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Influence of emerging technologies deployment in residential built stock on electric energy cost and grid load

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Abstract. High penetration rates of novel building energy technologies has prompted a growing concern about their microeconomic effect and grid influence. Deployment of photovoltaic (PV), solar water heating (SWH) systems and energy storage solutions, in addition to the growth of electric vehicles (EV) fleet, are reshaping the structure of built stock and lead to the changes in its electric energy demand profile. Long-term forecasting of such structural changes is necessary to guide the decision-making process that would satisfy the needs of both, energy consumers and the suppliers. Whereas electric energy price model is one of the key influencing factors of technologies acceptance for households, peak loads and grid feed-in determine the needed capacity of power grids. The objective of this study was to assess both, the aggregated cost of energy and the changes in cumulative load profiles that are excepted by 2050 for one of residential building typologies in Norway. Methodologically, it was achieved with descriptive statistics, stochastic forecasting and detailed energy performance simulation. Annual electric energy cost for consumers were evaluated under six pricing models. The results suggested that time-of-use and variable maximum power extraction models represent the lowest and the highest extremes in energy cost. At the aggregated level, peak load will decrease in range 1% to 13% compared to current level. Peak PV feed-in will reach up to 40% of peak load by 2050.

1. Introduction

Renewable energy technologies and energy conservation measures together with the emerging electric mobility solutions are penetrating the residential built stock rapidly. The motives and the consequences of such shift have to be studied in a systemic manner [1] to ensure the compliance to long-term strategic development plans for communities.

The benefits for consumers typically involve achieving the economic [2] and possibly environmental objectives [3] that may result from the reduced energy use and from power feed-in on the long term. More detailed analysis, however, suggests that these technologies may cause even further inconsistency in grid interaction [4]. Hence, their deployment at a large scale may require added power generation capacity and grid reinforcement. For the Norwegian power system this issue becomes even more challenging given that electricity is the major source of energy for space heating. Thus, Norwegian power grid development and maintenance for the

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period 2016 - 2025 will be supported by NOK 140[1] billion of investments [5].

Under such investment strategies, the expected increase in electric energy nominal price for households is 30% by 2025. In addition, a number of changes in electric energy pricing model will be introduced [5] by the Norwegian Water Resources and Energy Directorate (NVE). This brings to the necessity to evaluate the future costs of electric energy under various pricing methods.

Forecasting the future state of built stock is crucial for developing further power grid investment plans and energy pricing methods. Realistic long-term, large-scale energy forecasting models need to account for: 1) Detailed information on how certain technologies affect the energy performance at a single building level; 2) Typological complexity, variability, and dynamic nature of built stock; and 3)Uncertainty in consumers' decision to accept a certain novel technology.

"White-box" energy performance simulation is considered as an effective tool used to evaluate the results of technological interventions applied at a building level. Large-scale energy planning, however, is hindered by additional challenges, associated with the heterogeneous structure of building stock. Figure 1 illustrates the variability of energy use for residential buildings in Norway. A number of factors lead to significant variance, even within the same building type [6]. It can be attributed to the properties of envelope, energy supply system, appliances and occupant behaviour. Appropriate statistical methods that quantify this variability should be used at the model development and validation steps to minimise the error [7].

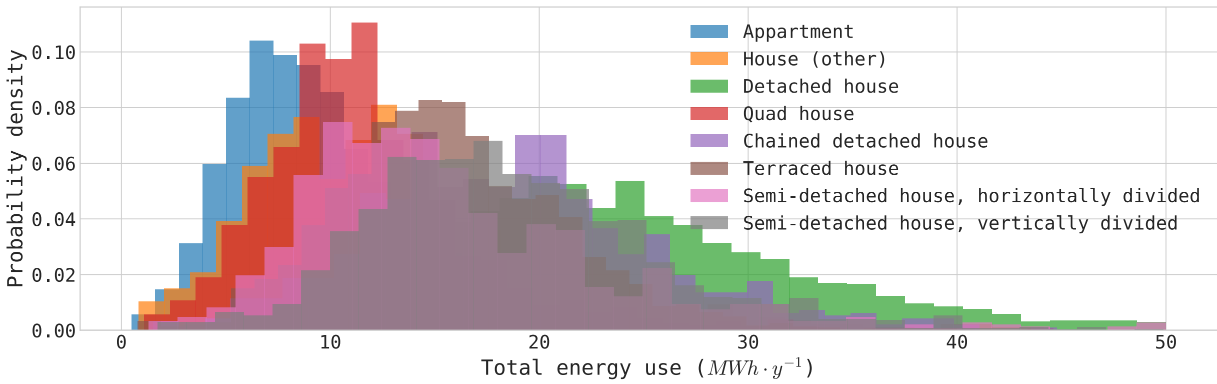

Figure 1. Energy use in the Norwegian residential built stock - univariate distribution

The deployment of novel technologies in buildings has a large number of underlying sources of variability that cannot be accommodated by deterministic modelling principles. Social and economic environment, amongst the other factors that affect the decision-makers, can be considered as random variables. Studying the dynamic evolution of such random phenomenas has to involve stochastic forecasting with the appropriate tools from probability theory [8]. This enables to account for a full spectrum of likely future outcomes, to quantify the uncertainties and thus, serves as a basis for well-informed strategic planning. Consequently, stock-wide influence of novel technologies on future electric energy prices and on power grid needs to be estimated in a quantitative, probabilistic terms. Developing the feasible methodological approach to achieve such objective is the key reasoning behind this study. It is exemplified with one residential building typology - semi-detached house divided vertically. The approach involves typological sampling, detailed building energy performance simulation, and stochastic forecasting. For the exemplification purposes, four technologies were considered: EV, PV, domestic hot water tank (DHWT) and SWH system.

[1] As of May 2019, 1 NOK = 0.1018 EUR.

2. Methodology

The suggested methodology consisted of five steps:

- Descriptive statistics - estimating central tendency, dispersion and distribution of variables within the typology to establish key properties of the representative building;
- Detailed energy performance simulation of the representative building without and with the technologies under the study and all possible combinations of those;
- Statistical simulation of stock-wide acceptance of technologies;
- Aggregation of the resulting cumulative energy costs under the available pricing methods;
- Aggregation of grid load and grid feed-in.

For detailed energy performance simulation, IDA-ICE software was used. Analytical tasks were carried out in Python programming language using the following libraries: 1) NumPy, SciPy, Statsmodels, and Networkx for numerical computing and simulation; 2) Pandas for data wrangling; 3) Matplotlib and Seaborn for data visualisation.

2.1. Descriptive statistics

The analysis of Norwegian Energy Performance Certificates (EPC) was carried out at this step. The background related to the dataset, as a component of EPBD [9] implementation in Norway, are available in source [10]. Amongst 18100 records for all the residential building categories listed in Figure 1 except apartments, semi-detached house divided vertically reached 9.7% by records count, 9.0% by heated floor area and 9.3% by energy use. The distribution of samples based on heated floor area (m^2) is illustrated in Figure 2.

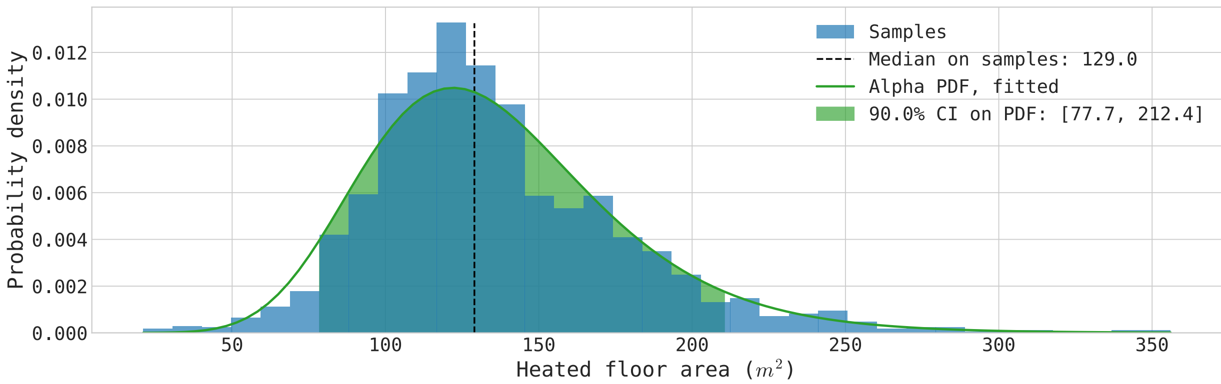

Figure 2. Heated floor area - univariate distribution (data-specific and theoretical best fit)

It was found that Alpha Probability Density Function (PDF), compared to other theoretical PDFs, describes this variable in the dataset best. For this type of PDF with its specific parameters, 10^{th} and 90^{th} percentiles, or confidence interval (CI) is [77.7, 212.4]. Subsequent steps in the methodology focused on this range only.

Further analysis of the EPC dataset revealed that 60% of buildings within this typology were constructed before 1990, as concluded earlier in source [11]. An additional step was aimed at describing the energy intensity within the building typology. Figure 3 illustrates the linear relationship between the age of buildings and the energy intensity. The figure indicates that the energy performance of buildings constructed before 1990 remains relatively poor. They contribute significantly to the stock-level energy use and their refurbishment should be of priority. The overall linear trend was further used for model validation, as elaborated in section 2.2.

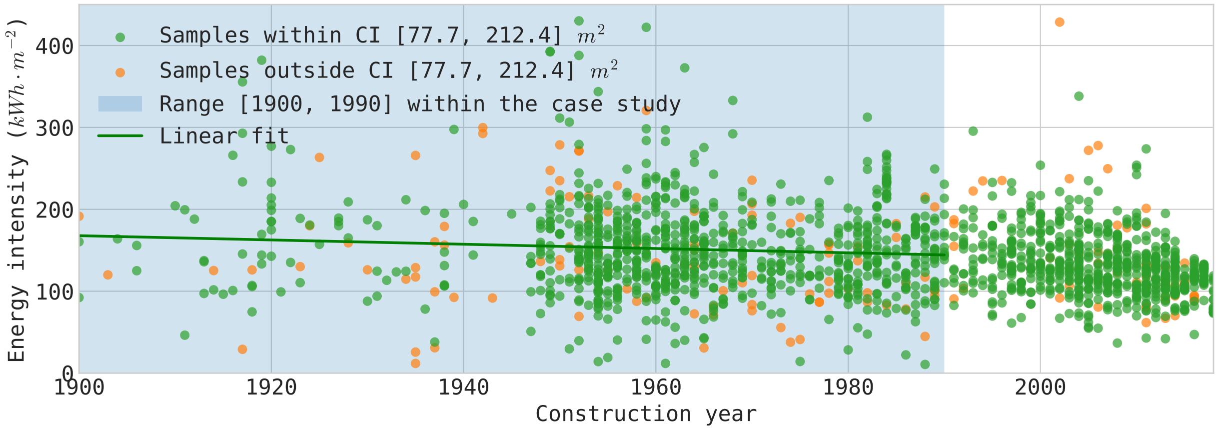

Figure 3. The relationship between building's age and energy intensity

2.2. Energy performance simulation

Based on the information from previous section, a selected representative building was two-storey, three-bedroom, single-family house built under the standards available before 1990. Heated floor area of the building modelled (122.2 m^2) close to the medium value for this typology (129.0 m^2 as specified in Figure 2). The unit was located at the end of a terraced building to represent the worst-case scenario. It was assumed that electricity is the only source of energy for space heating and domestic hot water (DHW) supply. A multi-zone model of the building was developed in IDA-ICE [12] with climate data for Bergen, Norway. Based on NS3031 [13], the heating system was designed for a desired temperature of 21/19 $°C$ in occupied/non-occupied hours during the coldest period of the year. The internal gains, electrical appliances, and DHW use were modelled in detail to take into consideration occupant behaviour as shown in [14].

The outputs of energy performance simulation for this (seed) model are load and energy use profiles on hourly basis over one year of operation. Simulated annual specific energy use was compared against standards (178 kWh/m^2 [15]), other source [16] and the EPC dataset (Figure 3) as a model calibration step.

A calibrated seed model was further extended with all unique combinations of four technologies: EV, PV, DHWS and SWH (Table 1).

Electric load profiles for EV defined based on the data for the most common commercial solutions [17]. Model inputs related to technical specifications for PV systems derived from manufacturers and distributors [18, 19]. A list of unique combinations of technologies in Table 1 accounted for the technical relationship between SWH system and the DHW tank - DHWT with the demand management mechanism is an independent component whereas SWH does requires DHWT for its operation.

The annual load and building energy use profiles were simulated for all the combinations of technologies listed in Table 1. Load profiles over the three coldest days are illustrated in Figure 4 for the simplest (seed) and the most complex models. As a convention, a reversed PV power profile displayed here. This subset of the load profiles, when the demand for space heating is highest, demonstrates the key differences between the models:

- PV power, if self-consumed, enables to decrease grid load substantially. The mismatch between PV generation and peak load, however, makes such benefit insignificant for grid stability;
- SWH system in combination with DHW tank are instrumental in reducing the total load

Table 1. Unique combinations of technologies

Index	EV	PV	DHWT	SWH	Comment
1					Seed model (none of the technologies accepted).
2	■				Battery capacity 22 kWh. 50% charging daily.
3		■			PV area 16 m^2. 4000 kWp installed capacity.
4			■		Volume 200 l. Heater capacity 2 kW.
5			■	■	Collector area 16 m^2. 200 l storage tank.
6	■	■			
7	■		■		
8		■	■		
9	■	■	■		
10	■		■	■	
11		■	■	■	
12	■	■	■	■	All technologies accepted.

during the peak periods. Their performance varies strongly in response weather conditions;

- EV may contribute substantially to the afternoon peak if no advanced charging control/scheduling used.

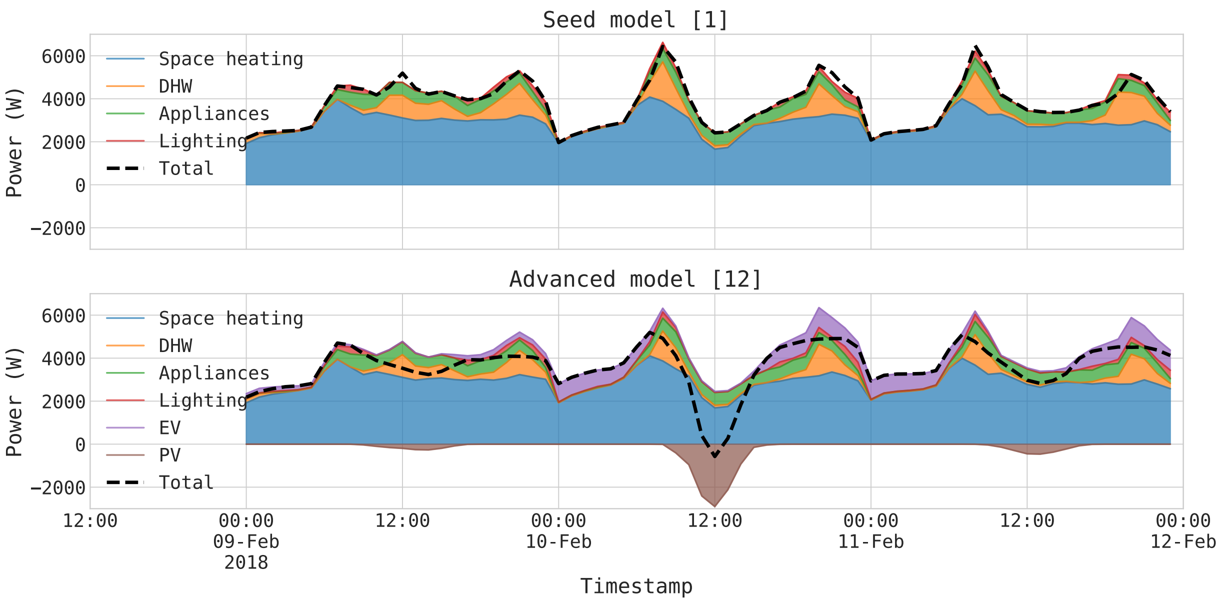

Figure 4. Load/feed-in profiles for model [1] (top) and [12] (bottom)

2.3. Stochastic model

This section is concerned with developing a stochastic model used to predict a stock-wide penetration level of novel technologies. The key concept is stochastic process of building's evolution. It defines the sequence and the time steps with which the technologies can be accepted in one building. The acceptance of any technology in a building is denoted by a discrete (binary) random variable X:

$$X = \begin{cases} 0, & \text{if technology is } \textbf{not accepted} \\ 1, & \text{if technology is } \textbf{accepted} \end{cases} \tag{1}$$

Variable X is characterised by the synthetic parameter - technological acceptance rate (TAR). TAR reflects the probability P with which any of the available technologies will be accepted $(X = 1)$ at the time step t, such that:

$$P\{X = 0\} + P\{X = 1\} = 1 \tag{2}$$

Under the absence of perfect knowledge, TAR is meant to encapsulate all kinds of judgments and influencing factors that drive the decision to accept any technology. Through social advertisement, economic incentives and other energy-related programs at the municipal or national scale, this parameter can be influenced.

Given that at some time step t, variable X yields an acceptance, the exact technology is drawn from a random, uniformly distributed variable denoted as U which is one realization of an exhaustive list of the available technologies $u = \{EV, PV, DHWT, SWH\}$. Thus, when the first acceptance occurs:

$$P\{U = EV\} = P\{U = PV\} = P\{U = DHWT\} = P\{U = SWH\} = \frac{1}{4} \tag{3}$$

A general form of Equation 3 for the acceptance n is:

$$\forall n \in [1,\ 4], \quad \forall U \in u \qquad P\{U = u\} = \frac{1}{5 - n} \tag{4}$$

The overall process resembles a random walk over the discrete filed with inconsistent time step. Figure 5 illustrates one sample path with TAR $= 0.07$ as a network graph. Current state of the building always corresponds to the seed model. The final state, however, depends on if/how many acceptances occurred and which technologies were drawn, but always has a reference model in Table 1.

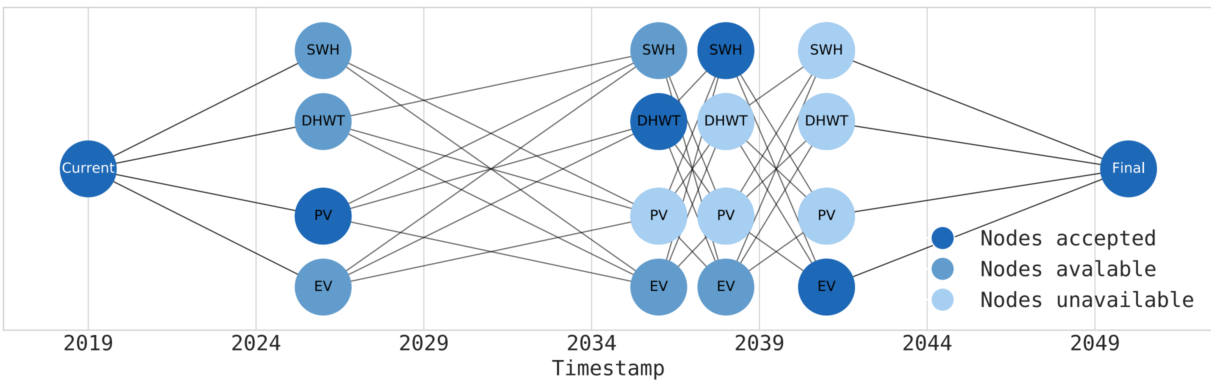

Figure 5. Sample path - acceptance of technologies in the building

Such simulations were carried out for each out of 1000 individual buildings within the synthetic built stock. Its final state can be presented as a bar chart in Figure 6, illustrating a number of times when each unique combination of technologies can be observed in 2050 under TAR $= 0.07$. The results in Figure 6 represent one possible outcome (trial) of the built stock evolution. To address the objectives of the study, 1000 trials were simulated, where TAR takes

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a random value from continuous normal (Gaussian) PDF with mean value $\mu = 0.05$ and the standard deviation $\sigma = 0.015$.

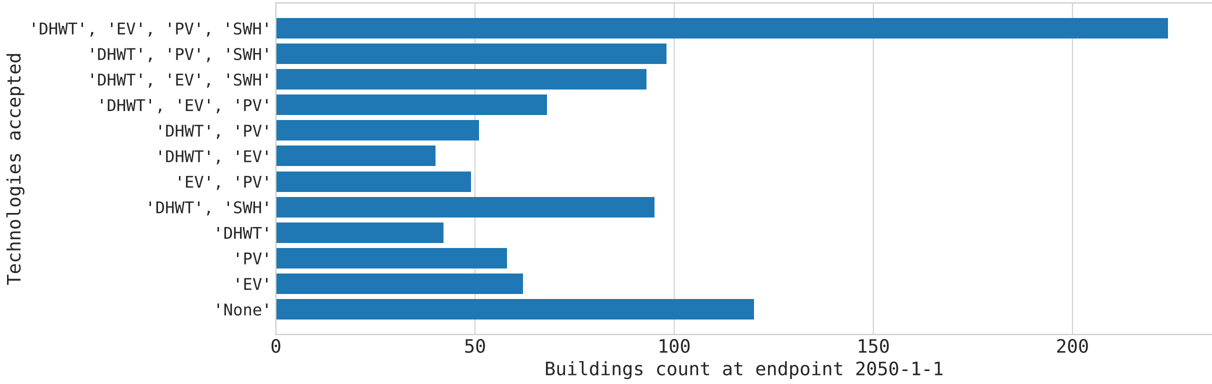

Figure 6. Number of buildings per combination of technologies accepted

Given that simulated final states of built stock are available, the corresponding data on grid interaction from the reference models and the energy price can be aggregated to the stock level.

2.4. Energy price calculation methods
Currently in Norway, the electricity bill for residential building owners consists of two elements: energy and electricity grid fee. Further, the electricity grid fee consists of energy part and a constant part. This constant part should reflect the power demand of a user, but in the current grid fee model it is not considered. Finally, this means that the electricity grid fee is not reflecting the real electricity grid cost caused by the power demand of residential buildings.

In this study, the energy cost was based on the Nord Pool hourly data for 2017. The energy cost was calculated by using hourly electricity demand and the hourly electricity cost from the Nord Pool market. The grid fee part may be defined in different ways depending on the model. In this study, the six models were analysed: 1) the current spot price model, 2) the current period model, 3) the maximum measured power model with the constant coefficients over the year, 4) the maximum measured power model with the variable coefficients over the year, 5) the subscribed power model with 4 kW subscribed power, and 6) the time of use model. The specific values for each of these models were provided from Haugaland Kraft. In the case of the electricity export, the feed-in tariff, when the building installed PV, a possible income for the building was calculated. This income was calculated in the same way as the grid fee cost for each model, except that each element was weighted 80% and 25% was taken for the taxation. An incentive to motivate building owners to install PVs would be to decrease the taxation, but this was not analysed in this study. For each of the scenarios in Table 1, monthly and annual electricity cost for each of the six pricing models were calculated. Due to effectiveness of the paper, the pricing models are not introduced in detail mathematically. Currently, in Norway there are some suggestions for the feed-in tariff, but it is not yet widely used. The values used in this paper were discussed with the company Haugaland Kraft.

3. Results
Given the simulation procedures and assessment methods discussed above, the results represent the likely levels of penetration of technologies under the study. The associated grid interaction and the prices for energy are elaborated here.

3.1. Aggregated grid interaction

In Figure 7 illustrates 1000 load duration curves aggregated to the synthetic stock level. Each curve reflects an evolved unique stock, composed of buildings with various combination of technologies (Table 1) in 2050. For comparative purposes, aggregated duration curve from seed model is displayed also.

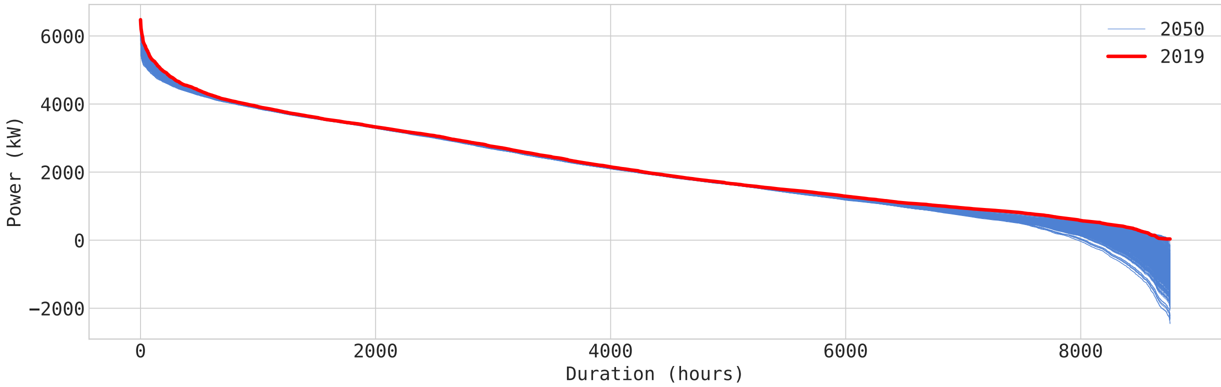

Figure 7. Aggregated load duration curves

It can be observed that the middle part of the curves remains unchanged. Substantial changes, however, are expected in peak loads and at grid feed in. Peak load observed on the annual basis is expected to decrease between 1% and 13%. The running time with low loads will change, which can be attributed to higher levels of self-sufficiency. The figure indicates that under this case study, extra peak power generation will not be necessary since additional load caused by the the EVs will be compensated by PV and SWH systems. Penetration of PV systems would yield significant levels of peak grid feed-in which can reach up to 40% of peak load.

3.2. Cumulative electricity cost

Cumulative annual cost for electricity, according to six pricing methods discussed in Section 2.4 and under various TAR, are illustrated in Figure 8.

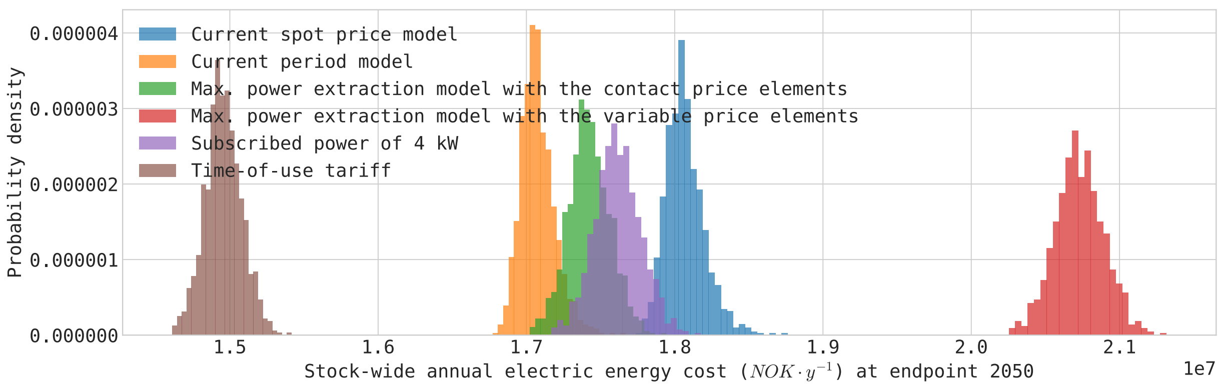

Figure 8. Aggregated electric energy costs per pricing model

It is evident from the Figure 8, that time-of-use tariff and variable maximum power extraction models refer to the lowest and the highest electric energy price under any acceptance of novel technologies. Overlapping variance makes it more challenging to establish preferences between the other four models. Thus, under high TAR (left part of each histogram), cost for energy with the spot price model will be lower compared to subscribed power (or contract maximum power) model with low acceptance of novel technologies.

4. Discussion

A methodological procedure, proposed in this study, accounts detailed information at the building level and random causality behind the acceptance of novel technologies. Modelling principles (and the results) are not idealised by deterministic scenario modelling, but benefit from probabilistic approaches instead. The likely developments of grid interaction and energy price are evaluated, providing the necessary background for informed energy planning.

As elaborated in Section 2.1, a dynamic stochastic process relies strongly on synthetic TAR. More detailed analysis of consumers' willingness to deploy [20] each particular technology, their economic, environmental and social motives, is needed to produce more accurate results.

The dataset and the pricing methods used to assess the stock-wide cost for energy are limited by those currently available. The results are sensitive to any future changes in e.g. taxation mechanisms, incentives for energy efficiency measures and/or low energy use. With methodological and instrumental toolset used in this study, the feasibility of such strategic initiatives can be assessed.

5. Conclusions

Meeting future strategic energy- and environment-related plans for cities and communities requires a consideration of structural changes in the built environment. These changes are, to the large extent, shaped by the penetration of novel technologies, particularly in the residential buildings. This study evaluated two key aspects of such changes in the future grid stability and cost for energy. The scope covered EV, PV, DHWT, and SWH systems deployment. These objectives were achieved through a comprehensive methodological approach that involves descriptive statistical analysis, building energy performance simulation with model calibration step and stochastic forecasting of built stock evolution. It is exemplified with one residential building typology in Norway. The results suggested that for the given case study, additional power demand is not likely to occur, regardless of increased use of EVs. PV feed-in, however, would reach substantial levels (up to 40% of peak load), depending on the penetration rates for the PV systems. Considering different pricing methods, those based on the pricing of power extraction would cover better electricity grid cost, while they would result in highest electricity cost for the building users. The limitations of the study are associated with narrow scope and data scarcity. However, it was shown that the methodology is applicable for the analysis of future developments of built stock and answering the given research questions. Large scale energy planning and policy making, therefore, may benefit from the approaches and methods provided in study.

Acknowledgments

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