it includes a combination of operational uncertainty and a sufficient fine time resolution to model demand response, which to our knowledge, has not been done in any earlier studies of long-term general energy system models. Boßmann and Eser [9] reviewed various DR models, offering comprehensive insights into previous studies and models. We use a two-stage stochastic programming approach in TIMES to model DR and investigate how it can increase the value of the flexibility provided by Norwegian hydropower. In our study, DR is defined as load shedding and load shifting. TIMES-Norway is formulated as stochastic linear programming and therefore DR operation depends on the short-term uncertainties in the system.

Models that are limited to analyses of power systems have some similar approaches in common. For example, Marañón-Ledesma and Tomasgard [10] combined long-term investment and short-term uncertainty in a power market model with DR for Europe by using the European power market model called EMPIRE [11]. EMPIRE is formulated as multi-horizon stochastic programming model [12], and its structure is similar to that of the TIMES model used in our study.

Another study to analyze the effect of operational DR on long-term investment in power systems was conducted by Lohmann and Rebennack [13], who used linear and partial-log demand functions to model short-term DR in a long-term capacity expansion model. After including the demand function as a new constraint, Lohmann and Rebennack [13] compared different methods to solve a concave maximization problem and concluded that the tailored Benders decomposition method is much faster than the generalized Benders decomposition method and monolithic approach. These studies show that the European power system will benefit from implementing DR. Some of the important effects are a lower level of load consumption during the peak load time, generation reduction, and investment reduction in storage capacity and transmission.

Furthermore, deterministic models have been used to study DR in power markers; for example, Misconel et al. [17] used the European electricity market model ELTRAMOD to implement DR. The model evaluated the benefit of DR application in two European decarbonization pathways that include decentralized and centralized power systems. The results show that the solar power profile has a higher correlation with the time pattern of DR potential than the wind power profile. Balasubramanian and Balachandra [18] developed a mixed-integer linear programming model with incentivized DR, which they applied to their case study of the Karnataka state electricity system in southwest India. The authors demonstrate that DR programs are an efficient way of smoothing electricity prices, enhancing available capacity utilization, and postponing capacity expansion.

With regard to energy system models, previous approaches to modelling DR have been deterministic. Gills [4] implemented DR, using deterministic linear programming (LP), in a renewable energy mix energy system model (REMix). He used REMix to study energy curtailment and power plant generation in Germany and found that the main benefit of DR was a decreased need for investment in peak power production capacity. Li and Pye [3] used the deterministic UK TIMES model to evaluate the effects of DR on the residential sector and electric vehicles (EVs) in the UK. Their study revealed that DR reduces the requirements for storage and increases the share of low-carbon power in the energy system. Pina et al. [14] used a deterministic TIMES model to evaluate the influences of flexible residential loads to supplement variable renewable energy on a Portuguese island. Their results showed that DR would delay the need for investment in new renewable power plants. Schledorn et al. [16] applied soft linkage between an energy system model and a DR model, in which the modelled DR as a set of ordinary differential equations. After considering price-based DR control, their results provided a demand profile for the energy system model. Gilson Dranka et al. [19] used the Open-Source Energy Modelling System (OSeMOSYS) to investigate the role of energy efficiency and demand response in the Brazilian energy system and found that implementing DR led to reduced CO_2 emissions and reduced total system costs. In addition, they found that investments in energy efficiency and DR together increased the energy system benefits. Anjo et al. [20] used OSeMOSYS to develop a Portuguese power system model in order to investigate the long-term effects of DR. They considered three scenarios with different carbon emission assumptions (business as usual, carbon-free, and without heavy carbon emissions) until 2050 and their results showed that all scenarios benefitted from DR, as there were decreases in total cost and capacity installed and increases in the share of renewable capacity. All of the above-discussed results show that the role of DR depends on the energy mix of the countries in question. Norway has significant hydropower resources and can serve as a flexibility provider to neighboring countries.

One of the purposes of our study is to see how DR complements the flexibility of Norwegian hydropower. In a previous study, Kirkerud et al. [15] used the deterministic energy system model BALMOREL to investigate the role of DR in northern Europe. Their results showed that space heating and water heating were the primary sources of DR in Norway and Sweden. Additionally, they showed that DR variable cost was low enough to compete with regulated hydropower, which is the two countries' primary source of flexibility. In our model, we have formulated short-term uncertainties that can take into account different weather-dependent stochastic scenarios when considering the interplay between DR and hydropower.

Several papers address short-term uncertainty in long-term models through the application of stochastic programming without the implementation of DR. Different sources of short-term stochasticity are wind production, PV production, hydropower production and inflows, electricity demand, heat demand, gas demand, and electricity prices. The trade-off between including all sources of short-term uncertainties and increasing computational effort should be considered [21]. Both Jin et al. [22] and Feng et al. [23] used long-term energy system models with uncertain parameters, such as electricity demand and natural gas price. Furthermore, Gill et al. [24] used stochastic mixed integer programming to evaluate the effect of hydro inflow uncertainty on the generation capacity expansion planning (GCEP). Seljom et al. [8] included uncertain parameters for wind, PV, and hydropower production, as well as uncertain prices and demand in a TIMES model to investigate the effect of zero-energy buildings on the energy system.

In this paper the TIMES model is designed to cover the entire Norwegian energy system with multiple end-use sectors and energy carriers. This enables us to link energy sectors and investigate how DR potential from various sectors may affect the power consumption profile and the interaction with hydropower reservoirs. In our approach, we explicitly formulate long-term inelastic demand, but use DR to provide short-term elasticity. The DR potential depends on different processes and can be activated based on the availability of DR in each time slice. We use multi-horizon stochastic programming to formulate the problem [12]. We have different stochastic sources of renewable energy in the system, such as wind and solar, which can affect the operation of hydropower and DR. The Norwegian power system is highly interlinked with the European system, which is short on flexibility due to the high share of stochastic renewable energy and further prospects. Therefore, one of our important research questions is whether DR in Norway can release more flexibility from the hydropower system for export to neighboring countries.

The TIMES model includes long-term capacity expansion decisions and short-term stochastic operations to meet the future energy service demand by minimizing system cost [25]. Energy system models such as TIMES do not typically include a complex transmission network [26]. Also, the TIMES-Norway model does not include details of a power system's technical constraints (e.g., ramps rates, minimum

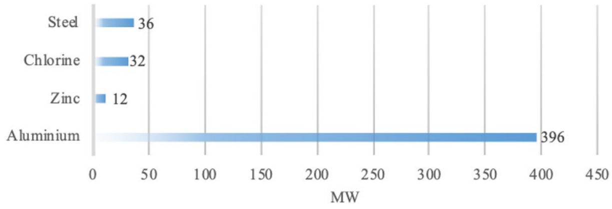


Fig. 1 The load shedding potential for energy-intensive processes in Norway

necessary generation) because the Norwegian system is primarily hydropower-based. These limitations may lead to underestimations of the value of flexibility and DR.

The paper is organized as follows. The next section provides a short overview of Norway's DR potential and costs. Section 2 presents the TIMES-Norway model. Section 3 describes how to model DR in TIMES. Section 4 analyses the effects of DR on the Norwegian energy system and its export. Section 5 presents our conclusions.

2 The DR potential in the Norwegian energy system

In this section, we elaborate on the costs of DR and the potential in terms of volume. Electricity consumption is discussed in relation to three main consumer groups: industrial, residential, and commercial.

We study demand response in terms of two types of DR interventions: load shedding and load shifting. Load shedding is applied to decrease electricity consumption during a given period, whereas load shifting moves electricity consumption between periods. In line with Gills [27], the following terms are used to describe parameters and properties for DR interventions. *Shifting time* defines the maximum duration until load that has been advanced or delayed in load shifting needs to be balanced again. *Intervention time* reflects a limit in the duration of changes in the normal demand pattern, namely the number of consecutive time periods that can be affected by shedding or shifting. *Intervention limit* defines the number of DR interventions of a specific type within a given time frame, such as a day.

2.1 The DR potential in Norwegian industries

In Norway, the main sources of DR potential are electricity and heat demand from the industrial sector [28]. Figure 1 shows that in Norwegian industries it is possible to achieve 476 MW of load shedding potential for different processes [27]. Such processes are not able to shift their electricity consumption but can switch to other sources of energy. In our model, the only energy source for these processes is electricity, and the load shedding could be done by either substitution with other fuels or stopping production.

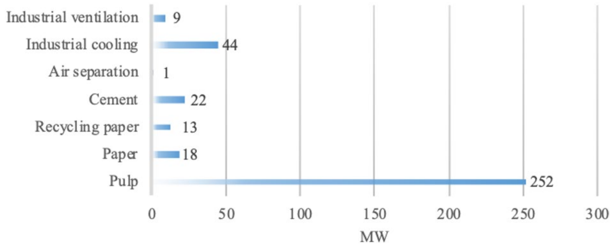


Fig. 2 Industrial processes and their load shifting potential in Norway

We model load shedding in industry with an intervention time of up to 4 h, meaning that load can be shed in four consecutive hours and then be normal for at least 1 h, after which a new DR intervention may start. Load shedding can be activated up to 40 times per year as a model assumption. This is consistent with different process specifications and the DR potential estimations by Gills [27], Paulus and Borggrefe [29], and Stadler [30].

The Norwegian industrial sector can provide 359 MW of load shifting potential (Fig. 2). For most processes energy consumption can be shifted for up to 24 h (shifting time), except in the case of industrial ventilation, for which only 2 h shifting time is possible.[1] During these processes DR interventions can last up to 3 h, with the exception of industrial cooling (2 h) and industrial ventilation (1 h). This means that the energy in the shifting process needs to be balanced within the shifting time, but can deviate from the original load by 2–3 consecutive hours at most. The load shifting potential can as a model assumption be exploited 365 times per year, but industrial cooling and ventilation enable the activation of DR potential by up to 1095 times per year [27]. Figure 2 shows different industrial processes and their load shifting potential.

The cost linked to DR technology includes investment (e.g., cost of installing storage systems, smart meters, data exchange devices), variable costs (such as losses because of load reduction), and fixed costs (such as the cost of data exchange). Investment costs are high for cross-sectional technologies (e.g., ventilation, refrigeration), and small for electricity-intensive technologies (at most 1€ per kW). By contrast, variable costs of activating DR are negligible for cross-sectional technologies and considerable for electricity-intensive technologies. The opportunity costs of load shedding in electricity-intensive industries can be calculated based on company cost structure and electricity price. The opportunity costs of load shedding are significantly higher compared to load shifting due to the presence of multipurpose storage capacity [31].

The total cost of DR consists of fixed costs and variable costs. Variable costs comprise electricity price, and the cost of energy and materials. In Eqs. (1)–(4), the structure of costs is the same as presented by Gruber et al. [31]:

[1] Shifting time refers to the maximum numbers of hours in which a process can shift electricity consumption.

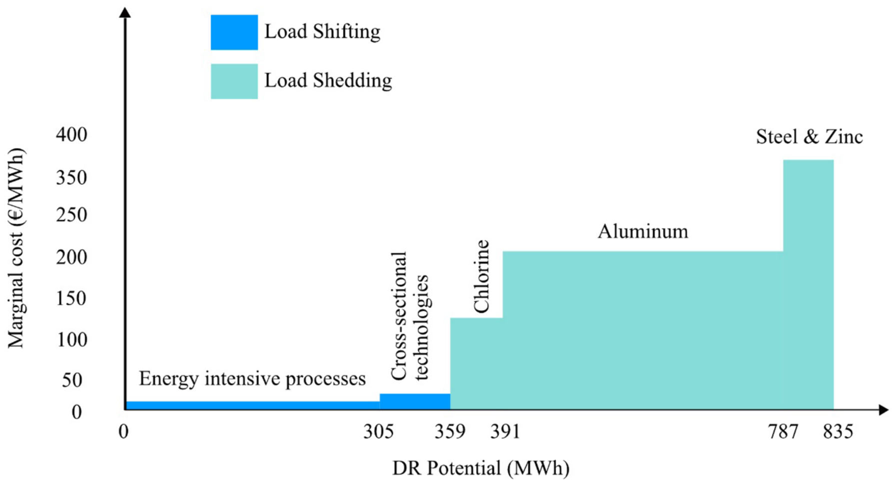


Fig. 3 Merit order of demand response (DR) in the Norwegian industrial sector (load shifting and load shedding)

$$P = M + VC + FC \tag{1}$$

$$VC = P_{el} + P_{ma} + P_{en} \tag{2}$$

$$Pr = P - VC = M + FC \tag{3}$$

$$OC = Pr + P_{el} \tag{4}$$

where P is sale price, P_{el} is electricity price, M is margin, P_{ma} is material cost, VC is variable cost, P_{en} is energy cost, FC is fixed cost, Pr is profit, OC is opportunity cost.

The cost structure plays a crucial role in facilitating the modelling of DR programs. In the case of load shifting, the marginal cost of energy-intensive processes such as making cement, pulp, and paper, and recycling paper is less than 10 €/MWh, with a 305 MW potential. In addition, cross-sectional technologies, such as industrial ventilation, cooling, and air separation have 54 MW DR potential, with a marginal cost of 16 €/MWh. The marginal cost of load shedding is in the range 100–350 €/MWh [27, 29, 30]. The Norwegian DR potential and related marginal costs in the industrial sector are shown in Fig. 3.

2.2 The DR potential in the Norwegian residential sector

The DR potential in Nordic countries, including Norway, is elaborated by Saele and Grande [32]. The DR potential in the Norwegian residential sector is categorized in Fig. 4, which shows that the main share comes from space heating and heating water, mainly using load shifting.

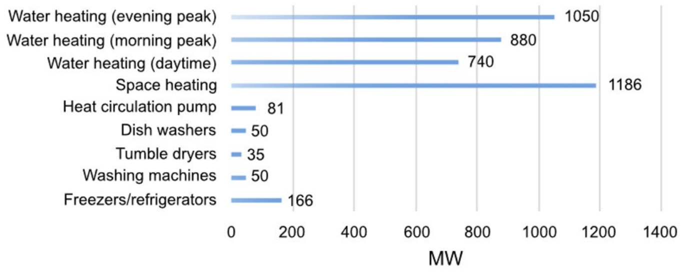


Fig. 4 Distribution of potential load shifting sources in Residential DR

Table 1 Compensation cost in the Norwegian residential sector

Load shifting interval (min)	Average compensation cost (€/kWh)
5	0.004
15	0.011
30	0.019
60	0.032
180	0.061
300	0.057
600	0.058

The residential DR potential is ca. 2300–2600 MW. Stadler [30] describes different processes, as well as the possible DR potential for each process. For example, he reports that the DR potential from space heating and hot water is largely influenced by outdoor temperature.

Freezers and refrigerators can shift electricity consumption for up to 2 h, in which case the DR intervention time would be 1 h. This means that demand could be either increased or decreased in hour 1 and balanced in hour 3, while hour 2 would have normal demand. This source of DR can be activated 1095 times per year. Washing machines, tumble dryers, and dishwashers do not have any limitations regarding the number of DR interventions, but the maximum shifting time is assumed to be 6 h. A heat circulation pump is able to shift electricity consumption for 2 h and the maximum intervention time is just 1 h. This DR potential can be activated 1095 times per year, in line with [27].

The investment cost of implementing DR varies widely, from 0 to 250,000 €/MW, but the average investment cost is ca. 45,000 €/MW. The processes that are managed remotely, such as heating and air conditioning processes, need higher investment than other groups due to their installation costs [10].

We have calculated the cost of residential DR services based on the data presented in Table 1 and the work of Safdar et al. [33]. The cost of DR is the

Table 2 Residential compensation costs in the TIMES-Norway model

Source of residential DR potential	Average compensation cost (€/MWh)
Water heating	30.6
Space heating	30.6
Heat circulation pump	25.4
Freezers/refrigerators	25.4
Dishwashers/tumble dryers/washing machines	4.0

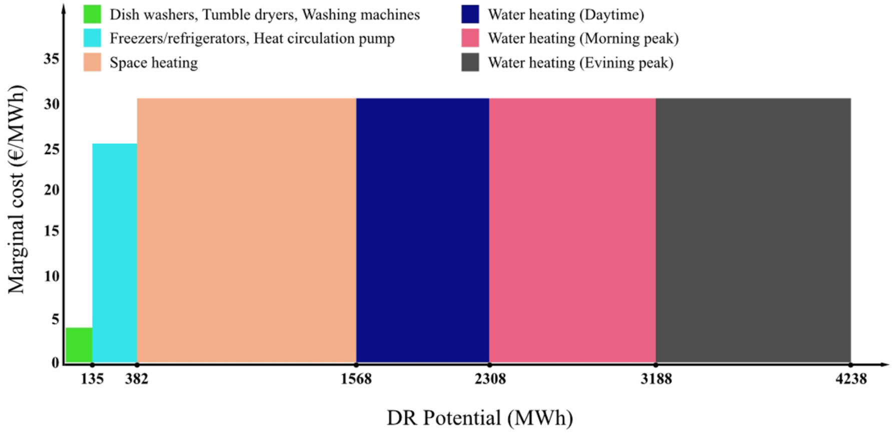


Fig. 5 Merit order of DR in the Norwegian residential sector

average compensation cost that persuades consumers to shift electricity consumption. Table 1 was prepared by using Eq. (5), where the compensation cost for activating the load shifting mechanism depends on the certain load, l_n during operation period t_n. In addition, energy price P_e and compensation expected by consumers, *Comp*., are two important factors in the equation, which relates to both market and consumer behavior.

$$\text{CCost} = \frac{\sum_{n=1}^{N} \left(l_n \times t_n\right)}{1000} \times P_e \times \text{Comp.} \tag{5}$$

By considering the maximum shifting time for each source of DR and the average costs from Table 1, we can calculate the average compensation costs in the Norwegian residential sector. Using the average value can contribute to the simplification of the time-dependent cost. Hence, in this paper the maximum load shifting potential and the average compensation cost for each technology are time independent. However, the calculation of more detailed Norwegian compensation costs is beyond the scope of this paper. Identifying such costs is a major challenge in DR analyses, as consumers with

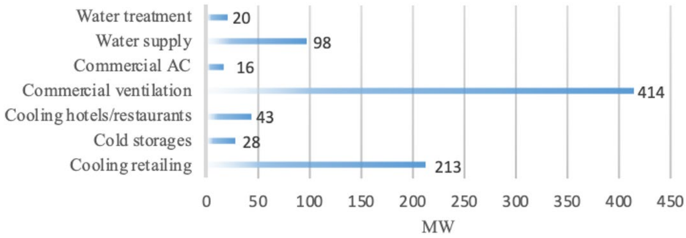


Fig. 6 Load shifting shares of different commercial processes

Table 3 Commercial compensation costs in the TIMES-Norway model

Source of commercial DR potential	Average compensation cost (€/MWh)
Commercial ventilation and AC	16.5
Water treatment and supply	26.0

different utility functions from various countries/regions have different preferences. The compensation costs for the Norwegian residential sector are summarized in Table 2.

The merit order of DR in the Norwegian residential sector is presented in Fig. 5.

2.3 The DR potential in the Norwegian commercial sector

The Norwegian commercial sector can provide around 832 MW of load shifting potential, but the load shift duration is at most 2 h and the DR intervention time is 1–2 h. These potentials can be activated up to 1095 times per year [27]. Figure 6 shows different commercial processes in relation to each source of load shifting potential.

Detailed information about the cost of DR in the commercial sector is not available. However, it has been reported that commercial air conditioning (AC) and ventilation have the lowest costs [34]. Furthermore, Verrier [35] claims that the cost of load shifting in the commercial sector is bounded by the costs of DR in the residential and industrial sectors. DR potential from sources such as cooling hotels/restaurants and cooling retail outlets are not considered in our model, due to lack of data. We used data in Table 1 and information provided by Álvarez Bel et al. [34] and Verrier [35], to make a rough estimation of the costs of DR in commercial sector. The results are summarized in Table 3.

3 The energy system model with demand response

In this section we first give an overview of the TIMES-Norway energy system model and second a more detailed description of the implementation of demand response.

3.1 IFE-TIMES-Norway model

IFE-TIMES-Norway [36] is a long-term optimization model of the Norwegian energy system and is generated by the open-source TIMES (the Integrated MARKAL-EFOM System) modelling framework [37]. In this paper, we denote it TIMES-Norway. TIMES models are mainly used for modelling energy and environmental systems at global, national, and regional energy systems in the medium- and long term [25], and they cover the interplay and competition between resources, energy carriers, conversion technologies, and end-use demand. TIMES models minimize the total discounted cost of the energy system to meet the demand for energy services for the analyzed model horizon. The energy system cost includes investments in both supply and demand technologies, expenses related to the operation of capacity, fuel costs, income from energy export, and cost of energy import.

The TIMES model used in this paper was developed by the Institute for Energy Technology (IFE) and the Norwegian Water Resources and Energy Directorate (NVE), and it is a simplified version of the IFE-TIMES-Norway model [38]. The model is a technology-rich model of the Norwegian energy system that is divided into five regions corresponding to the current electricity market's spot price areas. The model provides operational and investment decisions from the starting year, 2015, towards 2050, with seven model periods within this model horizon. Each model period is divided into 48 sub-annual time slices, with each season is represented by 12 2-h time slices. The model has a detailed description of the end use of energy, and the demand for energy services is divided into 15 end-use categories within industry, buildings, and transport in each region. It should be noted that in this paper the energy service demand is treated as inelastic and fixed. Energy services refer to the services provided by consuming a fuel and not the fuel consumption itself. For example, the transport demand for personal cars is an energy service, whereas the fuel used to fuel the cars is the fuel demand. Each energy service demand category can be met by existing and new technologies using different energy carriers such as electricity, bioenergy, district heating, and fossil fuels. Consequently, in each time slice in the model, the use of energy carriers (e.g. electricity) is a model result and not a model input. Other input data include fuel prices, electricity prices in countries with transmission capacity to Norway, renewable resources, and technology characteristics such as costs, efficiencies, and lifetime and learning curves.

The transmission capacity within and outside the regions included in the model is a model input based on current capacity and ongoing transmission capacity expansion. The electricity prices in the included regions are endogenous, as they are the dual values of the electricity balance equation, while the electricity prices in the countries with trading capacity with Norway, which include Denmark, Sweden, the United Kingdom, Finland, Netherlands, and Germany, are a model input.

The model includes two types of hydropower plants: reservoir plants and run-of-the-river (RoR). They comprise two different types: existing plants and new plant options with different investment costs. The capacity for existing plants is a model input, whereas the capacity for the new plant options requires endogenous investments. As opposed to the ROR plants, with seasonal-dependent electricity

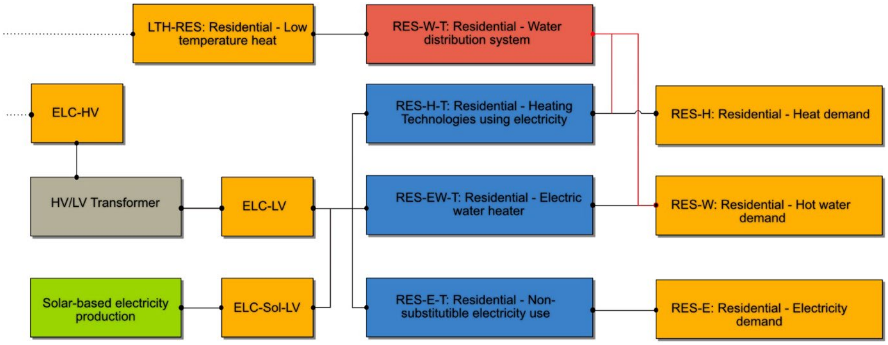


Fig. 7 The residential energy system in Norway

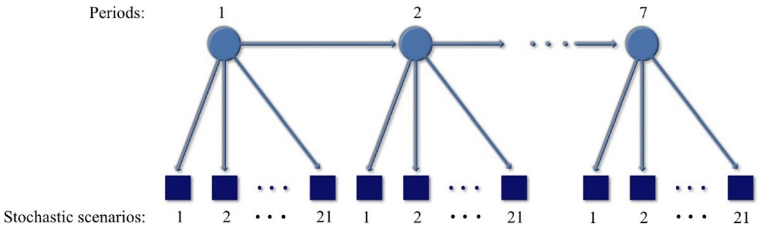


Fig. 8 A scenario tree for a two-stage stochastic model in TIMES

generation, the reservoir plants are flexible between the model's time slices. The annual electricity generation from the reservoir plants is constrained by an annual capacity factor, namely the annual production over the maximum theoretical production over the course of 1 year.

Existing wind power technology and wind power technology under construction is an input to the model. Furthermore, for each region, new sources of wind power are modelled by 10 technology types that have different costs, operational conditions, and upper potentials in each region. Additionally, solar power is split into building applied photovoltaics (PV) on commercial buildings and residential buildings.

Figure 7 is a schematic diagram of the Norwegian residential energy system. Heat demand and hot water demand are satisfied by low temperature heat and electricity. DR processes have similar marginal costs to shift hot water and space heating demand, whereas the demand profiles as the main driver for changing the electricity prices have different patterns.

3.2 TIMES-Norway modelling of short-term uncertainties

We used two-stage stochastic programming to model short-term uncertainties in the generation of wind power, solar power, and hydropower. The TIMES-Norway model decides to invest in new processes/technologies and transmission capacities for each long-term period. The decision about long-term periods is connected to short-term uncertainties in a scenario tree.

Figure 8 is a schematic diagram of a scenario tree for a two-stage stochastic model in TIMES. It represents seven investment-decision periods (blue dots). One investment period covers several years and includes short-term operational decisions (blue rectangle). Figure 8 shows a representation with 21 scenarios for operations in each investment period. Increasing the number of scenarios can make the model more realistic but will lead to considerable computational effort. Representation of the stochastic variables in the scenario tree is based on moment matching and statistical analysis. For more details of the scenario generation method used in our study see [39].

3.3 Mathematical modelling of DR

Below we give an overview of indices, sets, variables, and parameters:

Indices and sets	Description
$l \in L$	Set of periods relating to long-term investments
$p \in P$	Set of processes
$a \in A$	Set of electricity transmission links
$d \in D$	Set of DR processes
$\omega \in w$	Set of operational scenarios
$s \in S$	Set of time slices
$n \in N$	Set of regions
$t \in T$	Set of years
$k \neq s \in S$	Set of time slices used to shift activity
Variables	
x_{pl}^{Pro}	Capacity investment of process p in period l
x_{al}^{Tra}	Capacity investment of transmission a in period l
x_{dl}^{DR}	Capacity investment of DR process d in period l
y_{pnwsl}^{Pro}	Generation by process p in region n through scenario w at time slice s during period l
y_{anwsl}^{Tra}	Net import
y_{dnwsl}^{DR}	DR activity by DR process d in region n in scenario w at time slice s during period l
Parameters	
P_w	Probability of each scenario
c_{pl}^{Pro}	Investment cost of process p in period l
c_{al}^{Tra}	Investment cost of transmission a in period l
c_{dl}^{DR}	Investment cost of DR process d in period l
v_{pl}^{Pro}	Operational cost of process p in period l
v_{dl}^{DR}	Operational cost of DR process d in period l
PV_l	Present value

The simplified two-stage stochastic TIMES-Norway model with DR is given by

$$\mathrm{Min}Z = \sum_{l\in L} PV_l \times \left\{ \begin{array}{c} \sum_{p\in P} c_{pl}^{\mathrm{Pro}} x_{pl}^{\mathrm{Pro}} + \sum_{a\in A} c_{al}^{\mathrm{Tra}} x_{al}^{\mathrm{Tra}} + \sum_{d\in D} c_{dl}^{DR} x_{dl}^{DR} + \\ \sum_{\omega\in w} P_w \sum_{s\in S} \sum_{n\in N} \left[\sum_{p\in P} v_{pl}^{\mathrm{Pro}} y_{plns\omega}^{\mathrm{Pro}} + \sum_{p\in P} v_{dl}^{DR} y_{dlsn\omega}^{DR} \right] \end{array} \right\} \tag{6}$$

subject to

$$\sum_{p\in P} y_{pnwsl}^{\mathrm{Pro}} + \sum_{d\in D} y_{dnwsl}^{DR} + \sum_{a\in A} y_{anwsl}^{Tra} = De_{nwsl} \quad n \in N,\ s \in S,\ w \in \omega,\ l\epsilon L \tag{7}$$

For all other general constraints see [40] and [41].

Equation (6) shows the objective function that is formulated as a two-stage stochastic program. The objective function minimizes the net present value of energy system costs. The first stage covers investment decisions (x) and the cost of long-term investment regarding different processes, such as generators (c_{pl}^{Pro}), transmission lines (c_{al}^{Tra}), and DR (c_{dl}^{DR}), in period l. The second stage includes all short-term operational decisions (y), the operational cost of generators (v_{pl}^{Pro}), and the operational cost of DR (v_{dl}^{DR}) in period l. Short-term operational decisions ($y_{plns\omega}^{\mathrm{Pro}}, y_{dlsn\omega}^{DR}$) can take different values in different stochastic scenarios w.

Equation (7) represents the balancing equation. Demand,De_{nwsl}, in region n in scenario w at time slice s during period l should be satisfied by the summation of energy generation,y_{pnwsl}^{Pro}, by process p and DR operation,y_{dnwsl}^{DR}, by process d and net import,y_{anwsl}^{Tra}, in transmission link a in the same region, scenario , time-slice, and period.

Load shifting reduces production in specific time slices by shifting energy consumption from those points, called downward regulation, and increases energy consumption in other points, called upward regulation. We have applied the storage process in TIMES in order to model load shifting (because in storage, as in DR, the balance over time is a main feature), but with some modifications to make it possible to define overlapping time window sub-intervals for shifting in a stochastic programing formulation. For example, water preheating during off-peak load time instead of water heating during peak load time can decrease total cost. The process is similar to charging a battery when electricity is cheap and discharging during peak load time.

The load shifting potential, $S_{dlns\omega}^{DR}$, in each time slice is modeled in Eq. (8). It is limited by the available capacity of DR process d, x_{dln}^{DR}. The DR capacity is not the same in different time slices, and therefore an availability factor, $\beta_{dlns\omega}^{Af}$, is applied to adjust the DR capacity for each time slice s, period l, and scenario ω. Moreover, the DR service can be activated a limited number of times during a year. This feature is represented by a factor, CA_d, scaling the number from 1 year down to the 12 time slices.

$$S_{dlns\omega}^{DR} \leq CA_d \times \beta_{dlns\omega}^{Af} \times x_{dln}^{DR}, \quad d \in D,\ n \in N,\ s \in S, \omega \in w,\ l \in L \tag{8}$$

Each DR process d in Eq. (8) has an available capacity, x^{DR}_{dln}, limited by availability factor, $\beta^{Af}_{dlns\omega}$, for each time slice. Thus, the maximum available capacity may vary between time slices.

Equation (9) shows the activity of processes p, $y^{Pro}_{plns\omega}$, in region n in scenario w at time slice s during period l bounded above by the maximum available capacity of processes p, x^{Pro}_{pln}, in region n during period l and defined with the availability factor of processes p,$\beta^{Af}_{plns\omega}$, plus the available DR activity of processes d, $y^{DR}_{dlns\omega}$, for each time slice.

$$y^{\mathrm{Pro}}_{plns\omega} \leq CA_p \times \beta^{Af}_{plns\omega} \times x^{\mathrm{Pro}}_{pln} + y^{DR}_{dlns\omega}, \quad p \in P,\ n \in N,\ s \in S,\ \omega \in w,\ l \in L,\ d \in D \tag{9}$$

Three factors may influence the net DR activity in time slice s for process d, $y^{DR}_{dlns\omega}$, as described in Eq. (10): the sum of DR activity shifted to time-slice s from all other time slices k in period l (upward regulation), $\sum_k SI^{DR}_{dlnk\omega}$, the amount shifted from this time slice (downward regulation), $SO^{DR}_{dlns\omega}$ as well as load shedding, $SH^{DR}_{dlns\omega}$, in region n in scenario w.

$$y^{DR}_{dlns\omega} = \left(\sum_k SI^{DR}_{dlnk\omega} \right) - SO^{DR}_{dlns\omega} + SH^{DR}_{dlns\omega}, \quad d \in D,\ n \in N,\ s \in S,\ \omega \in w,\ l \in L \tag{10}$$

For load shifting, the equality between upward regulation, $\sum_k SI^{DR}_{dlnk\omega}$, and downward regulation, $SO^{DR}_{dlns\omega}$, in region n in scenario w during period l is described in Eq. (11), after making sure that the sum of upward regulation in time slices k are equal to the downward regulation in time slice s.

$$\sum_k SI^{DR}_{dlnk\omega} = SO^{DR}_{dlns\omega}, \quad d \in D,\ n \in N,\ s \in S,\ \omega \in w,\ l \in L \tag{11}$$

We have also defined a process to generate a commodity called "flexibility," which is supplied to specific processes in the industrial sector (e.g., chlorine, aluminum, steel, zinc) to model load shedding. The process is bounded with the load shedding potential and related availability factors. In Eq. (12), load shedding for process d, $SH^{DR}_{dlns\omega}$, in region n in scenario w at time slice s during period l is implemented in the same way as in the other general processes and decreases a part of energy-service demand. The DR potential and all limitations regarding load shedding processes have been defined only for downward regulation.

$$SH^{DR}_{dlns\omega} \leq CA_d \times \beta^{Af}_{dlns\omega} \times x^{DR}_{dln}, \quad d \in D,\ n \in N,\ s \in S,\ \omega \in w,\ l \in L \tag{12}$$

Modelling load shifting requires defining time window sub-intervals. In our model with 12 time slices for a representative season, we decompose upward regulation $\sum_k SI^{DR}_{dlnk\omega}$ into 12 flexibility commodities, DR1 to DR12. Maximum shifting time must be represented. In Eq. (13) this is illustrated for DR activity in period l with a maximum shifting time of two time slices (e.g., heat storage):

$$\sum_{k=2}^{3} SI_{dlnk\omega}^{DR1} + \sum_{k=3}^{4} SI_{dlnk\omega}^{DR2} + \cdots + \sum_{k=1}^{2} SI_{dlnk\omega}^{DR12} = \sum_{k} SI_{dlnk\omega}^{DR}, \quad d \in D,\ n \in N,\ \omega \in w,\ l \in L \tag{13}$$

Equation (13) shows that the summation of upward regulation in region n in scenario w during period l from time slice 1 to time slice 12 is split into 12 different commodities, DR1 to DR12, with a duration of 2 h. It should be noted that by defining different commodities, any time slice can do both upward and downward regulation. Equation (14) defines downward regulation $SO_{dlns\omega}^{DR}$ in time slices s for $s = 1,\ldots,$ 12:

$$\sum_{k=2}^{3} SI_{dlnk\omega}^{DR1} = SO_{dlns\omega}^{DR}, \quad d \in D,\ n \in N,\ s = 1, \omega \in w,\ l \in L$$

$$\sum_{k=3}^{4} SI_{dlnk\omega}^{DR2} = SO_{dlns\omega}^{DR}, \quad d \in D,\ n \in N,\ s = 2, \omega \in w,\ l \in L \ldots,$$

$$\ldots,$$

$$\sum_{k=1}^{2} SI_{dlnk\omega}^{DR12} = SO_{dlns\omega}^{DR}, \quad d \in D,\ n \in N,\ s = 12, \omega \in w,\ l \in L \tag{14}$$

In Eq. (14), downward regulation in region n in scenario w during period l at time slice 1, $SO_{dln1\omega}^{DR}$, should be equal to upward regulation at time slices 2 and 3, $SI_{dln2\omega}^{DR1}$ and $SI_{dln3\omega}^{DR1}$ using process DR1. Upward regulation at time slices 3 and 4 is defined by DR2. Hence, it is also possible to define intervals with marginal overlapping to provide more flexibility to the model.

4 Results and discussion

In this section we compare the case with and without DR technology in order to show the effects of DR on the energy mix, regulated hydropower income, and electricity prices from 2020 to 2050. RoR plants are not included in the analysis because they are not flexibility providers. Therefore, regulated hydropower is hereafter referred to a hydropower. Additionally, we discuss how DR impacts the Norwegian energy system's capability to provide flexibility to neighboring countries.

DR operation in the period 2020–2050 has an upward trend, during which the space heating in residential buildings contribute 83–90% of the total DR operation. The other important source of DR is hot water in residential buildings (6–14%), while industry provides only 3–5% of the total DR operation.

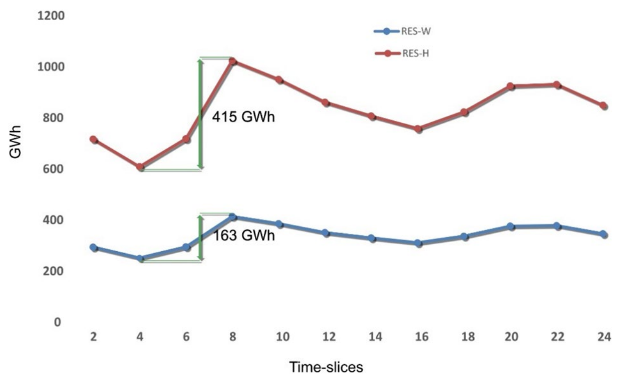


Fig. 9 Residential space heating (RES-H) and hot water (RES-W) demand, winter, 2050

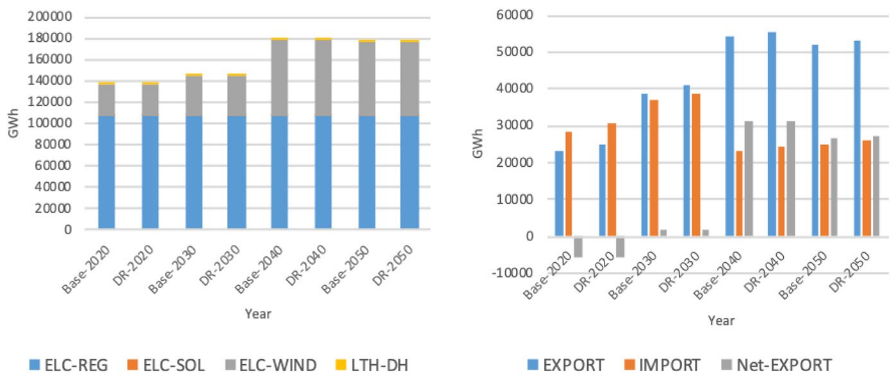


Fig. 10 Expected annual power production and trade

The reason residential space heating activates a high share of the total DR operation in comparison with residential hot water is evident in Fig. 9. Indeed, the volume of space heating demand is higher than hot water demand, and the difference between peak and valley in the space heating demand curve is more than twice that for hot water. In addition, the annual availability factor of residential technologies for space heating is higher. By using DR processes to minimize system costs, electricity price peaks are shaved by changing the space heating and hot water curves. Each time slice represents 2 h. The demand volume is deterministic, but considering short-term uncertainty for the supply side will affect the DR operation.

The DR operation does not affect the expected annual power production considerably, while the electricity export and import increase. Although the volume of net export after implementing DR is roughly similar to the case without DR, DR increases the volume of trade (import and export). Figure 10 shows a comparison of expected annual production of regulated hydropower (ELC-REG), solar power (ELC-SOL), wind power (ELC-WIND), and low temperature heat from district heating (LTH-DH) in Norway, as well as trade with neighboring countries with and

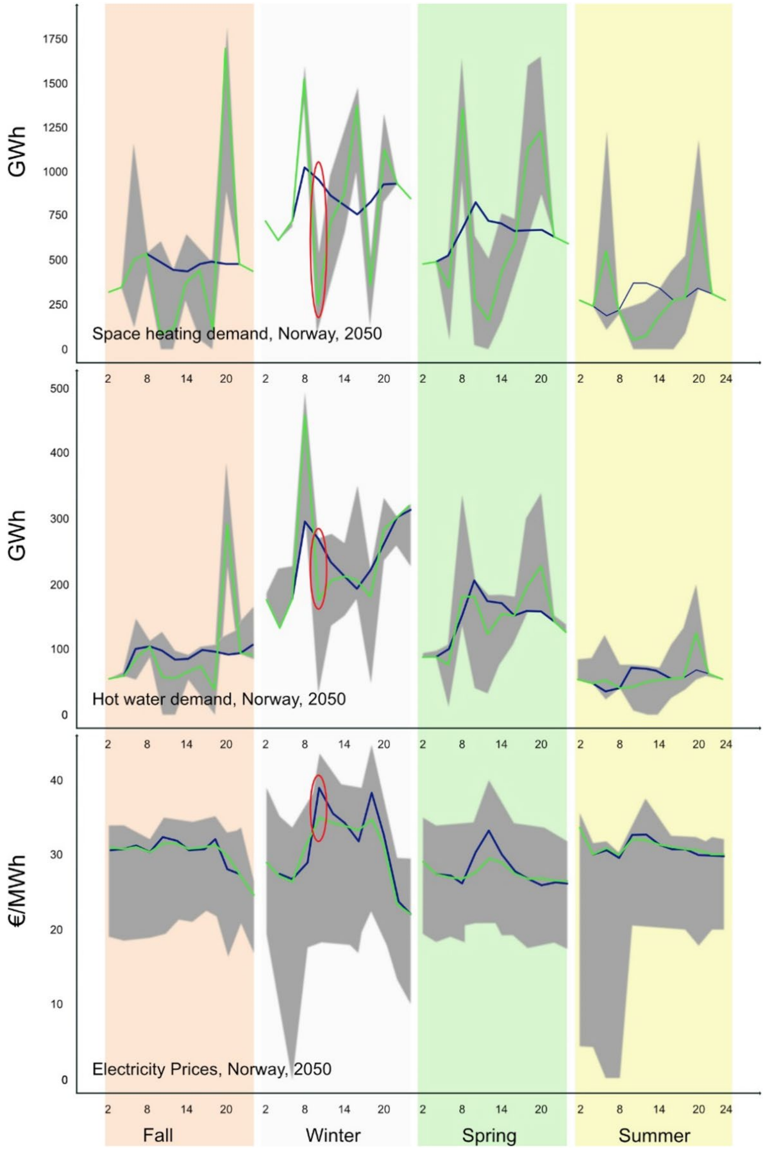


Fig. 11 Stochastic electricity prices and DR operation for hot water (RES-W) and space heating (RES-H) in 2050

without DR technologies. DR operation changes the volume of trade by smoothing electricity prices and changing short-term operation of generators.

Figure 11 presents the influence of DR operation on hot water and space heating demand in relation to electricity prices in 2050. The gray areas show the range of stochastic scenarios. Our study considers 21 stochastic scenarios; the minimum values of all scenarios build the lower boundary of the shaded area,

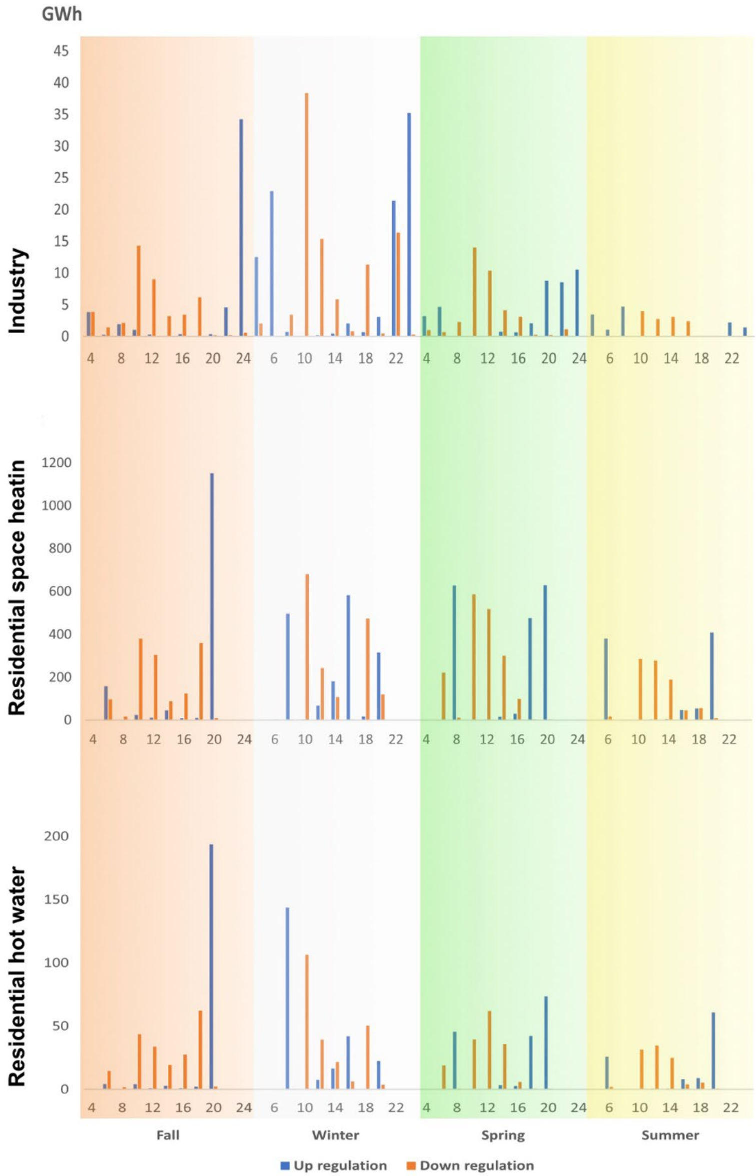


Fig. 12 The expected operation of DR operation in 2050

and the maximum values build the upper boundary. The blue line shows the median of stochastic electricity prices before using DR technologies, whereas the green line shows the median values after implementing DR. The uppermost chart shows how DR operation changes the output of residential technologies dedicated to supply energy to space heating demand, the middle chart shows the

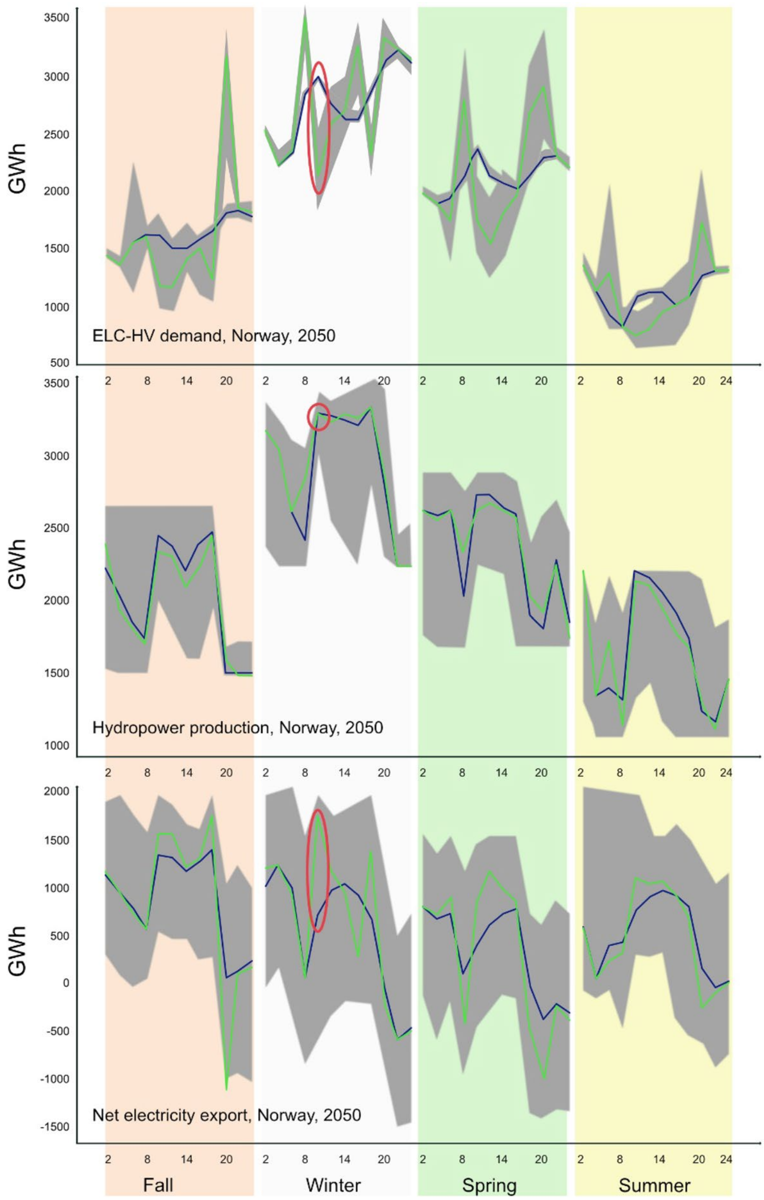


Fig. 13 The effects of DR on REG and trade profile, Norway, 2050

same process corresponding hot water demand, and the lowermost chart shows the effect of DR operation on electricity prices. For example, by looking at time-slice 10 from winter specified by the red line in the charts, it can be seen that the DR process results in lower level of output from residential technologies. Therefore, it is expected that lower electricity prices will be seen at the same time.

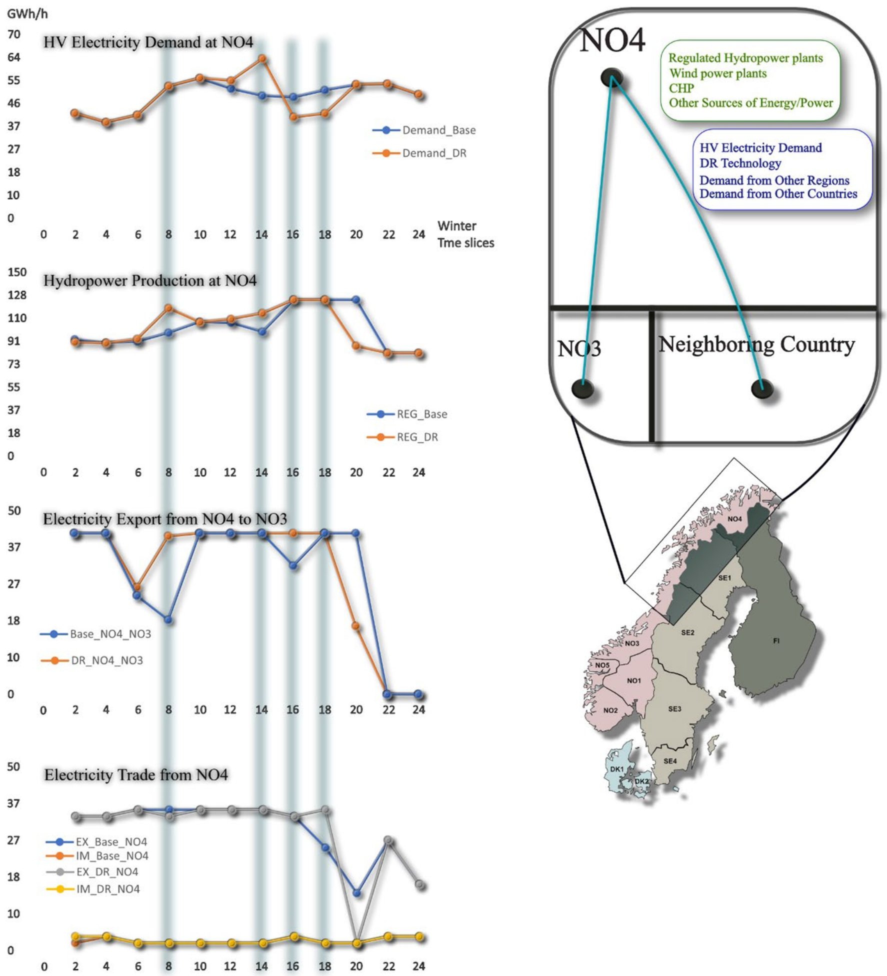


Fig. 14 The effects of DR on REG and trade profile at NO4, winter, 2050

The lowermost chart shows that DR shaves the peaks of electricity prices. Once DR operation decreases the demand volume in a specific time slice, the energy system experiences lower electricity prices and either power generators should reduce power production, or the system should export the extra power. Figure 12 illustrates the expected DR operation in 2050.

Figure 13 shows how stochastic DR operation affects short-term Norwegian hydropower production and net electricity export in 2050. For instance, in winter, downward regulation at time slice 10 leads to a higher volume of net export, while hydropower production is not influenced.

DR can affect electricity prices by changing demand profiles. Hydropower generation (REG), as the crucial source of flexibility in Norway, should adapt to that. Therefore, after implementing DR, we have a new profile for regulated hydropower

Table 4 DR operation from NO4-TS12 to NO4-TS18, Winter, 2050

Time slice	12	14	16	18
Upward regulation	16	74	–	–
Downward regulation	–	–	41	49

(REG). In addition, lower electricity prices and the new REG profile change the volume of electricity trade with neighboring regions and countries.

Figure 14 illustrates how DR technologies may influence REG and electricity trade at node NO4 by considering only one stochastic scenario for the sake of simplicity. NO4 is a long and narrow region located in the north of Norway. The node has a border with Russia, Finland, Sweden, and NO3. The supply side at NO4 consists of regulated hydropower plants, RoR power plants, combined heat and power (CHP) plants, wind power plants, and solar power plants. On the demand side, apart from high voltage electricity demand, trade with neighboring countries and NO3 affects the total electricity demand at NO4. Here, we discuss four time slices: TS8 (6–8 am), TS14 (12–2 pm), TS16 (2–4 pm), and TS18 (4–6 pm). DR does not affect high voltage electricity demand volume (HV-ELC) at NO4-TS8, but it increases HV-ELC at NO3-TS16. Therefore, NO4 uses the flexibility of hydropower plants and decreases the amount of electricity export to neighboring countries to meet extra HV-ELC at NO3. DR operations from NO4-TS12 to NO4-TS18 are presented by Table 4.

DR increases HV-ELC at NO4-TS14 in order to shift electricity demand from time slices 16 and 18. REG is not changed after implementing DR at NO4-TS16, and therefore NO4 exports the extra power to NO3. Down regulation at NO4-TS18 results in extra electricity export to neighboring countries.

NO2 is located in the south of Norway and by 2050 is connected with Denmark, the Netherlands, Germany, and the UK. The region is also linked with two neighboring regions, NO1 and NO5. The supply side at NO2 is dominated by hydropower plants, and the hydropower generation (REG) is used for local electricity demand or neighboring nodes. Therefore, by changing electricity demand profile at NO2, NO1, and NO5, DR is able to influence electricity trade between NO2 and neighboring nodes, as well as the REG profile at NO2. Figure 15 shows the effect of DR on REG and electricity trade at NO2 in winter 2050. We use the same nomenclature to refer to time slices and technologies. At node NO2, we investigate four time slices: 8, 16, 18, and 20.

Table 5 lists DR operations that are coincident with electricity demand deviation from the base case after implementing DR. At NO2-TS8 the system encounters upward regulation which increases HV-ELC. At the same time DR increases HV-ELC at nodes NO2 and NO5. Therefore, NO2 has to increase REG, while decreasing electricity export to NO1, NO5, and neighboring countries. Downward regulation at time slices 10 and 12 is the main reason that after applying DR, electricity demand is lower than the base case.

Upward regulation at time slice 16 leads to higher HV-ELC at NO2, NO1, and NO5. At NO2-TS8, the system decides to meet the extra demand by reducing electricity export to neighboring countries. This decision helps NO2 to supply more

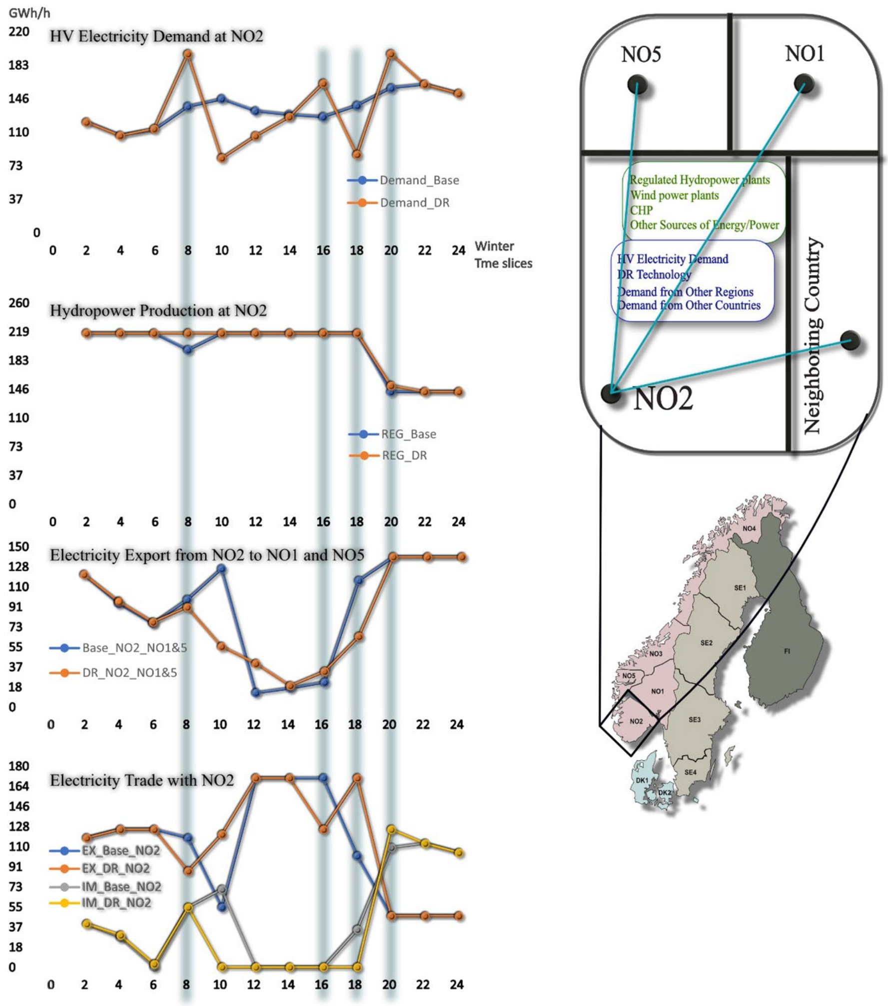


Fig. 15 The effect of DR on REG and trade profile at NO2, winter, 2050

Table 5 DR operation from NO2-TS12 to NO2-TS18, winter, 2050

Time-slice	8	10	12	16	18	20
Upward regulation	294	–	–	187	–	230
Downward regulation	–	325	141	–	269	–

electricity to NO1 and NO5. By contrast, downward regulation at time slice 18 results in lower HV-ELC at NO2, NO1, and NO5. This means that NO2 is able to export more electricity to neighboring countries, while electricity export to NO1 and NO5 experiences lower volume. DR at time slice 20 does not have a similar effect on NO1, NO2, and NO5. Upward regulation at NO2-TS10 and NO5-TS10 causes

Table 6 Income growth rates of hydropower plants in five Norwegian regions

Region	2020	2030	2040	2050
NO1	0.01	−0.03	−0.03	−0.04
NO2	0.01	0.00	−0.01	−0.01
NO3	0.00	−0.01	−0.01	0.00
NO4	0.00	0.00	−0.02	−0.01
NO5	0.01	−0.02	−0.02	−0.01

higher HV-ELC at these nodes, while downward regulation at NO1-TS10 results in lower HV-ELC. The system decides to meet the extra HV-ELC at NO2 by importing electricity from neighboring countries and generating more hydropower.

By using the electricity prices and hydropower production of the stochastic scenarios in each region, we can calculate the expected income over the scenarios and the percentage changes in hydropower plants' income after applying DR technology. The results are shown in Table 6.

5 Conclusions

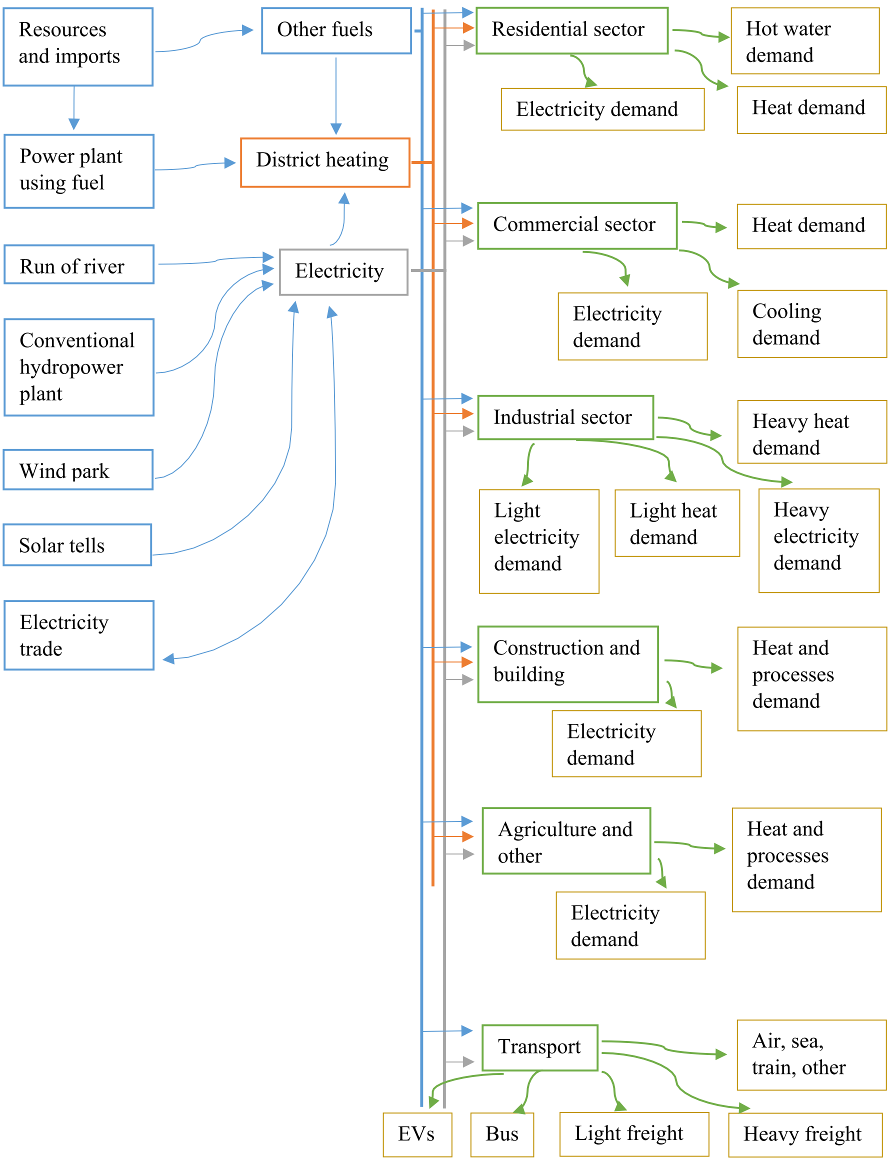
The main contributions of our paper are investigation and analysis of the role of DR in the Norwegian energy system and implementation of DR with stochastic programming in TIMES. We have used the model to study how DR would affect the use of flexibility provided by Norwegian hydropower. In our study, DR strategies are limited to load shedding and load shifting in the industrial and residential sectors.

The results show that Norwegian DR operation mainly comes from space heating demand in residential buildings. By changing electricity trade or electricity production in each price region, DR affects the demand side through upward and downward regulations when balancing the demand and supply sides. Hydropower generation depends on different parameters, such as electricity demand and trade at each specific node, electricity prices, and flexibility demand at neighboring nodes. Our study shows that after implementing DR, flexibility export increases, and electricity import at low prices increase because DR shifts demand from peak load with high prices to off-peak load time with low prices. Hence, both export and import increase, while net export before and after applying DR processes is the same (Fig. 10).

DR smooths electricity prices. In our model, the hydropower production profile is affected by DR because the stochastic factors of the energy system determine the possibility of DR operation in each time window, and hydropower can provide flexibility with higher value than before. At the same time, electricity prices are smoothed, a factor that could decrease the income of hydropower producers, while the system benefits. DR operation can decrease curtailment for renewables, and/or provide an opportunity to generate more intermittent production by incentivizing long-term investment in RES. Our study suggests formulating DR as a short-term elastic demand and considering the short-term weather-dependent uncertainties. In our study, the electricity export/import prices that the model uses to compare with

Norwegian electricity prices are deterministic. Therefore, improving the model linkage between European power system prices and the Norwegian energy system could improve the analysis.

Appendix A. Schematic diagram of the TIMES-Norway model



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Data availability The data that support the findings of this study are available on request from the corresponding author, Mohammadreza Ahang.

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