

# Energy flexibility in buildings: future scenarios across diverse climate zones in Europe

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**Abstract**—Sustainable Positive Energy Neighborhoods (SPENs) must manage energy demand and supply efficiently to maximize self-generated renewable energy and reduce grid dependence. This study develops a scenario-based investment model to assess energy flexibility options in SPENs. This integrates photovoltaic systems, battery storage, electric vehicles and heat storage with flexibility mechanisms. By incorporating forecasts from various sources on energy parameters and spot prices, the proposed model offers insights into the evolution of flexibility in SPENs from 2030 to 2050. The results reveal distinct regional flexibility strategies—northern Europe favors EV-driven flexibility due to lower PV output and stable prices, while southern regions rely more on storage—with technological advancements emerging as the primary driver of future flexibility.

**Index Terms**—Energy flexibility, future scenarios, LP optimization model, sustainable plus energy neighborhoods, spot price forecast

## I. INTRODUCTION

### A. Motivation

Buildings are a major contributor to EU's greenhouse gas emissions, accounting for approximately 34% of energy-related emissions [1]. As the energy sector rapidly transforms with the large-scale deployment of renewable energy and the electrification of heating and transport, new challenges arise in balancing supply and demand. In this evolving landscape, energy flexibility in buildings is becoming increasingly relevant. With the rise of intermittent renewable sources and electric vehicles, energy flexibility can play a crucial role in ensuring a resilient and cost-effective energy system. SPENs offer a promising framework for enhancing energy flexibility while sharing investments with the community. However, the rapid evolution of markets and technologies introduces uncertainty in investment decisions. Future energy prices, regulatory frameworks, and technological advancements are difficult to predict, making it challenging to determine optimal strategies for green technology adoption. To address this issue, this paper presents an optimization model for green technology investments in buildings, focusing on flexibility and its role in adapting to an evolving energy

landscape. The proposed approach aims to anticipate future trends, providing insights into the optimal deployment of flexible technologies to enhance sustainability and economic performance. This is done through a scenario-based optimization model that evaluates different energy assets configurations across four different climate zones, Norway, the Netherlands, Spain and Austria, considering projection for 2030, 2040, and 2050.

### B. State of the art

Buildings' flexibility can be achieved through various strategies, as identified in previous studies [2]. These include demand response, energy storage, and load-shifting techniques, enabling buildings to actively participate in energy markets, enhance grid stability, and generate economic savings. A comprehensive review of assessment methodologies categorizes flexibility evaluation into empirical, simulation-based, and optimization-based approaches [3]. Among these approaches, optimization-based methods, such as linear programming models, are employed to identify cost-effective flexibility strategies, aligning with the methodological framework adopted in this paper. Unlike simulation-based methods, which primarily focus on operational aspects and replicate real-world behavior, this study incorporates investment decision-making, broadening the scope of flexibility assessment.

Advanced models, including machine learning techniques, are already being utilized to predict building flexibility based on historical energy consumption, weather data, and occupancy behaviours [4]. However, these approaches are currently limited to short-term horizons, typically within 24 hours or a few days. Further research is needed to extend these predictive capabilities over longer periods.

Other studies have explored stochastic modelling approaches to optimize energy management, such as Stochastic Dynamic Programming used in Home Energy Management Systems to evaluate long-term flexibility impacts [5]. Similarly, [6] has modelled prosumers managing their energy consumption through flexible assets, optimizing shiftable loads based on market conditions and self-consumption strategies. These methodologies emphasize the need for advanced tools capable

of predicting uncertain factors, such as weather variations and energy prices. However, they do not provide insights into the optimal sizing of energy assets or how these may evolve in response to flexibility requirements, key aspects that influence both cost savings and revenue generation.

### C. Contribution

The primary objective of this paper is to analyze potential energy flexibility mix within SPENs. The key contribution of this study lies in combining time-series forecasting of spot prices between 2030 and 2050 with the analysis of flexibility assets in SPENs. To achieve this, a scenario-based approach has been developed, outlining distinct drivers that influence the flexibility mix of future buildings across four different climate zones in Europe. The methodology has been described in Section II. Section III presents the results in terms of energy bill reduction and discusses them in Section IV. Future work is suggested in Section V, and Section VI concludes the paper.

## II. METHODOLOGY

The methodological framework developed specifically for this paper consists of four steps:

- Step 1. Scenario development: establishing storylines to set boundary conditions based on socio-technical, economic, and policy-driven factors. This includes defining various future pathways based on these factors.
- Step 2. Models' inputs and assumptions; setting the boundary conditions for the flexibility model on step 3.
- Step 3. Flexibility model: a mathematical optimization model to quantify flexibility's role in balancing energy supply and demand inside the building.
- Step 4. Evaluation of flexibility indexes; the economic impact of flexibility will be quantified.

### A. Scenarios creation

The methodology for scenario development is adapted from a framework designed to explore Europe's transition towards a low-carbon energy system [7]. This methodology employs a three-dimensional topology, capturing the main drivers and uncertainties of the energy transition: societal trends, technological advancements, and policy interventions.

Figure 1 illustrates the three-dimensional topology and how these drivers derive in the three different scenarios: *Societal Commitment (SC)*, *Techno-Friendly (TF)*, and *Direct Transition (DT)*. Table 1 summarizes how the divers shape each scenario.

The scenarios involving policy axe will consider a reduction in electricity bill taxes, increased subsidies, and the absence of penalties for excess energy injected into the grid. The social axis emphasizes public participation in the energy transition, allowing external control over energy access and enabling load

shifting. Finally, the technology axis assumes an optimistic advancement in technological assets, improving both cost and performance.

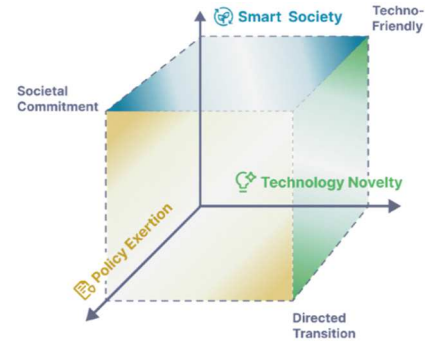


Figure 1 Scheme of the three different scenarios

Table I Summary of the main characteristics per each scenario

	DT	SC	TF
<b>Load-shifting of appliances</b>	No	Yes	Yes
<b>Efficiency of the energy assets</b>	Higher	Lower	Higher
<b>Specific cost of the energy assets</b>	Lower	Higher	Lower
<b>Load-shifting of the EV demand</b>	No	Yes	Yes
<b>Policies that do not penalize the injection of renewable energy</b>	Yes	Yes	No
<b>Policies that reduce taxes or increase the subsidies</b>	Yes	Yes	No

### B. Input model and assumptions

- Energy demand

Load profiles were generated using *LoadProfileGenerator*, a tool that simulates household energy consumption based on behavioral patterns and geographical location [8]. Real data was not used due to its unavailability and/or limited compatibility, which would have made comparison more complex.

- Technology parameters

The technology parameters are based on photovoltaic (PV) systems, residential battery storage, electric vehicles (EVs), and heat storage. For PV systems, the input parameters include production profiles, and cost projections. Production profiles were established using the web-based simulation tool PVGIS [9]. Cost projections are derived from literature sources, with optimistic estimates based on [10] and more conservative based on [11]. The cost of residential battery storage systems was estimated using a methodology similar to that for PV panels, relying on reports [11] and [12] to project future investment costs. EV parameters include forecasted market penetration, battery cost, and battery size. The penetration rate was projected using the methodology outlined in [13], and the results are reported in the Appendix. Battery costs were assumed to align with those of residential storage systems. Battery capacity was projected under the assumption that today's highest laboratory-tested lithium-based battery density will become the standard by 2050, with the average battery size in EVs remaining constant. Heat storage was modeled using empirical market data, with investment costs for heat tanks and heat pumps based on current market prices. These parameters

remained fixed across all scenarios, assuming that heat storage technology is already mature and unlikely to undergo significant advancements.

- Energy bill components

These components are based on forecasts of excess energy remuneration, spot prices, taxes, and subsidies.

For excess energy remuneration, a market-based pricing system was chosen, where producers receive payments at the wholesale price minus a percentage for grid and administrative costs. In the TF scenario, this reduction grows over time, reflecting the assumption that excess energy exports will be disincentivized to reduce grid congestion.

Electricity bills for the final users include spot prices, taxes, and grid fees. In the TF scenario, taxes remain at 20%, whereas in other scenarios, they drop to 5% to encourage renewable energy adoption. A fixed average grid fee for all the countries of €320/year is considered, based on Eurostat data [14].

Modeling flexibility requires time-series profile of spot prices, which, along with production profiles, shape the operation of flexibility assets. To address this, the EMPIRE model, a capacity expansion tool for the European power system, was utilized to forecast spot prices from 2030 onward [15]. This multi-horizon stochastic program integrates short-term operations (hourly) with long-term planning, aiming to minimize total discounted power system costs until 2060. It accounts for uncertainties in energy demand and generation across the European market under perfect competition assumptions.

Subsidies and taxes play a crucial role in shaping renewable energy investments. In the TF scenario, subsidies are set to zero. In contrast, other scenarios include a 20% subsidy to offset taxes and promote the adoption of PV panels and storage batteries. A detailed table with the most important parameters is in Table 2.

### C. Flexibility model

The flexibility model is built using a Linear Programming (LP) optimization approach. This flexibility model is also an investment model; therefore, the sizes of energy-active assets are not predefined. Its primary purpose is to provide insights into how flexibility mix will be in the future in newly constructed buildings.

The objective function aims to minimize costs, including both investment and operational costs. The investment costs account for assets such as PV systems ( $IC_{PV}$ ), heat storage tanks ( $IC_{Heat}$ ), residential batteries ( $IC_{Bat}$ ) and EV batteries ( $IC_{EV}$ ). Operational costs include expenses related to energy consumption from the grid ( $C_{Imp}$ ), revenue from selling excess energy ( $R_{exp}$ ), and costs associated with battery usage ( $OC_{Bat}$ ). The general form of the objective function is presented in equation (1):

$$Obj F = Min \left( \sum_t (OC_{Bat} + OC_{EV} + C_{Imp} - R_{exp}) + IC_{PV} + IC_{Heat} + IC_{Bat} + IC_{EV} \right) (1)$$

The degradation of residential and EV batteries is explicitly considered. These batteries have a finite number of charge-

discharge cycles over their lifespan, with each cycle reducing the energy storage capacity and thereby affecting their value. Additionally, battery degradation due to calendar aging is accounted for. Furthermore, the EV battery is modeled with an availability profile based on different user behaviors.

The investment cost of the heat storage system is modeled as a shared cost among all apartments, given that it consists of a central unit. The heat storage system is treated as a battery, but with linearized energy losses from both the heat tank and the heat pump.

The main constraint in the model is the energy balance equation, which ensures that at any given time, the total energy supply, including imported energy, PV production, and battery discharge, matches the total energy demand. This demand accounts for both fixed and flexible loads, battery charging, and energy exports. Additionally, the energy bill for the building is calculated as the cost of imported energy minus the revenue from exported energy, with the condition that the total energy bill remains non-negative.

Table II Main parameters for each scenario

	TF			SC			DT		
	2030	2040	2050	2030	2040	2050	2030	2040	2050
Pv eff	0.24	0.29	0.34	0.21	0.23	0.24	0.24	0.29	0.34
Pv €/kW	313	232	152	644	580	525	313	232	152
EV kWh	113	177	240	96	132	168	113	177	240
Batt €/kWh	152	123	114	370	345	320	152	123	114
VAT	20%	20%	20%	5%	5%	5%	5%	5%	5%
Subsidy	0%	0%	0%	20%	20%	20%	20%	20%	20%
Grid tariff to sell	-	-	-	-	-	-	-	-	-
	40%	70%	100%	10%	10%	10%	10%	10%	10%

### D. Flexibility indexes

To evaluate the results obtained from the investment model, individual assets contributing to flexibility were analyzed separately. Their impact on users' final bills and achieved savings was assessed to determine which factor has the highest influence. In summary, the key contributing to flexibility include:

- EVs through demand load shifting and battery use
- Load shifting of certain appliances
- Wall battery
- Heat storage

The flexibility indexes are evaluated based on the actual impact of each factor on the bill compared to a reference bill, the amount a user would pay as a simple “prosumer” without leveraging flexibility (*Ref bill*). The reference bill is therefore calculated as the total cost of imported energy, minus self-consumption and excess energy sold.

Two types of flexibility indexes are defined: one for storage systems (EV battery, wall battery, and heat storage) and another for load shifting, as shown in equations (2) and (3).

For load shifting, the flexibility index is calculated as:

$$I_{Load-shift} = \frac{OpCosts_{ref,i} - OpCosts_i}{Ref\ bill} [\%] \quad (2)$$

where  $i$  represent different technologies related to load shifting. The numerator denotes the difference in costs before and after applying load shifting.

For storage systems, the flexibility index is:

$$I_{Storage} = \frac{Revenues_{discharge,j} - OpCosts_{Charge,j}}{Ref\ bill} [\%] \quad (3)$$

where  $j$  represents different storage technologies. The stored energy can either be used for self-consumption or sold back to the grid. To simplify the analysis, the battery's impact is evaluated by calculating the difference between the monetary value of discharged energy (valued at the bill price) and the monetary value of charged energy (valued at the selling price). The underlying assumption is that discharged energy is primarily used for self-consumption, whereas without the battery, the alternative would be purchasing energy directly from the grid.

### III. RESULTS AND DISCUSSION

#### A. EMPIRE results: spot prices

One of the key phases in the analysis is the use of the EMPIRE model to project future spot prices for different countries. As will become clearer later, this is a crucial parameter that significantly influences the choices within the flexibility model. Figure 2 presents the results for two countries: Spain and the Netherlands. The graph indicates that prices are expected to decline in the future. Specifically, the mean value in the Netherlands is projected to drop from 43.3 to 17.9 €/MWh. However, price volatility is expected to increase notably due to rising investments in renewable energy. This effect will be even more pronounced in Nordic countries. Volatility, which can be measured using the standard deviation, is expected to rise from 3.93 to 9.08 €/MWh in the Netherlands. By 2030, Spain's energy prices volatility is already expected to be high due to its existing energy mix, which is largely based on PV production. These results are aligned with other recent studies [16], [17].

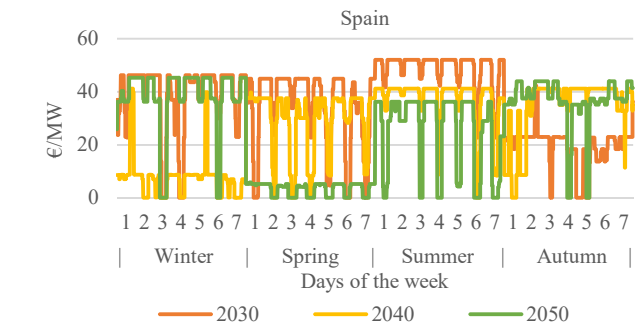
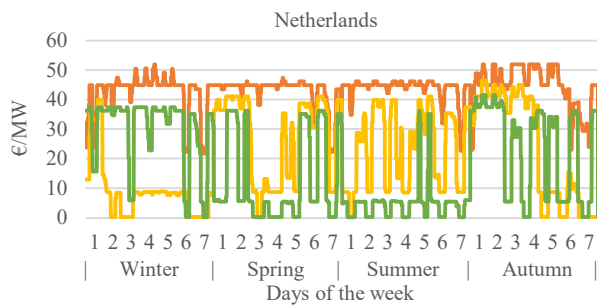


Figure 2 Spot prices for Spain and the Netherlands for 4 representative weeks in 2030, 2040 and 2050

#### B. Flexibility model results

The flexibility model generated numerous results due to the wide range of possible combinations. Initial results revealed a clear distinction between northern and southern countries. Austria and Spain had similar outputs, as did the Netherlands and Norway, due to similarities in solar production profiles and spot prices, both in terms of mean value and standard deviation. Only one result from each group, Spain and the Netherlands, will be presented here, the other two countries results are in the Appendix. Figure 3 presents the flexibility index values for each scenario, illustrating their progression over time and the contribution of different flexibility assets. If the graph shows the impact of a specific flexibility asset, it indicates that the model has identified it as economically viable.

In the DT scenario, technological advancements are combined with supportive policies, leading to the highest total percentage reduction among the three scenarios. By 2040 and 2050, the bill is reduced by 100%. In the Netherlands, EV batteries play a crucial role in bill reduction, with their contribution increasing significantly, especially in 2040 and 2050. In Spain, the contribution is more balanced between EV batteries and wall batteries during the same period. This difference arises from the higher penetration of EVs in northern countries, whereas in Spain, the need to store large amounts of solar energy generated during the day drives a greater reliance on wall batteries. Since EVs are typically unavailable during peak PV production hours, they are less effective for direct energy storage in Spain.

The total percentage reduction in this scenario is the highest among the three, highlighting the big impact of the policies, in particular the subsidies for the energy assets.

In the SC scenario, the overall reduction percentages are much lower compared to the DT scenario. Heat tank technology plays a more prominent role, particularly in 2050 for the Netherlands. This is due to the high cost and limited improvement of battery technology, making batteries unprofitable and leading to the adoption of heat tanks instead. This scenario is characterized by load shifting, but as seen in the graph, its contribution is not particularly significant, with the exception of EV load shifting, which has a larger impact.

The TF scenario exhibits intermediate reduction levels

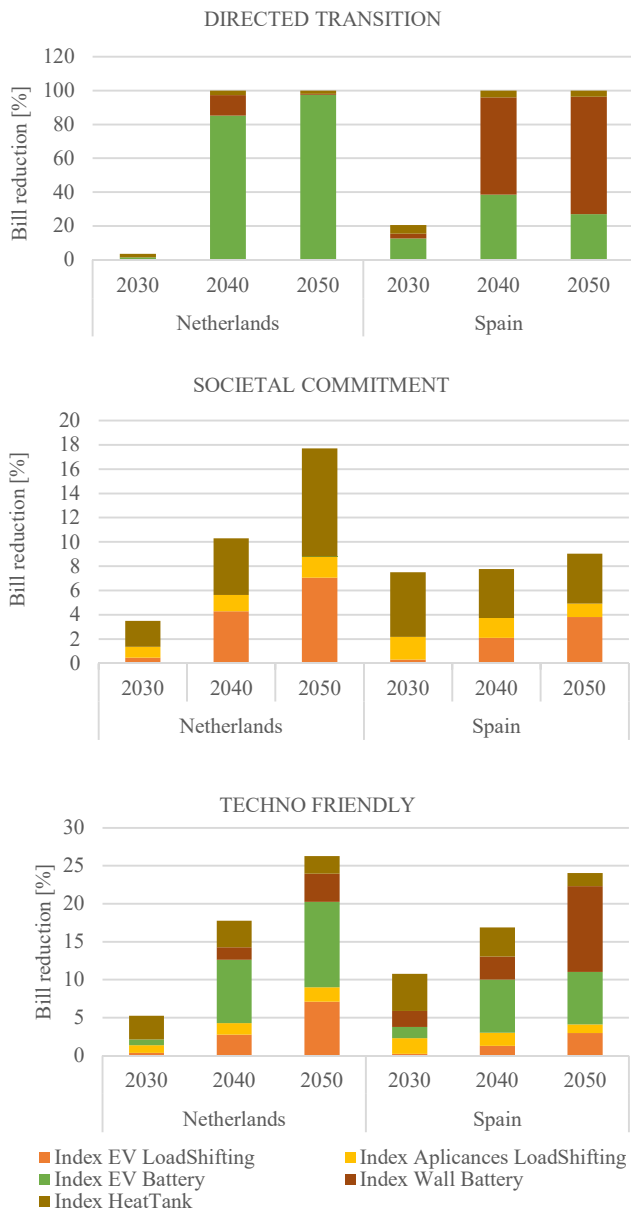


Figure 3 Cumulative flexibility indexes for Netherlands and Spain

between DT and SC. In the Netherlands, EV batteries and EV load shifting play a major role, with the percentage contribution growing steadily from 2030 to 2050. Spain shows a more balanced contribution of all technologies, with wall batteries and EV load shifting increasing their share by 2050, due to the increase in the penetration. This scenario suggests that the improvement in technology could contribute meaningfully, though not as aggressively as in the DT scenario.

In Spain, the contribution of flexibility is more significant, particularly in 2030, due to the already high volatility of energy prices. There is greater energy production, making it more advantageous to store energy for non-production hours when prices rise. The role of wall batteries is notable in 2040 and 2050, only in the cases in which the price for the investments

will decrease (scenarios DT and TF). For similar reasons, the heat tank is also more relevant in Spain, as it acts as a thermal battery. Load shifting has a low impact, remaining around 1-2%.

#### IV. LIMITATIONS AND FUTURE WORK

This study's optimization-based model assumed perfect forecasts, leading to potentially optimistic performance estimates. Future work should incorporate uncertainty modeling to better reflect real-world conditions.

Additionally, flexibility is only considered as a cost-saving measure, overlooking its potential as a marketable asset. Given that electricity cost reductions reach 100% in some cases, future research should explore how selling flexibility could provide additional revenue and ease grid congestion. Similarly, energy sharing schemes, which optimize local energy exchange and reduce costs, are not considered. As decentralized markets grow, assessing their financial and operational benefits is crucial.

The model also excludes heating load shifting, despite its accounting for relevant part of the total energy consumption. Integrating this aspect into future work would provide a more comprehensive view of building flexibility. Lastly, no sensitivity analysis was performed on specific variables, as the focus was on identifying key drivers of future energy flexibility. The use of multiple scenarios further complicates isolating the effects of individual parameters.

#### V. CONCLUSIONS

This study examines the evolution of energy flexibility in SPENs across different European climate zones. Using a scenario-based investment model, it evaluates various energy assets to optimize energy demand and supply, aiming to assess future flexibility trends and their economic impact.

The results indicate a clear difference in flexibility strategies and choices between northern and southern European countries. In northern regions, lower PV production and more stable spot prices reduce the need for flexibility solutions, particularly in energy storage. However, the higher penetration of EVs in these regions counterbalances this trend by increasing flexibility needs.

The findings also show that flexibility will play an increasingly significant role across all climate zones in Europe. The growing share of renewable energy sources (RES) in every country is expected to drive greater energy price volatility, thereby amplifying the need for energy flexibility solutions.

While the results emphasize the importance of strong policy support, they also suggest that flexibility assets may not necessarily require subsidies to be economically viable. Another key finding is the relatively low impact of load shifting compared to other flexibility technologies. Furthermore, under optimistic forecasts, technological advancements emerge as the most influential factor shaping the future flexibility mix.

These insights reinforce the need for strategic investments and innovation in flexibility solutions to ensure a resilient and adaptive energy system in the coming decades.

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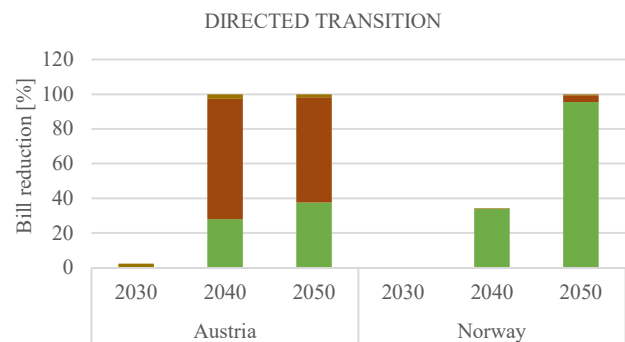
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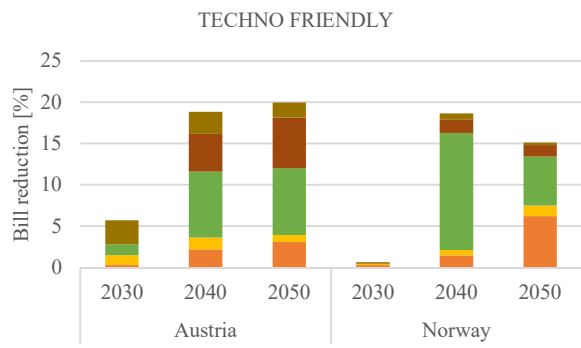
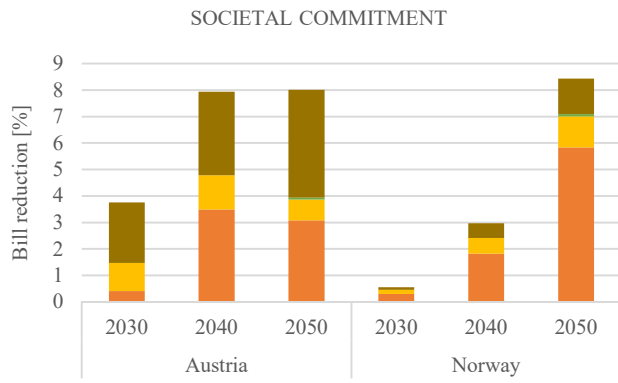
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## VI. APPENDIX

	Year of Ultimate Grey Band	Initial EV share	Share 2030	Share 2040	Share 2050
Spain	2040	0.6%	3.0%	18.8%	65.5%
Netherlands	2030	3.7%	7.6%	39.5%	89.5%
Norway	2025	19.8%	24.6%	62.8%	96.3%
Austria	2030	2.1%	6.1%	38.4%	89.4%

Table III Ev penetration





- Index HeatTank
- Index EV Battery
- Index EV LoadShifting
- Index Wall Battery
- Index Appliances LoadShifting

Figure 4 Cumulative flexibility indexes for Austria and Norway