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Impact of activating energy demand flexibility in the building stock: A case study of Norway as a highly electrified country in the European power market

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ABSTRACT

On the transition towards an electrified European energy system, flexible electricity use is crucial. The building stock, including electric vehicles, can offer flexibility, but it is still unclear towards which objective the flexibility should be provided. Further, it is complicated for end-users to react to market prices. This paper investigates how buildings adapt their electricity use by following pre-defined tactics, known as heuristics, instead of market prices. Two heuristics are studied in two future scenarios compliant with European renovation policies. Based on the responses towards the heuristics, this study explores how flexibility from the Norwegian building stock impact electricity production and cross-border exchanges towards 2040. Results show that hourly electricity delivery to the building stock can be strongly modified, resulting in decreased peak electricity delivery by 10%–12% in 2040 when following the heuristics. Nevertheless, findings suggest limited impact on the strategic investments in the power market as flexible Norwegian hydropower adapts production patterns towards economic and operational stability in response to the demand-side load modifications. Further research should continue exploring local impacts of flexibility heuristics, including grid bottlenecks and on-site electricity production integration, and refine assumptions about hydropower flexibility in aggregated power system models.

1. Introduction

The European energy system is increasingly reliant on renewables, necessitating flexible electricity use to manage variability and ensure stability. The building stock, including electric vehicles (EVs), are emerging as key flexibility providers [1]. However, the objectives for this flexibility are unclear, both related to the potential conflict between European and local objectives [2] and the potential difference between individual and coordinated price signals [3]. Significant socio-economic-technical barriers exist for large-scale deployment of demand response related to deployment of small-scale end-users [4] and their coordinated representation through aggregators [5].

Aligning end-user electricity consumption with market prices is complex due to the distributed nature of building energy use, which is often not managed by professionals. Despite ongoing initiatives [6], implementing market-driven strategies at the building stock level remains intricate and uncertain. Even in the domain of modeling, coupling end-use flexibility with market price signals is complex because the two variables influence each other. Flexible energy demand responds to the price signal, which in turn is affected by end-use flexibility when this is applied in large scale. This creates a need to iterate between these variables until convergence is achieved. This has been the approach adopted by Sartori et al. [7], where one major outcome was that buildings remain fundamentally price-takers, and even if energy demand becomes flexible in the entire building stock, this has only a marginal impact on the energy price formation. The need to decouple flexibility responses from price formation justifies adopting some pre-defined tactic on how to use flexibility. Throughout this paper, such a tactic will be referred to as a heuristic approach to how flexible demand respond to price signals. One heuristic was indeed attempted in that project, although the linking between energy demand model and energy system model was challenging. Still, more knowledge is needed on how end-user flexibility heuristics at the national level might influence operation and investments in the European power system.

This paper addresses the knowledge gap by exploring strategies to harness flexibility in the electricity consumption of the Norwegian building stock. Norway is the focus due to it is highly electrified heating

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Abbreviations

A2A	Air-to-Air
ASHP	Air-source heat pump
DH	District Heating
DHW	Domestic Hot Water
DR	Demand Response
Eff	Efficient energy efficiency level
EMPIRE	The European Model for Power System Investment with Renewable Energy
EPBD	Energy Performance of Buildings Directive
EV	Electric Vehicle
GSHP	Ground-Source Heat Pump
KPI	Key Performance Indicator
LTRS	Long-Term Renovation Strategy
NTN	No Thermal Network
PS	Point-Source
PV	Photovoltaic
Reg	Regular energy efficiency level
S-COP	Seasonal Coefficient of Performance
SH	Space heating
Vef	Very efficient energy efficiency level
WB	Water-Borne
ZEN	Zero Emission Neighbourhood

systems compared to other European countries. Two heuristics are studied within two EU renovation policy compliant scenarios [8]: (1) flattening electricity use and (2) a time-of-use tariff [9]. By simulating these heuristics, the resulting load changes in electricity consumption are estimated. Furthermore, the impact on the electricity system is examined, both in Norway and in the exchange and investment changes in the surrounding EU countries, when the Norwegian building stock adjusts its load based on these heuristics. By solving a stochastic capacity expansion problem, future pathways towards 2040 are compared both with and without these flexibility responses, to understand their influence on strategic and operational decisions.

The remainder of this paper is structured as follows: Section 2 presents relevant literature to further clarify the contribution of this paper. Section 3 presents the methodology, while Section 4 presents the case study setup and assumptions. Section 5 presents and discusses the results, before the paper is concluded in Section 6.

2. Background

This section presents relevant literature that motivates this study before clarifying its contribution to the scientific literature.

2.1. Flexibility by buildings and electric vehicles

Flexibility in buildings have been shown to have significant potential. Gils [10] first assessed the potential for flexible demand in the European power system, identifying over 60 GW of load modification available hourly. He noted the highest demand response (DR) potential in building energy use for cooling and heating. Ahang et al. [11] confirmed that in Norway, cost-efficient demand-side flexibility is mainly related to residential heating. In the US, Murphy et al. [12] found flexibility in residential and commercial buildings to be highly flexible, although ambitious electrification scenarios for transport significantly increase flexibility potential from EV charging.

Flexibility in EV charging is becoming a crucial factor as global EV adoption accelerates. Global EV adoption is rising, with a projected 35% sales share by 2030 and Norway already at 88% in 2023 [13]. The growing demand for EV charging, integrated with Norwegian buildings, challenges the grid [14]. Emerging smart charging solutions are being explored. Sadeghian et al. [15] reviews smart charging, highlighting cost savings and reduced renewable curtailment. Sørensen et al. [16] show that EV charging flexibility, which allows for time shifting of charging activities, offers significant flexibility potential, e.g. within the residential sector. Borozan et al. [17] conducted a study in Great Britain to demonstrate how EV charging flexibility can potentially reduce the necessary investments in the electricity system. Szinai et al. [18] focus on how two different end-user tariffs for EV charging can affect the grid operating costs in California. Similarly, Gunkel et al. [19] concluded that EV flexibility substantially decreases system costs within the context of European transmission system development.

2.2. Modeling the future buildings stock and renovation rates

Buildings have a long lifespan, with 85%–95% of current buildings expected to remain by 2050 [20]. Thus, energy savings towards 2040 will primarily come from renovating existing buildings. However, data on renovated floor area are often inferred from investment statistics. Further, the term ‘renovation’ varies widely, from interventions, regular maintenance, to simple repairs, making it challenging to forecast potential energy savings [21].

The EU Green Deal policy indicates that the annual renovation rate of building stock in Member States ranges from 0.4–1.2% [22]. It calls for a Renovation Wave initiative to at least double this rate by 2030 [8].

Maduta et al. [23] found that implementing the Energy Performance of Buildings Directive (EPBD) in Member States’ Long-Term Renovation Strategies (LTRS) could reduce final energy consumption from buildings by 41% by 2050, compared to 2019. This aligns with Cambridge Econometrics [24], who projected that a 3.5% renovation rate would cut heating demand by 50% by 2050, compared to 2022. Additionally, increased heat pump adoption could further reduce annual heating energy demand by 40% by 2050. Both studies rely on optimistic renovation rate assumptions. Maduta et al. [23] report Member States’ planned rates in their LTRS ranging from 1%–6%, with most targeting 1.5–3.0%. Cambridge Econometrics [24] assumes an increase from 1% in 2020 to 3.5% for 2030–2050. These ambitious rates are political targets rather than historical values.

There is confusion regarding historical renovation rates and differences between residential and commercial sectors. Both the Renovation Wave initiative [8] and the latest EPBD recast [20] clarify that the weighted annual energy renovation rate is around 1%, consistent with an EU study [25]. In the weighted energy renovation rate, primary energy demand reduction from all activities is included (renovation, new construction, demolition). It does not directly measure the square meters renovated annually. The same study estimates ‘one-off’ deep renovations, involving major improvements like added insulation and better windows, at 0.2–0.3%, while step-by-step renovations with minimal energy savings per step dominate the market [25].

This study adopts a maintenance-based approach to renovation rates for an ageing stock, aligning with the Renovation Wave objective to at least double the weighted annual energy renovation rate. Further details are provided in Sections 4 and 5.

2.3. Electricity system capacity expansion with demand flexibility

Traditionally, the larger energy systems have been studied with the assumption of inflexible demand profiles. However, in recent years, demand flexibility has increasingly been recognized as a key to unlock more efficient systems by improved utilization of available resources, and to integrate higher shares of variable renewable energy. In this regard, De Jonghe et al. [26] extend traditional linear capacity expansion frameworks to account for demand flexibility.

Including demand flexibility in large-scale energy system analyses typically involves a linking of two or more models. Backe et al. [27]

couple an European level model with a neighborhood level model to investigate the effect of investments and operation of the building stock on European decarbonization strategies. Findings indicate that large-scale deployment of local energy systems reduces the cost of meeting climate targets.

Demand flexibility can also be endogenized by directly including the flexibility model at the system-level model. Misconel et al. [28] assessed the value of demand response (DR) in two scenarios of a future EU energy system completely based on renewables, and they find that activation of DR has a better correlation with solar photovoltaic (PV) rather than wind, thus saving more system costs and CO2 emissions in a decentralized, PV dominated scenario. Barani et al. [29] found that the total costs in the European power system from 2020 to 2050 could be reduced by about 1% if residential flexibility is optimally scheduled.

Models can be extended with a bi-level framework. Asensio et al. [30] presents a model considering consumer response to real-time pricing and investments in distribution and generation. Cheng et al. [31] focuses on district and multi-regional interactions under different carbon caps. A multi-level framework provides insights and fully exploits demand flexibility without iterative modeling. However, controlling decentralized flexibility at the system level is computationally demanding, especially in multi-level models, limiting the scope of the analysis.

Some research has examined the impact of building stock measures on the energy system. Seljom et al. [32] analyze the Scandinavian energy system with extensive Zero Emission Buildings, noting significant effects on investment decisions, such as reduced wind power investments. They highlight the need for further research on the flexibility of building stock and its system-wide impacts.

2.4. Contribution

While literature on flexible energy use in broader systems is expanding, existing studies primarily focus on optimal responses within controllable systems or dynamic market integration. However, there is a gap in research on the interaction mechanisms between the future building stock and the wider system. This study addresses this gap by combining two realistic, data-based simulation models to examine the impact of heuristics applied to the Norwegian building stock, including EVs, on the European electricity system towards 2040.

This paper contributes to the following research questions:

- What are the impacts of flexibility strategies on the Norwegian building stock's electricity consumption compliant with EU renovation policy, and how do these adaptations affect the combined electricity consumption in the Norwegian building stock?
- How do adjustments in the Norwegian building stock's electricity consumption, guided by heuristics, influence power market strategies in Norway and neighboring countries up to 2040?

3. Method

The research questions are addressed by integrating the FLEXor model for the built environment with the EMPIRE model for the European electricity market.

3.1. FLEXor

FLEXor is a simulation and optimization tool for energy generation, demand, and use in the built environment. It is implemented in Python and uses the Pyomo software package for formulating, solving and analyzing optimization models. A detailed description of FLEXor can be found in [33].

FLEXor comprises interconnected models that handle user inputs, activate sub-models, and define system topology. These include component models (building envelope, domestic hot water (DHW) tanks, electric batteries, heat sources, EV charging, PV systems), functional models (energy costs, fixed energy demand), and a model for demand profiles via PROFet [34]. The PROFet tool is built on the tool presented by Lindberg et al. [35] and was validated by Mohammadabadi et al. [36]. PROFet estimates typical energy demand of buildings based on actual measurements. The data has hourly resolution, and is split in thermal and electric specific demand. The thermal demand depends on weather input, specifically outdoor air temperature.

3.1.1. Building types and archetypes

FLEXor models three building types: Houses, Apartments, and Commercial buildings at three energy efficiency levels: *regular* (Reg), *efficient* (Eff), and *very efficient* (Vef). Commercial buildings average various types, including offices, shops, hotels, and schools. Efficiency levels refer to the thermal envelope: *regular* reflects the current stock, *efficient* aligns with the building regulation TEK10 [37], and *very efficient* matches Passive House standards [38], applicable only to new buildings.

Building types should not be confused with building archetypes. An archetype is a notional building that represents a segment of the stock, and is characterised by certain attributes. FLEXor models several archetypes, resulting by the combination of attributes listed in Table 2. These include the type of building along with several other attributes.

3.1.2. Heating technologies

Three characteristics of heating technologies influence building energy use: their prevalence in the building stock, installed capacity based on building type and weather, and energy efficiency. Details on the assumptions regarding prevalence and installed capacity is presented in Section 4.

Table A.7 shows the efficiency and performance parameters of heating technologies. Non-heat pump components have constant efficiency. Heat pumps' seasonal coefficient of performance (S-COP) varies with supply and source temperatures, calculated per SN-NSPEK 3031:2021 guidelines [39]. The auxiliary electric heating component has a constant efficiency of 99%.

In this study, wood use in fireplaces is treated differently from other technologies. It is only available in residential buildings and is influenced by seasons, days of the week, and times of the day, rather than outdoor temperatures. Wood use is directly controlled by occupants and assumed to be used from September 16 to May 15. On weekdays, use from 7:00 to 8:00 and 16:00 to 23:00 is assumed, covering 12% of space heating (SH) demand. On weekends, use from 8:00 to 23:00 is assumed, covering 19% of SH demand.

3.1.3. Electric demand in district heating

The district heating (DH) load is supplied by various heat producing technologies in the DH system. Some of these technologies, specifically heat pumps and electric boilers, require electricity input to deliver heat to the DH system. Therefore, the electric load resulting from the DH load needs to be extracted. To split the DH load on various DH heat technologies, a merit-order effect in the DH grid is assumed. Splitting of the DH load profile then involves two steps:

1. **Calculate capacities:** The DH load profile is sorted in ascending order, creating a load duration curve. The merit-order assumption is employed to calculate capacities for each technology based on the fraction of energy to be supplied by the technologies.
2. **Split load profile:** The capacities obtained from the first step together with their merit order is used to split the original DH load profile on the DH heating technologies for each time step.

Table 1
Summary of the characteristics of the three heuristics analyzed in this study.

Heuristic	Description	Available flexibility
Baseline	Buildings follow typical demand pattern.	No
Flat	Buildings use flexibility to flatten demand and avoid energy losses.	Flexible EV charging, Thermal mass, Flexible DHW tank
Time-of-Use	Buildings use flexibility to respond to static prices varying by season and time of day.	Flexible EV charging, Thermal mass, Flexible DHW tank

The total energy shares coming from various DH technologies in Norway are reported each year.[1] Values from 2022 are used, assuming the energy share represents the merit-order and that fossil oil and gas is replaced by bio oil as peaking unit, giving the following merit-order and fractions:

1. Waste incineration: 47.9% (base)
2. Biomass: 32.1% (mid)
3. Heat pumps: 9.4% (mid-high)
4. Electric boilers: 7.2% (peak-low)
5. Bio oil: 3.4% (peak)

3.1.4. Weather data

To calculate the energy demand and use of the building stock in Norway's five market areas under various meteorological conditions, outdoor temperature and global radiation data from January 2015 to December 2019 were collected from the Norwegian Center for Climate Services [40]. The weather stations used for each market area are listed in Table A.8. Missing weather data were interpolated, copied from nearby stations, or matched with similar conditions from other days. Less than 0.01% of the data required corrections.

The PV model in FLEXor uses the Global Solar Energy Estimator [41], which requires global horizontal radiation and either diffuse horizontal radiation or diffuse fraction to calculate PV system electricity yield. The collected weather data includes only global horizontal radiation. The diffuse fraction is estimated from this using the *erbs* function from the *pvlib* library in Python [42], based on the homonymous model [43].

3.1.5. Heuristics

The three heuristics drive energy flexibility in buildings using different objective or penalty functions, represented as price signals, in the energy optimization problem.

All heuristics are pre-defined operational strategies independent of dynamic market prices. They approximate general tactics of the building stock that could impact the power market without direct market price links. This study uses simulations to compare these tactics and their potential benefits. Details of the heuristics' operational strategies and available flexibility technologies are summarized in Table 1.

The first heuristic, *Baseline*, represents buildings with no flexibility actions, following typical energy demand patterns. In FLEXor, this heuristic is modeled as an optimization problem aiming to minimize energy delivery, with no flexibility options.

The objective function for this heuristic is as follows:

$$\min \sum_{t=0}^{T} \left[y_{imp}(t) + q_{imp}(t) + fu_{imp}(t) - y_{exp}(t) * p_{exp} \right] \quad (1)$$

where $y_{imp}(t), q_{imp}(t)$, and $fu_{imp}(t)$ are the electricity, district heating, and fuel delivery, respectively; $y_{exp}(t)$ is electricity feed-in to the grid; and p_{exp} is a penalty on the electricity feed-in, set to 0.1 to discourage the model from favoring feed-in over delivery and to avoid simultaneous delivery and feed-in.

The second heuristic, *Flat*, incentivizes flattening the load profile while minimizing energy losses. It smooths peaks and avoids deep valleys and sudden changes in energy demand, which benefits grid operation by combining peak shaving and valley filling. This objective is based on physical quantities (hourly energy use and variation) and is therefore a static penalty signal. The flattening applies to each building's energy use, which is independent of other buildings or the grid.

The objective function used for this heuristic is as follows:

$$\min \sum_{t=0}^{T} \Bigg[\Big(\big(y_{imp}(t) - y_{exp}(t)\big) - \big(y_{imp}(t-1) - y_{exp}(t-1)\big) \Big)^2 + \Big(q_{imp}(t) - q_{imp}(t-1) \Big)^2 + \Big(y_{imp}(t) + q_{imp}(t) + fu_{imp}(t) \Big) * p_{imp} + y_{exp}(t) * p_{exp} \Bigg] \quad (2)$$

Moreover, a 5% limit is set to the increase of the annual energy demand – with respect to the *Baseline* heuristic – in each building. The penalties p_{imp} and p_{exp} have a value of 0.5.

The third heuristic, *Time-of-Use* (ToU), uses historical spot prices (2015–2019) to create average profiles for each season (winter, summer) and day type (workdays, weekends). Prices are divided into low (below 30% of peak), medium (30%–70%), and high (above 70%) levels. Fig. A.16 shows the hours allocated to each price level by market area, season, and day type.

Grid tariffs, representing distribution costs, are split into energy consumption (NOK/kWh) and monthly peak power demand (NOK/kW). The grid tariff is calculated such that its energy cost matches the ToU price, and the monthly peak power cost equals the energy grid cost for the *Green* scenario. This results in a 50/25/25% cost distribution between the ToU cost, the grid energy cost, and the grid peak power cost, which balances the priority between the price signals. The same absolute values for the grid tariffs are used for both scenarios.

The objective function in FLEXor minimizes building energy costs based on market area prices and grid costs:

$$\min \Bigg[\sum_{t=0}^{T} \Bigg(\Big(c_{Elgrid,ene} + c_{el}(t) \Big) * y_{imp}(t) + \Big(c_{DHgrid,ene} + c_{DH}(t) \Big) * q_{imp}(t) + c_{fu} * fu_{imp}(t) - y_{exp}(t) * c_{el}(t) \Bigg) + \sum_{m=0}^{M} \Bigg(c_{Elgrid,ppm}(m) * y_{imp}^{max}(m) + c_{DHgrid,ppm}(m) * q_{imp}^{max}(m) \Bigg) \Bigg], \quad (3)$$

where $c_{Elgrid,ene}$ and $c_{DHgrid,ene}$ are energy grid tariffs; c_{El}, c_{DH}, and c_{fu} are ToU prices for electricity, district heating, and fuels; $c_{Elgrid,ppm}$ and $c_{DHgrid,ppm}$ are monthly peak power tariffs; and y_{imp}^{max} and q_{imp}^{max} are monthly peak deliveries.

3.1.6. Aggregation

FLEXor operates at the single building level (archetypes) and scales up results using RE-BUILDS, a dynamic model simulating the long-term development of the Norwegian building stock. RE-BUILDS, initially described by Sandberg et al. [44] and adapted by Sartori et al. [45], differentiates buildings without waterborne heating systems and their geographical distribution in various climatic areas and sub-areas without district heating networks. This combination is similar to the approach between PROFet and RE-BUILDS described by Lien et al. [46].

[1] https://www.fjernkontrollen.no/.

3.2. EMPIRE

The European Model for Power system Investment with Renewable Energy (EMPIRE) is an open-source, multi-horizon stochastic linear program analyzing investments and operations in the European electricity market up to 2060 [47]. It examines how future projections of electricity demand, fuel prices, technology costs, climate policy, and operational characteristics influence long-term investments and short-term operations. EMPIRE provides country-level results for generation, storage, and cross-border transmission investments and operations in five-year steps. Each country is defined as an electricity market node in a network graph, where arcs represent transmission between electricity markets. All countries are represented as a single electricity market node, except for Norway which is split into five electricity market nodes reflecting its market setup in Nord Pool.

The model aims to transition the European electricity system towards 2060 at the least cost, simulating the market under perfect competition with assumed technology cost developments and climate policy constraints. While primarily supporting investment decisions, EMPIRE also represents operations, optimizing hourly decisions within representative weeks across several stochastic scenarios. These decisions include hourly dispatch of electricity production, storage, and cross-border transmission for all countries and investment periods up to 2060. Considering operational uncertainty endogenously is crucial for supporting future electricity market investment decisions, which is argued by both Seljom and Tomasgard [48] using the TIMES model and by Backe et al. [49] comparing the impact of using deterministic versus stochastic capacity expansion in the electricity market.

For more details on the mathematical formulation of EMPIRE, please refer to the software documentation in the open source repository [47].

3.2.1. Stochastic scenario generation

Compared to other electricity system capacity expansion models with large shares of variable renewables [50], EMPIRE consolidates three key characteristics:

1. Multiple investment periods considering the lifetime of existing and new assets;
2. Hourly operations in representative weeks within each investment period; and
3. Uncertainty regarding hourly operations in representative weeks by considering several stochastic scenarios.

In each stochastic scenario and investment period, EMPIRE models unique operational realizations for representative weeks across four seasons, including hourly electricity demand and availability from wind, solar, and hydropower. Investments in generation, storage, and cross-border transmission are unique per market node and period, with hourly operations adapting to consistent investments. Scenarios are sampled from five years of historical data, maintaining cross-correlation and equal probability. These scenarios directly input into the stochastic program, ensuring investment decisions consider uncertain renewable output and its correlation with electricity needs.

In this paper, 10 unique stochastic scenarios for each season and investment period are sampled. The sampling-based scenario generation algorithm used in this paper is presented in Algorithm 1 based on the stratified sampling as explained in [49].

Data: Operational scenarios Ω, electricity market nodes $\mathcal{N}$, hourly historical profiles for Ξ stochastic processes for all $\mathcal{N}$ (2015-2019), future investment periods $\mathcal{I}$, seasonal partition of the year $\mathcal{S}$, stratified partition of each season $\mathcal{F}$ ($|\mathcal{F}| = |\Omega|$), valid starting hours $\mathcal{H}^*$ (Monday midnight), length of regular scenarios l^{reg}, length of peak scenarios l^{peak}.
Result: Representative operational scenarios for all Ξ, Ω, $\mathcal{I}$, $\mathcal{N}$, and $\mathcal{S}$.

```
for i ∈ I do
    for ω ∈ Ω do
        for s ∈ S do
            Randomly select sample year
              y ∈ {2015, 2016, ..., 2019};
            Randomly select starting hour h ∈ H* within year y,
              season s, and stratum f_ω ∈ F;
            Sampling interval = [h, h + l^reg];
            Extract data for all Ξ in sampling interval for all
              nodes N;
        end
        Randomly select peak sample year
          y ∈ {2015, 2016, ..., 2019};
        h* = hour with highest aggregated electricity demand
          in y for all n ∈ N;
        Peak interval 1 = [h* − l^peak/2, h* + l^peak/2];
        Extract data for all Ξ in first peak interval;
        h** = hour with highest electricity demand in y for any
          n ∈ N;
        Peak interval 2 = [h** − l^peak/2, h** + l^peak/2];
        Extract data for all Ξ in second peak interval;
    end
end
```

Algorithm 1: The sampling-based scenario generation algorithm used to randomly produce stochastic scenarios.

3.2.2. Future electricity load profiles and load modification

When modeling the electricity market towards 2060 in five-year steps in EMPIRE, future hourly electricity demand is based on historical load profiles from the ENTSO-E Transparency Platform [51] and annual demand projections from the ENTSO-E TYNDP 2022 Scenario Report [52]. Norway's hourly load profiles are adjusted using results from FLEXor, following the method in [2], which is detailed below. This methodology relies on having results on flexibility responses from FLEXor on the same time scale as EMPIRE, namely five-year steps.

First, quantify the hourly electricity load profile for all countries. For nodes not modeled in FLEXor, use historical data from [51]. For nodes modeled in FLEXor, estimate the non-FLEXor load profile by subtracting combined hourly electricity load profiles from FLEXor from the historical demand. The combined FLEXor loads include all building types and heat distribution types without flexibility dispatch (Section 3.1.1), plus the electric demand in DH (Section 3.1.3). Smooth the raw non-FLEXor load if needed (see Appendix B).

Second, scale historical loads to future investment periods. For each five-year period, representative hours with an annual scaling factor α_h are weighted based on the season hour h represents. Scale the hourly load using α_h and $\frac{1}{|\Omega|}$ to estimate the annual expected electricity demand $D^*_{i,n}$. Calculate the ratio $S_{i,n}$ between future demand $D_{i,n}$ and historical demand $D^*_{i,n}$ to linearly scale all loads. Future demand estimates are from [52]. For nodes in FLEXor, non-FLEXor demand projections are taken from [53,54].

Non-FLEXor sectors, mainly industrial, have seasonally independent electricity demand. An alternative to linear scaling with $S_{i,n}$ is baseload addition for future demand projections. Calculate the difference between future demand $D_{i,n}$ and historical demand $D^*_{i,n}$, divided by the number of hours in a year, to get $A_{i,n}$. Add $A_{i,n}$ as a constant baseload to all loads.

Both linear scaling and baseload addition have limitations. For non-FLEXor loads, use a 50% linear scaling and 50% baseload addition approach. For other countries, use linear scaling.

Finally, add FLEXor loads to non-FLEXor loads. FLEXor projects PV installation in the building stock by 2040 (Table 3), which can result

Table 2
Building attributes classifying archetypes in FLEXor. The allowed configurations of the heating system (Sub-area, Building type, Heat distribution, and Heat source) results in 15 unique load profiles.

Attribute	Count	Description
Market/Climate area	5	NO1, NO2, NO3, NO4, NO5
Sub-area	3	Urban, large-scale district heating; Sub-urban, small-scale district heating; Rural, no thermal network (NTN)
Building type	3	House (Hou.), Apartment building (Apt.) Commercial building (Comm.)
Heat distribution	2	Point-source (PS), Waterborne (WB)
Heat source	6	Direct electric heating (Direct el.) District heating (DH) Ground source heat pump (GSHP) Air source heat pump (ASHP) Air-to-air heat pump (A2A) Biomass based (Other)*
Efficiency level (thermal envelope)	3	Regular (Reg), Efficient (Eff), Very efficient (Vef)
New technologies (EV and PV)	2	Yes No

*excl fireplace, see Section 3.1.2.

Table 3
Key characteristics of the building types.

	House	Apartment building	Commercial building
Area [m^2]	150	1120	3600
DHW tank vol. [ltr]	188	960	1029
DHW tank power [kW]	1.9	12.0	18.4
Average number of flexible EVs per building [–]	1	12.8	5
PV inst. cap. [kWp]	8.2	26.9	220.1

Table 4
Summary of the two future building stock scenarios *Green* and *Green+*.

Scenario assumption	Green	Green+
Building heating technology development	Transition to a mix of DH, heat pumps, and direct electric heating by 2040	Transition to a mix of DH, heat pumps, direct electric heating by 2040
Building stock development	Stock size +18% by 2040 Hou.+Apt. renovation rate 1% Comm. renovation rate 1.5%	Stock size +18% by 2040 Hou.+Apt. renovation rate 1% Comm. renovation rate 1.5%
Building efficiency level development	Current standard on new buildings, 20% of renovated buildings are energy upgraded	Passive house standard on new buildings, 100% of renovated buildings are energy upgraded
Buildings connected to district heating	Unchanged from 2020	Unchanged from 2020
PV and flexible EV development	Gradual increase from zero to levels in Table 3 by 2040	Gradual increase from zero to levels in Table 3 by 2040

in negative hourly grid imports for an entire price zone. Assume any excess PV generation is curtailed.

4. Case study

The impact of energy flexibility in the building stock on the energy system is investigated using two scenarios and three heuristics (Table 1). The scenarios represent development paths for the Norwegian building stock, while the heuristics represent typical energy use profiles or flexibility strategies. Both models provide results from 2020 to 2040 in five-year steps, considering different weather realizations.

FLEXor considers characteristics summarized in Table 2. All combinations are considered, although some combinations do not allow for certain technologies (e.g., point-source heating excludes district heating). FLEXor also considers five weather years (2015–2019) and five electricity market areas within Norway.

Table 3 shows key characteristics for each building type. These assumptions are consistent across all dimensions in Table 2, except for the average number of flexible EVs. The average number of flexible EVs and installed PV capacity starts at zero in 2020 and increases until 2040. By 2040, each building type has the average number of EVs and PV systems shown in Table 3.

Although there was some PV in Norway in 2020, this assumption is fair since the total grid-connected PV capacity was 106 MWp in 2020 [55]. Spread across over 4.2 million buildings [56], this amounts to less than 0.03 kW per building. The assumption of zero flexible EVs in 2020 is justified as existing EVs were not flexible.

The total number of optimization runs for FLEXor is determined by the combination of attributes listed in Table 2, considering that not all heating system combinations are allowed (e.g. Point-Source with District Heating, or GSHP in urban sub-area), nor generate unique load profiles (e.g. House with Direct el. gives the same profiles regardless of the sub-area). In addition, the same archetypes are optimized in five weather years and according to three heuristics. Altogether, this results in 6,750 building optimization runs for FLEXor, covering 2020 to 2040 in five-year steps. For EMPIRE, each simulation includes all five-year steps. EMPIRE is run for each heuristic and scenario, totaling 6 European optimization runs.

4.1. Scenarios

The development of the building stock in the *Green* and *Green+* scenarios is summarized in Table 4. The difference between the scenarios is the building efficiency level, with *Green+* assuming higher standards for new buildings and more energy upgrades during renovations.

Both scenarios are calculated with the RE-BUILDS tool [45], which estimates future building stock considering population, lifestyle parameters, demolition rates, and renovation rates. The RE-BUILDS tool has been used by Sandberg et al. [44] to address energy savings in the Norwegian building stock and extended to address Norwegian political targets in [57]. The 2020 building stock composition, serving as the starting point for both scenarios, is shown in Fig. 1.

The development of the building stock in both scenarios is shown in Fig. 2. These scenarios do not include any particular actions to favor access to thermal grids, nor conversions from point-source to waterborne heating systems. In both scenarios, the percentage of buildings connected to district heating remain the same as in 2020.

Fig. 3 shows the share of heating technologies in the building stock in 2020. Key characteristics include: Air-to-air (A2A) heat pumps are only in houses, houses are not connected to district heating (DH), and ground-source heat pumps (GSHP) are only in areas without DH grids. Table A.6 shows the installed capacities for different heating technologies in 2020, estimated for each building type, energy efficiency level and market area. Heat pumps and boilers are sized at 50% of the peak space heating (SH) demand, while all other technologies are sized to meet the combined peaks of SH and domestic hot water demand. Heat pumps always include an auxiliary electric heating component with a capacity equal to that of other technologies for the respective building type and market area.

By 2040, technology shares transition to a mix of DH, heat pumps, and direct electric heating in both scenarios. Houses with point-source (PS) heating use A2A heat pumps, while others use direct electric

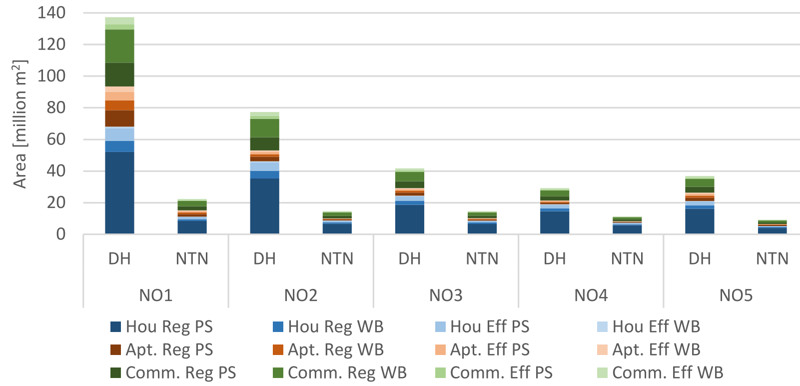


Fig. 1. Norwegian building stock in 2020 by market area, access to thermal heating network, building type, and heat distribution system, in million m^2. Hou = House, Apt. = Apartment building, Comm. = Commercial building, PS = Point source, WB = water-borne, NTN = No thermal network.

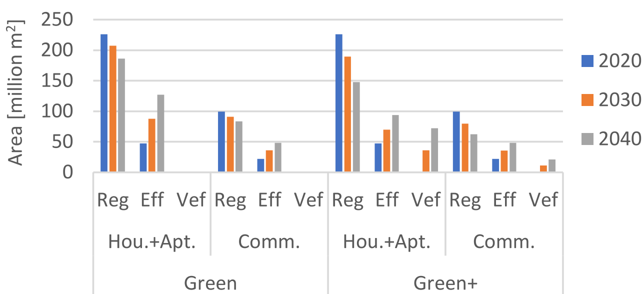


Fig. 2. Development of the residential (houses and apartment buildings) and the commercial building stocks under the *Green* and *Green+* scenarios, in million m^2.

heating. Buildings with water-borne (WB) heating and no thermal network (NTN) use air-to-water heat pumps (ASHP) in urban areas or GSHP otherwise. Fireplace use remains unchanged, and fossil fuel technologies are phased out. These transitions reach full conversion by 2040.

The *Green* scenario assumes no additional measures to reduce energy demand. New constructions follow current energy efficiency regulations and are considered *efficient*, with no *very efficient* buildings. Only 20% of renovations include energy upgrades, leaving 80% unchanged.

The *Green+* scenario focuses on thermal insulation. New constructions adhere to passive-house standards (*very efficient*), and all renovations upgrade buildings from *regular* to *efficient*.

Both scenarios assume the same total quantities of new construction, demolitions, and renovations, with the building stock 18% larger by 2040. However, efficiency levels differ.

FLEXor and RE-BUILDS models identify three renovation rates: natural renovation, energy efficiency upgrades, and building technology substitution. The substitution rate is higher than the natural renovation rate, depending on technology lifetimes. By 2040, energy-efficient heating technologies, EVs, and PV systems reach saturation with a 6% annual substitution rate.

The natural renovation rate is 1% for residential and 1.5% for commercial buildings (see Appendix C). In *Green*, the energy efficiency upgrade rate is 0.2% for residential and 0.3% for commercial buildings [25]. In *Green+*, it matches the natural renovation rate, upgrading all renovated buildings.

Assumptions differ from other studies, e.g. [23,24], which assume increased renovation rates for all efficiency measures. The model considers different lifetimes for building components, leading to varied renovation patterns. Technical systems may be replaced at high rates (6%), while *Green+* allows significant thermal envelope improvements. However, the total volume of thermal envelope interventions is not expected to increase, as the natural renovation rate is intrinsic to the building stock.

5. Results and discussion

The findings from the assessment of the building mass is presented before its impact on the European electricity market.

5.1. FLEXor: Assessment of the building mass

This section presents key results from FLEXor, where the heuristics' impact on the energy demand and consumption of the Norwegian building stock is quantified. The aggregated results for Norway are presented. Although the model provides results in five-year steps from 2020 to 2040, the following section shows results from 2020, 2030, and 2040.

5.1.1. Validation with statistical data

The scenarios in this study are validated based on assumptions from Section 4, by comparing the energy use to Norwegian statistics for 2020 [58]. A +5% correction factor is applied to commercial buildings to account for potential omissions in PROFet categories Heimar Andersen et al. [34]. Fig. 4 shows energy use of 48.5 TWh for residential and 30.3 TWh for commercial buildings, compared to 46.9 TWh and 31.4 TWh in the statistics, respectively. The total energy use difference is 0.5 TWh, an error of less than 1%, which is deemed acceptable for this study.

5.1.2. Energy demand in the building stock

Fig. 5 shows the energy demand in the Norwegian building stock as calculated with PROFet, as well as the PV generation, for 2020, 2030 and 2040 for the *Green* and *Green+* scenarios. The total energy demand of the building stock including electric vehicles increases by 14% and 8% in *Green* and *Green+*, respectively. In *Green*, the demand of the building stock, not counting the demand of EVs, increases from 80 to 84 TWh by 2040. In *Green+*, the demand decreases to 79 TWh. Nevertheless, this reduction is countered by the rising demand of EV charging, which reaches 7 TWh in 2040. Note that the space heating demand is an annual average across five weather years.

5.1.3. Electricity and district heating use in the building stock

Fig. 6 shows the average annual electricity and district heating use by buildings in Norway for 2020, 2030, and 2040 across two scenarios and three heuristics. The average considers five weather years. District heating uses close to 1% of the electricity used by buildings in all periods.

Electricity use slightly increases with *Flat* and *Time-of-Use* heuristics compared to *Baseline* due to higher heat losses from increased heat storage. The worst-case increase is 3% and 2% in 2030 for *Flat* and *Time-of-Use*, respectively, with heat losses falling below 1% by 2040. Solar production remains the same across all heuristics and scenarios.

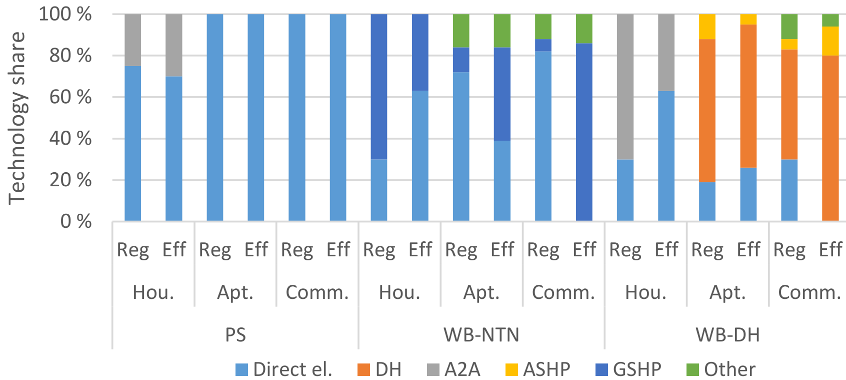


Fig. 3. Share of heating technologies in the building stock in 2020 by building type, heat distribution (PS or WB) and access to DH (NTN or DH).

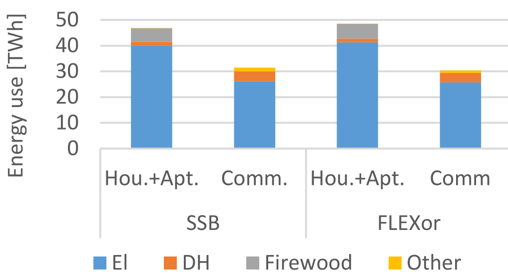


Fig. 4. Results of the model setup for 2020 vs. statistical data for the Norwegian building stock.

Annual electricity delivered to buildings decreases by 23%–25% in 2040 in the *Green* scenario compared to 2020, due to increased PV coverage and more efficient space heating technologies. The *ToU* heuristic causes the largest relative decrease. In the *Green+* scenario, electricity delivered decreases by 27%–29%, with *ToU* again causing the largest decrease.

District heating use increases in all heuristics and scenarios as the building stock grows, with a lower increase in *Green+* due to higher energy efficiency.

Differences between *Green* and *Green+* are minimal, with *Green+* using 2 TWh less electricity and 0.5 TWh less district heating by 2040. Both scenarios apply the same building technology changes, differing only in thermal envelope renovations. Despite a fivefold increase in energy efficiency upgrades, the overall rate remains limited to 1–1.5% per year over 20 years. Thermal envelope changes only impact SH demand, while DHW, electric specific demand, and EV demand remain unchanged.

Total energy reduction from 79 TWh in 2020 to 59–63 TWh in 2040 shows moderate savings compared to the Renovation Wave policy objectives [8] and the LTRS of several EU Member States [23]. Consider three factors for comparison:

1. The EPBD [20] definition excludes plug loads and residential lighting, while this paper includes electric specific and EV consumption.
2. Norway's renewable electricity generation and lack of natural gas infrastructure make it unique. The primary energy factor of 1.0 for all energy carriers [59] makes it harder to meet targets compared to the EU's factor of 2.5 (EN-ISO 5200-1:2017).
3. Energy demand estimates from PROFet are based on measurements, avoiding overly optimistic simulation values.

Energy consumption, as defined by the EPBD, decreases from 52 TWh in 2020 to 25 TWh in *Green* and 22 TWh in *Green+* by 2040, representing reductions of 51% and 57%, respectively. This equates to annual decrease rates of 2.6% in *Green* and 2.8% in *Green+*. This aligns with the Renovation Wave policy's goal to double the annual energy renovation rate by 2030, showing a factor 5 improvement. In comparison, energy consumption in the period 2010–2020 decreased from 55 TWh to 52 TWh, an annual rate of 0.5% (i.e. half the EU reference 1% weighted energy renovation rate [8]).

5.1.4. Electricity load duration in the building stock

Fig. 7 shows the load duration curve for the combined electricity loads produced by FLEXor in 2040 in the two future scenarios for the three heuristics. While the *Time-of-Use* heuristic changes which hours contain high and low loads, it does not drastically modify the load duration curve compared to *Baseline*. On the contrary, *Flat* generally lowers high loads and increases low loads compared to *Baseline*. In both scenarios, both *Flat* and *Time-of-Use* lead to lower peak load, while the lowest loads are also increased in *Flat* compared to *Baseline*. The peak load reduction is similar for *Flat* and *Time-of-Use*.

5.1.5. Key Performance Indicators (KPIs)

Three Zero Emission Neighbourhoods (ZEN) key performance indicators (KPIs) [60] were calculated for the three heuristics and two scenarios. These KPIs evaluate efficiency and flexibility actions in the building stock, focusing on electricity use, use during peak demand hours (7:00–9:00 and 16:00–18:00), and peak loads. The peak hours overlap with the most stressful hours of the Norwegian electricity grid identified by Utredninger [61]. Detailed descriptions and calculation methods are available in [60].

Fig. 8 presents the ZEN KPIs: the upper figures show absolute values, while the lower figures display percentage differences between *Flat* and *Time-of-Use* relative to *Baseline*. Flexibility actions significantly reduce electricity stress and peak loads with minimal increase in electricity use, primarily due to higher heat storage losses. Peak load reduction of 10%–12% is less than the 16% reported by Sartori et al. [7], but energy losses are reduced to 1% compared to 3%. The *Time-of-Use* heuristic excels in reducing electricity use during stress hours, influenced by penalizing ToU prices. The *Green+* scenario achieves 5%–8% reductions in KPI values compared to *Green*, with similar performance of flexibility heuristics relative to *Baseline* in both scenarios.

5.1.6. Photovoltaic generation capacity in the building stock

PV installations in the building stock are assumed to grow from zero in 2020 to saturation by 2040 (Section 4). Table 5 details the installed capacity, annual generation, and estimated curtailment, assuming PV surplus can only be shared between buildings in the same price zone. Significant PV generation is curtailed under the *Baseline* and *Time-of-Use* heuristics due to a lack of flexibility actions and ToU prices shifting use to non-PV hours. Conversely, the *Flat* heuristic aligns electricity use with PV production, minimizing curtailment by 95%–100% towards 2040. Note that *Time-of-Use* adapts to historical price levels with minimal influence from PV; it is also expected to reduce curtailment if responding to future price signals, where PV systems are likely to lower midday prices.

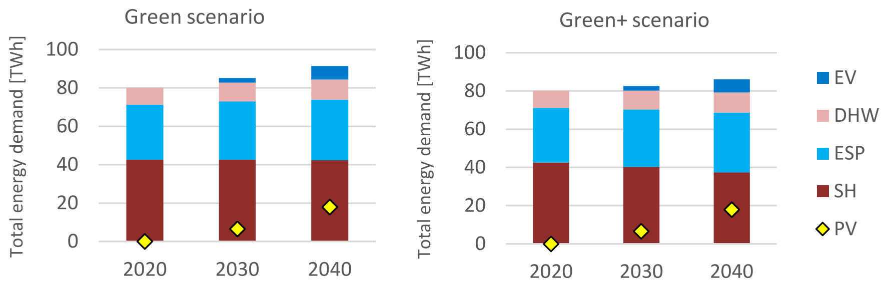
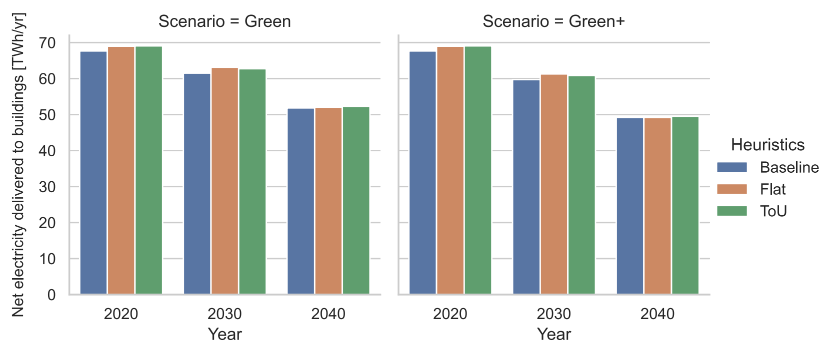
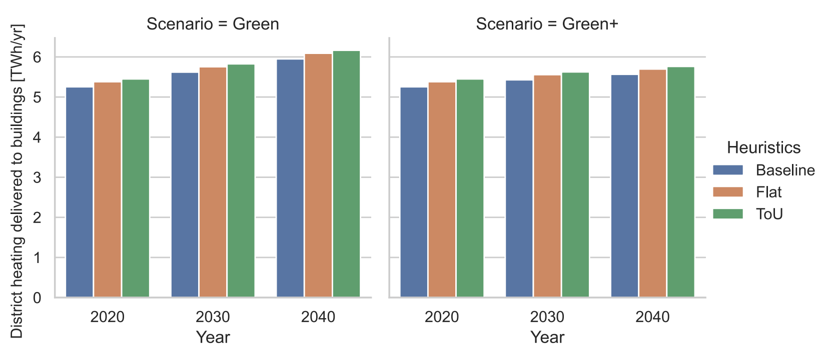


Fig. 5. Energy demand of the building stock as calculated in PROFet, and PV generation, by scenario. EV = Electric vehicle, DHW = Domestic hot water, ESP = Electric-specific demand, SH = Space heating.

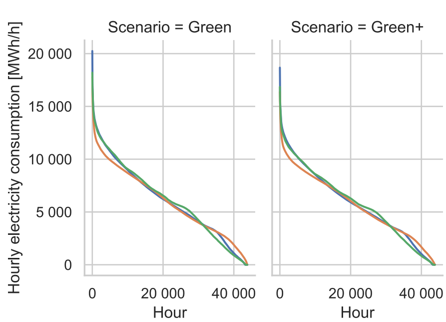


(a) Electricity

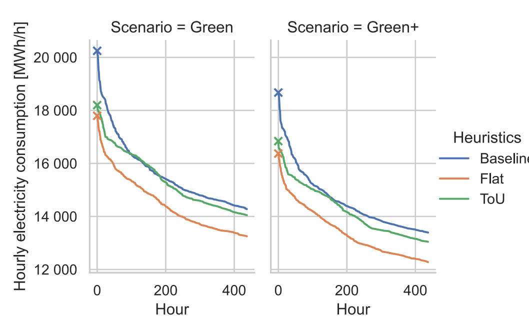


(b) District heating

Fig. 6. Annual electricity and district heating consumption by buildings in total for Norway in 2020, 2030, and 2040 by scenario and heuristic. The values are average annual values for five weather years.



(a)



(b)

Fig. 7. Load duration curve for the five-year period of 43 824 h (a) and from the 1% highest load hours (b) from FLEXor for Norway in total in 2040 in the two future scenarios for the three heuristics.

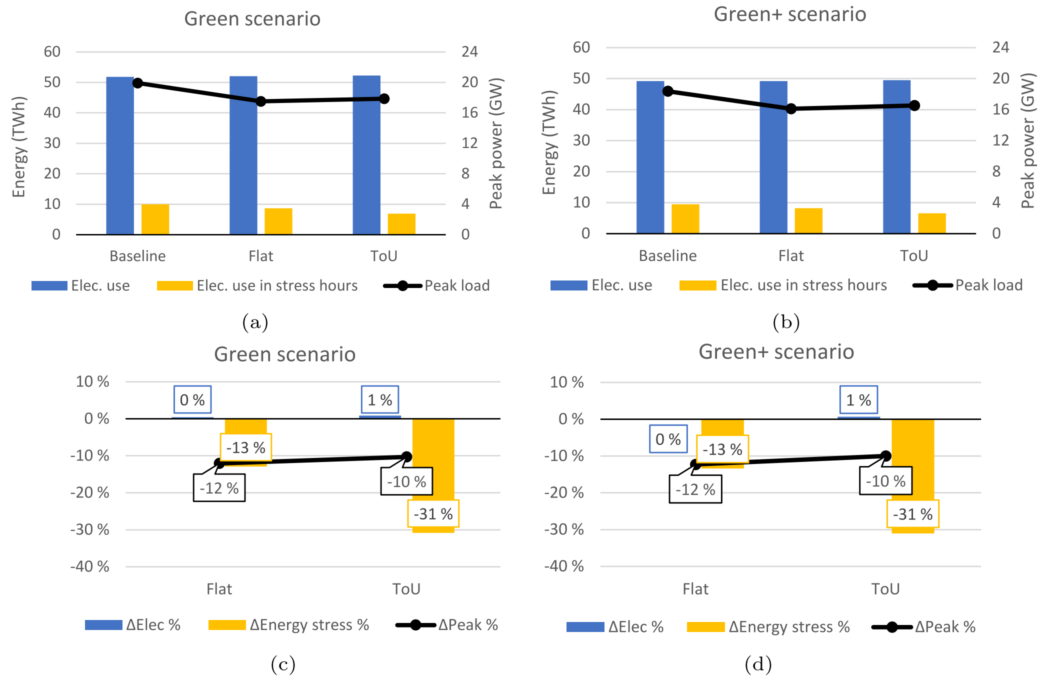


Fig. 8. KPIs of electricity flexibility in 2040 by heuristic and scenario in total values (a,b) and in relation to the *Baseline* heuristic (c,d).

Table 5
Development of onsite PV until 2040.

		2030	2035	2040
PV inst. cap. [GWp]		8.2	15.4	22.8
Generation [TWh]		6.4	12.0	17.8
	Baseline	0.0	1.0	3.9
Annual curtailment [TWh]	Flat	0.0	0.0	0.2
	Time-of-Use	0.0	0.9	3.4

5.2. EMPIRE: Impact on the european electricity market

This section presents key results from EMPIRE, where the impact of the heuristics on the European electricity market is quantified, with a focus on results until 2040. The model is solved until 2060 to avoid potential end-of-horizon effects.

5.2.1. European and Norwegian power mix development

Fig. 9 shows the development of the European power system towards 2040 for the *Baseline* heuristic in the *Green* scenario. The growth in electricity supply follows demand input from [52], and onshore wind grows most until 2030. By 2040, onshore wind comprises 34% of the European power mix, followed by nuclear (16%), offshore wind (15%), and solar PV (14%). Fossil fuels decrease by 59% compared to 2025, while hydropower remains stable.

In Norway, the power mix remains dominated by hydropower, making up 90% of Norwegian electricity production in 2025. By 2030, results show a large capacity expansion of onshore wind in mainland Norway, which increases from 5 GW in 2025 to 24 GW by 2040. Onshore wind expansion in Norway is optimistic given the current challenges [62]. Hydropower still delivers over 70% of Norwegian power production in 2040, with regulated hydropower more than 75% of total hydropower.

Results for the *Baseline* heuristic in the *Green+* scenario align with Fig. 9. The *Green+* scenario shows reduced electricity demand in Norway (−3 TWh in 2040), leading to less onshore and offshore wind in Sweden. Results for *Flat* and *Time-of-Use* also align with Fig. 9 for both scenarios. For more details on how *Flat* and *Time-of-Use* impact the European system compared to *Baseline*, see Section 5.2.5.

5.2.2. Electricity load profiles

Fig. 10 presents the mean and 95% confidence interval of Norwegian load profiles for 2030 and 2040 across all stochastic scenarios during winter and summer for three heuristics and the *Green* scenario. Spring and fall results are omitted as they resemble summer and winter, respectively. The *Green+* scenario shows similar patterns but with lower overall load. Load generally increases from 2030 to 2040 for all heuristics due to assumed growth in non-FLEXor loads in EMPIRE, which is partly compensated by reduced electricity delivery to the building stock resulting from FLEXor (Fig. 6).

The *Flat* heuristic flattens Norwegian electricity consumption in all seasons compared to *Baseline*, with the most significant flattening in winter. The key change is increased night load and decreased morning and afternoon load. The peak load reduction at system level is between 4%–6% (see Fig. 11), which is a more conservative result than the 5%–11% reported by Seljom et al. [63].

The *Time-of-Use* heuristic reduces load during historical high-price hours and increases night-time load compared to *Baseline*. Although Fig. 7 shows that *Time-of-Use* decreases the peak electricity delivery to buildings in 2040, the total peak load in Norway does not decrease with *Time-of-Use* because the high *Time-of-Use* loads coincides with high non-FLEXor loads (Fig. 11).

Fig. 10 shows that the increase in solar panels in the building stock (Table 5) in *Baseline* results in decreased midday loads. In contrast, *Flat* shows higher load during peak solar production, indicated by reduced solar curtailment (Table 5). The *Time-of-Use* heuristic responds to historical price patterns from a time with little solar in the mix, leading to less midday load increase compared to night load, especially in summer (Fig. A.16).

5.2.3. Hydropower flexibility in Norway

Total hydropower production is consistent across all heuristics and scenarios. Fig. 12 shows the mean and 95% confidence interval of historical hydropower production profiles in Norway for 2015–2019. Production generally follows historical load, with lower production at night and weekends, and higher production during morning and afternoon peaks. Daily patterns are similar across seasons.

Fig. 13 shows the mean and 95% confidence interval of Norwegian hydropower production profiles in 2030 and 2040 for all stochastic

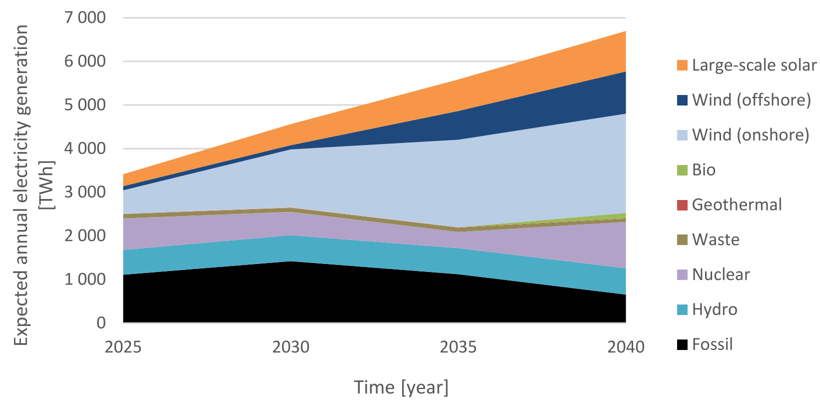


Fig. 9. Expected annual electricity generation in TWh by technology in EMPIRE for *Baseline* in *Green* scenario for all countries towards 2040.

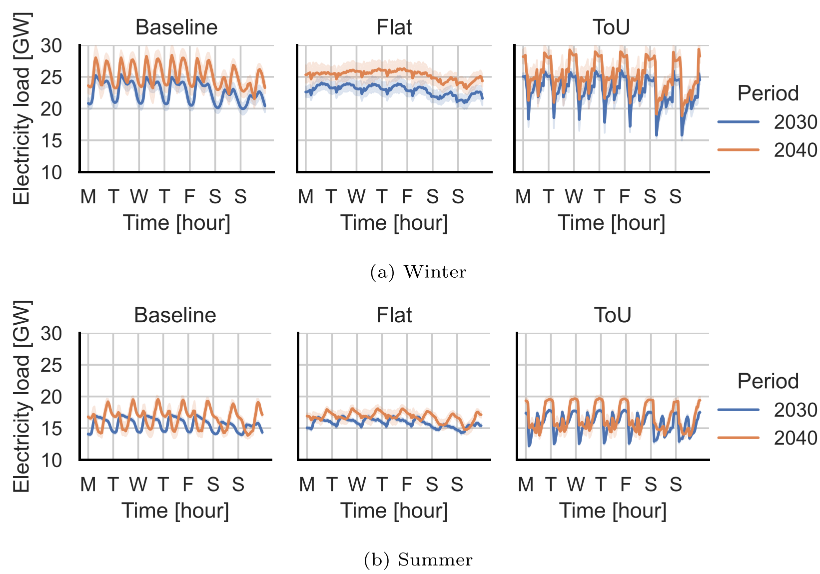


Fig. 10. Mean and 95% confidence interval for Norwegian electricity load profiles in all stochastic scenarios in EMPIRE by 2030 and 2040 for each heuristic in the *Green* scenario.

scenarios within each season for the three heuristics and the *Green* scenario. Results are similar in *Green+*.

Compared to historical profiles, hydropower production in Norway becomes more variable in 2030, indicated by a wider confidence interval. Production mostly follows load, especially during winter and fall, while wind and solar comprise 40% of the European electricity mix, producing three times more electricity than all European hydropower.

By 2040, hydropower production becomes even more variable as wind and solar constitute 60% of the European power mix, generating seven times more electricity than all European hydropower. This variability is pronounced during spring and summer, with midday output from regulated reservoirs dropping below 5 GW. Mean production profiles remain similar during winter, but variability increases in 2040 compared to 2030. Note that Fig. 13 presents 10 stochastic scenarios for each season, and the high output during Tuesday in summer in 2040 is a result of the specific weather years that are sampled (Algorithm 1).

The largest weekly variability is observed during spring and summer in 2040, with daily production differences exceeding 15 GW. Despite current short-term variability of around 10 GW during night-to-morning transitions, 2040 results suggest higher future flexibility, potentially overestimated when considering environmental impacts. Halleraker et al. [64] indicate up to 19 GW of eco-friendly ramping capacity in Norway, but further research is needed to better represent hydropower ramping limitations in an aggregated European model like EMPIRE.

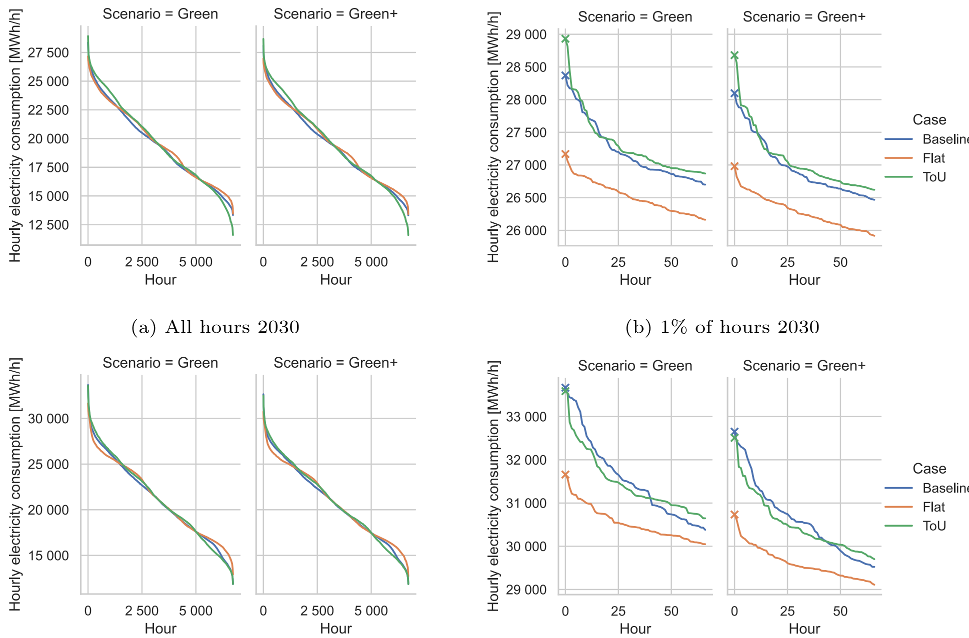
Fig. 13 highlights that Norwegian hydropower production closely adapts to load profiles derived from the heuristics in Fig. 10, due to the dominance of regulated reservoirs providing substantial supply-side flexibility within the European power system.

5.2.4. Electricity export from Norway

Fig. 14 shows the net annual expected electricity export from Norway by season. Export increases in *Green+* compared to *Green* due to decreased electricity use, while export decreases for *Flat* and *ToU* compared to *Baseline* due to increased electricity use (Fig. 6). The additional electricity use is minor compared to solar PV production (Table 5), enhancing net export from Norway [65].

In 2030, net export is higher in winter and fall compared to spring and summer. Increased export from energy efficiency in *Green+* is counteracted by decreased export from increased electricity use in *Flat* and *ToU*.

Net transmission capacity between Norway and neighboring countries increases from 9 GW in 2030 to 24 GW in 2040 across all heuristics and scenarios, including cables to offshore wind sites (+8 GW) and stronger connections to Sweden (+3 GW), Great Britain (+2 GW), Finland (+1 GW), and Germany (+1 GW).



(a) All hours 2030

(b) 1% of hours 2030

(c) All hours 2040

(d) 1% of hours 2040

Fig. 11. Load duration curve for 10 stochastic scenarios lasting one week in 4 seasons ($168 \times 4 \times 10 = 6720$ h) and from the 1% highest load hours from EMPIRE for Norway in total in 2030 and 2040 in the two future scenarios for the three heuristics.

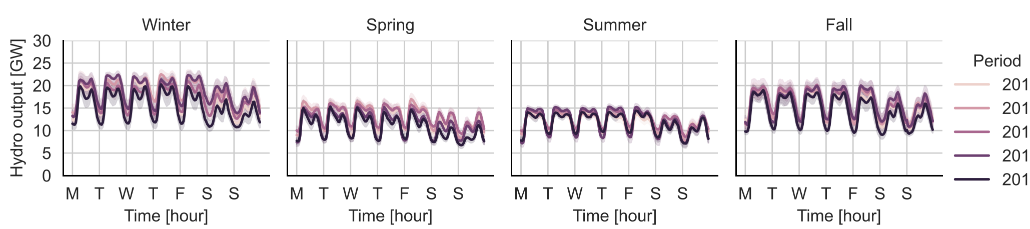
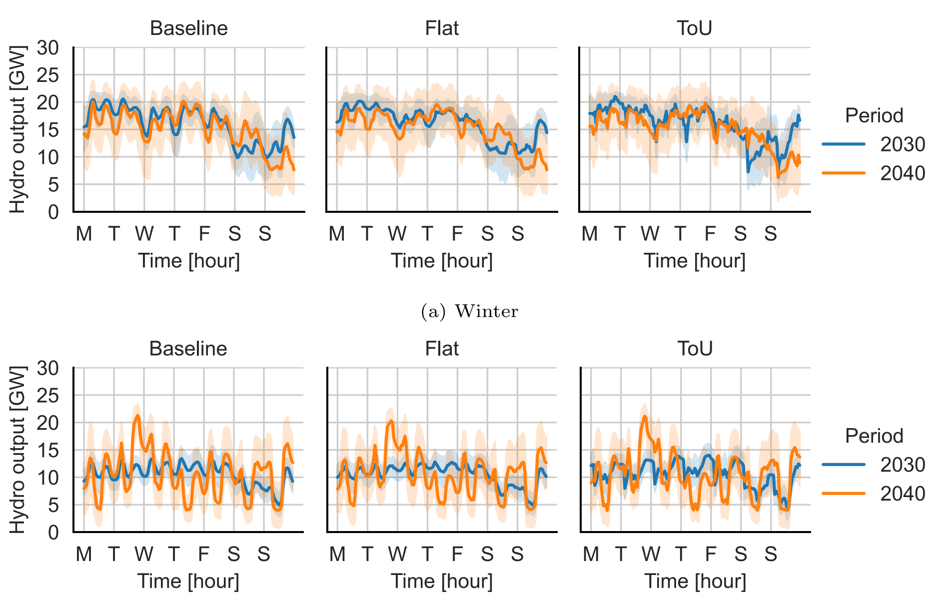


Fig. 12. Mean and 95% confidence interval for Norwegian hydropower production for historical data in the period 2015–2019.



(a) Winter

(b) Summer

Fig. 13. Mean and 95% confidence interval for Norwegian hydropower production for EMPIRE results across all stochastic scenarios by 2030 and 2040 for each heuristic in *Green* scenario (a–d).

Fig. 14. Net electricity export from Norway to connected countries by season for 2030 and 2040 in both scenarios for all heuristics.

Despite doubling transmission capacity, total net annual export from Norway decreases by 40% in 2040 compared to 2030 across all heuristics and scenarios. Net export is higher in spring and summer compared to winter and fall, due to higher load in Norway and more import from neighboring countries.

Fig. 15 shows the net export duration curve for Norway for all stochastic scenarios and seasons in 2030 and 2040. Net import occurs 16% of the time in 2030, with high utilization of export capacity. In 2040, net export flows are stronger, and net import occurs 50% of the time. Annual net export remains positive across all heuristics and scenarios, driven by onshore wind capacity expansion to 24 GW in 2040. Increased import in 2040 leads to more variable hydropower production (Fig. 13).

Fig. 15 shows less variation between heuristics in net export duration compared to the load duration curve (Fig. 11), suggesting similar annual net export across heuristics. Hydropower flexibility (Fig. 13) adapts to load profiles, enabling cost-optimal electricity exchange with neighboring countries.

5.2.5. European system impact of large-scale demand-side flexibility in Norway

As Norwegian hydropower adapts to the large-scale demand-side flexibility from the Norwegian building stock, EMPIRE results show similar investment decisions and total system costs across heuristics. In the *Green+* scenario, total European power system costs decrease by 0.1% compared to the *Green* scenario due to reduced electricity demand. Note that costs related to adopting the more ambitious *Green+* scenario are not considered. The demand decrease in *Green+* compared to *Green* (−3 TWh in 2040) accounts for about 0.04% of total electricity demand in EMPIRE by 2040, which means the cost savings are relatively high compared to the demand reduction. The cost savings in *Green+* is 80-90% due to savings in capital expenditure, specifically investment cost savings related to onshore wind, nuclear, and biomass.

For the *Flat* and *Time-of-Use* heuristics, total European system costs decrease by 0.01% compared to *Baseline*. Note that costs related to adopting the heuristics within the Norwegian building stock are not considered. Although small, the European system costs still decline when adopting the heuristics, despite the somewhat higher electricity delivery to buildings (Fig. 6). This suggests that the benefits of the heuristics in a European context outweigh their costs related to increased electricity delivery. Savings from the heuristics are mostly due to savings in operational expenditure in the European context. Both *Flat* and *ToU* lead to 0.04–0.12% more investments in wind and solar in the power mix. Wind and solar are assumed to have zero marginal costs such that their production replaces operational expenditure in thermal power plants fueled by fossil fuels, municipal waste, biomass, and nuclear fuel when adopting *Flat* or *ToU* compared to *Baseline*.

Table A.6
Installed capacities of heat pumps and other types of heating technologies in each market area by building type, in kW. HP = Heat pump, Reg = Regular building standard, Eff = Efficient building standard, Vef = Very efficient building standard.

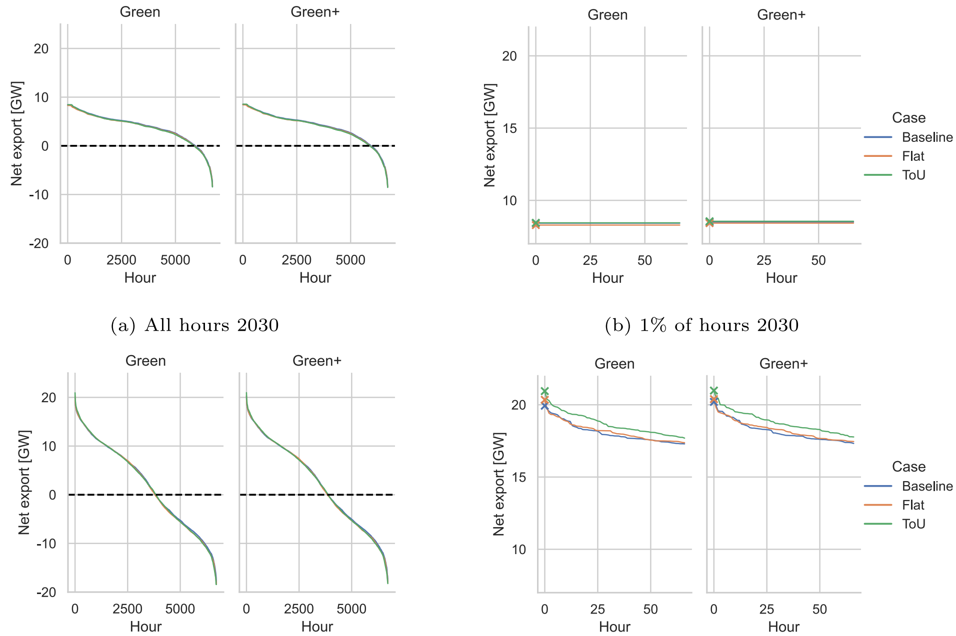
		House		Apt.		Comm.	
		HP	Other	HP	Other	HP	Other
NO1	Reg	3.4	8	28	67	225	482
	Eff	1.8	5	15	41	124	280
	Vef	1.3	4	11	32	85	202
NO2	Reg	3.4	8	28	67	225	482
	Eff	1.8	5	15	41	129	291
	Vef	1.3	4	11	32	91	215
NO3	Reg	3.4	8	28	67	229	491
	Eff	1.8	5	15	41	126	285
	Vef	1.3	4	11	33	87	207
NO4	Reg	3.1	7	26	63	204	439
	Eff	1.7	4	14	39	111	254
	Vef	1.2	4	10	31	75	182
NO5	Reg	3.0	7	25	61	195	422
	Eff	1.7	4	14	38	106	244
	Vef	1.2	3	10	30	71	175

5.3. Limitations

The results are based on many realistic assumptions, but there are limitations regarding robustness.

Both models are linear and/or convex, simplifying energy flows to make simulations computationally tractable. Further research is needed to understand the impact of these simplifications. FLEXor is validated with statistical data (Section 5.1.1), and EMPIRE is fully transparent and reproducible through its open-source repository [47].

The European model is solved to optimality within its assumptions, but results may not remain optimal if assumptions change. This study compares instances of EMPIRE with the same external assumptions across all heuristics and scenarios, so changes in results are due to differences between heuristics and scenarios. Stochastic models provide greater robustness than deterministic equivalents [49], but further research is needed to stress-test investment decisions towards 2040.



(a) All hours 2030

(b) 1% of hours 2030

(c) All hours 2040

(d) 1% of hours 2040

Fig. 15. Net export duration curve for Norway in all stochastic scenarios and all seasons, as well as the 1% highest export hours, from EMPIRE in total in 2030 and 2040 in the two future scenarios for the three heuristics.

Table A.7
Key parameters of the performance of heating technologies. SH = Space heating, Reg = Regular building standard, Eff = Efficient building standard, Vef = Very efficient building standard, DHW = Domestic hot water, T = Temperature, T out. = Outdoor air temperature, DH = District heating, GSHP = Ground sourced heat pump, ASHP = Air-sourced heat pump, A2A = Air-to-air.

	Efficiency % or S-COP[a]	Performance	SH supply T (Reg,Eff/Vef)	DHW supply T	Source T
El. heater	100%	Constant	–	–	
DH	100%	Constant	–	–	
GSHP	SH: 2.7–3.5, DHW: 2.4	SN-NSPEK	55/35	55	3
ASHP	SH: 2.0–2.7, DHW: 2.3	SN-NSPEK	55/35	55	T out.
A2A	SH: 1.3	SN-NSPEK	20	–	T out.
Other	100%	Constant	–	–	
Firewood	35%	Constant	–	–	

[a] S-COP = Seasonal coefficient of performance, case dependent and calculated according to the heat pump hourly calculation model specified in the SN-NSPEK 3031:2021.

Another limitation is the limited flexible technology options in FLEXor, which include flexible EV charging, building thermal mass, and DHW tanks. More flexibility options could strengthen the impact on the electricity system. The influence of future energy storage policies on flexibility options and electricity production remains uncertain. Future studies should consider these policy impacts, particularly on stationary batteries and thermal energy storage, to better understand the building stock's potential impact on energy system flexibility.

6. Conclusion

This study explores how flexibility heuristics impact electricity delivery to the future Norwegian building stock and the surrounding power market.

Results indicate that energy demand, including EVs, will increase by 8–14% towards 2040 despite thermal envelope efficiency improvements, due to rising EV charging and building stock growth. However, electricity delivery to the building stock can be reduced by 23–29% compared to 2020, thanks to efficient heating technologies and PV installations.

Speeding up renovations in the Norwegian building stock has limited impact on international electricity market decisions. However, within Europe, cost savings towards 2040 are larger from renovations-only in Norway (−0.1%) than from large-scale adoption of flexibility heuristics (−0.01%). Savings from a large-scale adoption of flexibility in the Norwegian building stock is based on heuristics rather than adapting towards market prices, which has been the main focus of this study.

Flexibility heuristics can reduce grid stress by lowering peak power delivery by 10–12% and shifting 13–31% of electricity consumption away from high-stress hours, with no more than 1% increase in energy consumption. Growing PV capacity may require curtailment if surplus generation cannot be used or exported. Flattening electricity use can reduce PV curtailment by 95–100% towards 2040.

Hydropower flexibility provides stability in the European power market towards 2030 and 2040, even with large-scale flexibility from the Norwegian building stock. However, flexibility in the building stock alters Norwegian hydropower production plans. Flattening electricity use could lead to more stable hydropower output, but variability will increase towards 2040 due to more variable renewables in Europe.

Future research should consider costs and benefits of hydropower production plans at the plant level and explore limitations to hydropower flexibility in an aggregated European power market, including environmental impacts.

CRediT authorship contribution statement

Stian Backe: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Benjamín Manrique Delgado:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Magnus Askeland:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Harald Taxt Walnum:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Åse Lekang Sørensen:** Writing – review & editing, Writing – original draft, Validation, Investigation. **Igor Sartori:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Microsoft Copilot to improve language and inspire python code for plotting results. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of competing interest

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

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Appendix A. Input parameters in FLEXor

See Fig. A.16 and Tables A.6–A.8.

Appendix B. Smoothing procedure for non-FLEXor loads in EMPIRE

This section describes how the time series data was smoothed when preparing input data to EMPIRE. The smoothing procedure was applied to the resulting time series when the historical electricity demand for each Norwegian price zone from [51] was subtracted by the hourly value of the combined electricity load profiles from FLEXor of the respective Norwegian price zone. The process was carried out as follows:

1. **Calculation of Mean:** For each zone and each hour, the mean was calculated for the same clock hour and the same weekday for the past four weeks. No calculation is done for the first four weeks, so smoothing for this period is ignored. For the rest of the time series, this calculation was done to establish a rolling mean that takes into account the cyclical nature of load, considering both the time of day and the day of the week. The calculation of the mean does not consider the current hour.
2. **Difference Calculation:** The next step was to calculate the difference between the rolling mean and the load. This difference provides a measure of how much the actual load deviates from the calculated mean.
3. **Load Check and Replacement:** A check was then performed on the load in each hour. If the load in a particular hour was more than 50% above or below the rolling mean, then that value was replaced with the same value from 168 h (one week) earlier. This step helps to smooth out any sudden spikes or drops in the load that are not consistent with the overall trend, and that are indicating poor data quality of the source.
4. **Special Case for NO1:** For the NO1 zone, a different threshold was used because this price zone has mostly loads that are already included in FLEXor. Therefore, subtracting FLEXor loads from historical loads is particularly prone to creating negative loads. To avoid any net negative load for non-FLEXor loads in NO1, a threshold of 75% was used instead of 50%. This means that if the load in a particular hour for the NO1 zone was more than 75% above or below the rolling mean, then that value was replaced with the value from one week earlier.

Fig. B.17 illustrates the hourly load profile over five years before and after the smoothing procedure for each Norwegian price zone. In the process of smoothing the time series data, a total of 1 878 h were smoothed. This constitutes approximately 4% of all hours over the span of five years. Note that the majority of the smoothing was applied to the NO1 zone. This indicates that the NO1 zone had more instances where the raw load deviated significantly from the rolling mean, despite the fact that NO1 had a higher threshold for smoothing than the other zones.

Appendix C. Renovation rates

RE-BUILDS is based on a dynamic building stock model by Sartori et al. [66], driven by socio-economic and demographic inputs like population growth, household size, and dwelling size. Technical indicators such as building lifetime and renovation intervals, with their probability functions, complete the model. This model shows that renovation rates stem from the need to maintain an aging stock, representing the natural renovation rates of a dwelling stock. Sartori et al. [66] consider renovation frequencies of 20, 30, and 40 years for different interventions: heating/cooling system substitution, window or roof replacement, and deep façade renovation, respectively. For step-by-step renovations of a building's thermal envelope (windows, façade, roof, foundations), the authors suggest modeling these as a single event with the frequency of the least frequent measure, spread over time using a probability distribution function. Thus, the renovation rate is an output of the model, representing the statistical opportunity to alter the thermal envelope properties of an archetype building.

Sandberg et al. [67] used the dynamic building stock model to simulate the development of dwelling stocks from 1900 to 2050 in 11 European countries, covering over half of all European dwellings. The simulations indicate future increases in renovation rates across these countries as the stock ages, but only to 0.6–1.6%, below the 3.0% political targets of many EU Member States' LTRS. Achieving a 3% renovation rate by 2030 would require reducing the average time between deep renovations to about 25 years.

For the commercial building stock, RE-BUILDS is partly based on the population's need for commercial buildings [44], with renovation

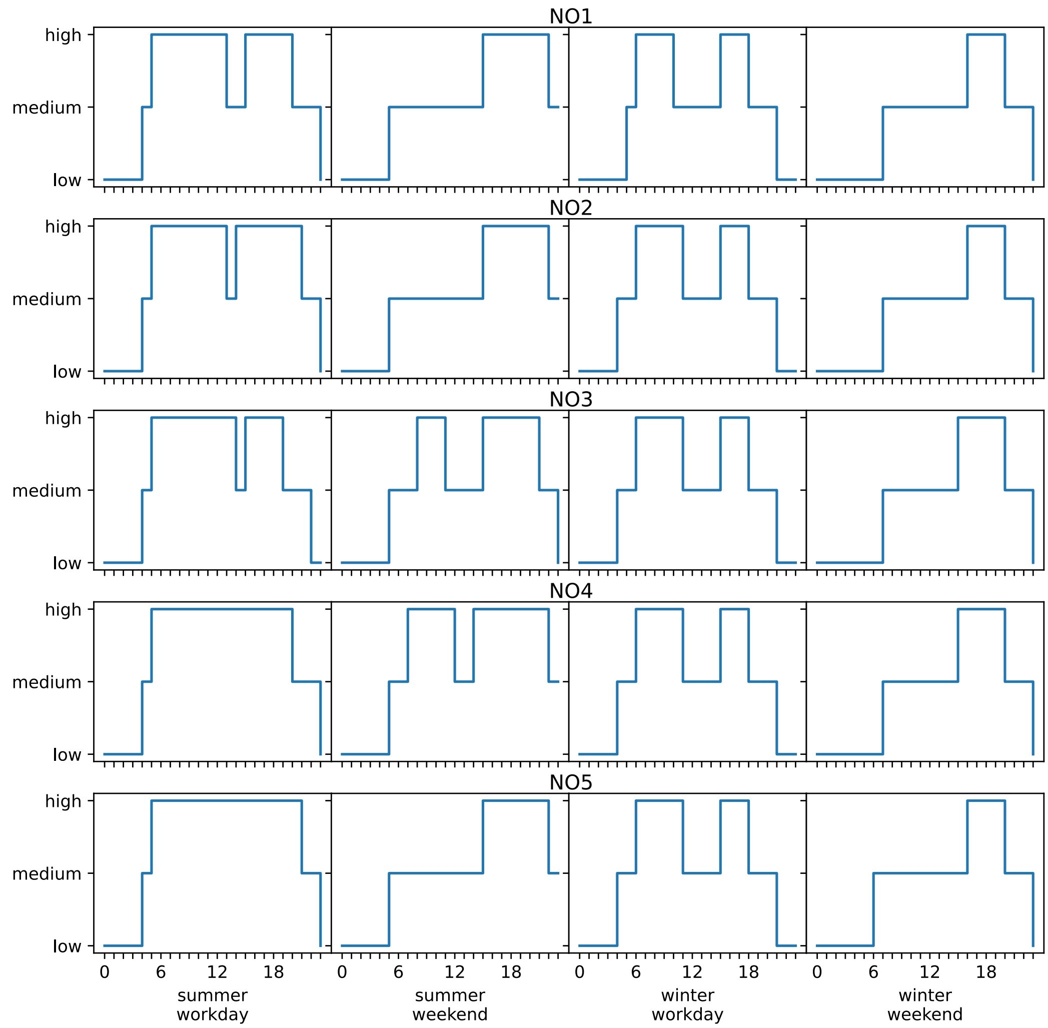

Fig. A.16. Price profiles for marked area, season and type of day.

rates estimated from empirical knowledge [68]. Due to the complex dynamics of the commercial sector, RE-BUILDS does not link renovation frequency to renovation rate. However, to estimate how often commercial buildings undergo major envelope renovations, one can refer to the renovation frequency in the residential stock model that results in the same renovation rate.

The RE-BUILDS model has been extensively used for both residential and commercial buildings in the Norwegian research project Flexbuild, calibrated against energy statistics from 2010–2020 [45]. It was also used in [69] to investigate energy savings potential in the building stock towards 2030 and 2050. All percentages refer to the total floor area of the building stock in 2010.

The following assumptions were made in these studies:

- For the residential sector, a 50-year renovation cycle results in an average renovation rate of about 1% for 2020–2050. Due to the aging stock, this rate trends upward, ranging from 0.9% to 1.1%.
- For the commercial sector, the average renovation rate is about 1.5% for 2020–2050, based on an assumed 2% rate that excludes the first 20 years after construction. The actual rate depends on the stock composition, reflecting a renovation frequency of about 40 years, indicating that commercial buildings are renovated more often than residential ones.

Table A.8
Weather stations representing each market area in Norway.

Market area	Station name	Station code
NO1	Rygge-Huggenes	SN17380
NO2	Landvik	SN38140
NO3	Kvithamar	SN69150
NO4	Tromsø-Holt	SN90400
NO5	Kvam-Aksneset	SN50110

Data availability

Data will be made available on request.

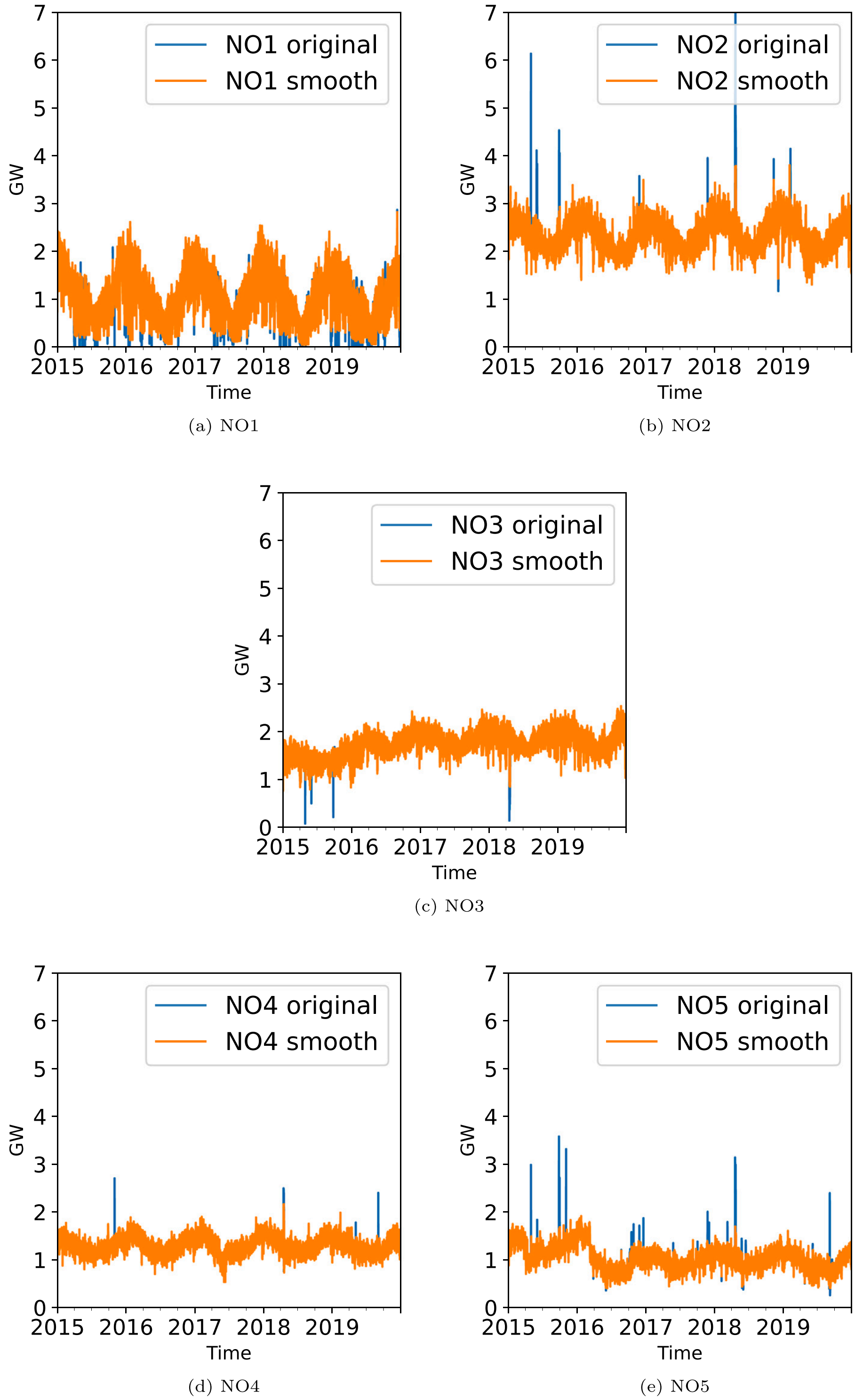

Fig. B.17. Resulting non-FLEXor loads after the smoothing (orange) compared to original (blue).

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