Applied Energy 367 (2024) 123404

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A complex mixed-methods data-driven energy-centric evaluation of net-positive households

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ARTICLE INFO

MSC:
0000
1111

Keywords:
Energy efficiency
Net-positive
Mixed-methods methodology
Demand flexibility

ABSTRACT

Following the Paris agreement, different policy incentives aiming at the reduction of carbon emissions have been introduced worldwide. Dwellings that benefit from increased renewables penetration, aiming at achieving net-zero and even net-positive energy balance, are being designed and deployed in different countries. This article presents a design mixed-methods approach, based on collected quantitative and qualitative data, to answer the “what”, “why” and “how” of energy prosumption in net-positive dwellings. We demonstrate the strong influence of domestic routines and dynamic energy import and export pricing on explaining energy-centric deviation from net-positive design ambitions. Findings from net-positive neighbourhood households, equipped with geothermal heating, solar generation and electric vehicles, in Norway further provide actionable insights on demand-side reduction and flexibility in energy consumption and how to achieve true energy net-positive balance. Specifically, our analysis demonstrates a significant gap between actual energy bills and user expectations, and potential energy cost reduction up to 10% on a per-activity basis through demand side flexibility in relation to dynamic tariffs as well as a maximum observed bill reduction of up to 50% compared to the baseline scenario for households not adapting their activities inline with dynamic tariffs.

1. Introduction

As many countries worldwide commit to net-zero goals, different approaches are being implemented to reduce carbon emissions, including the introduction of greener means of transportation such as electric vehicles (EVs), switching to renewable energy sources (RES) and the establishment of carbon-neutral communities. Smart districts and local energy communities deploy housing that attempt to accommodate residents’ needs while minimising the carbon footprint of living spaces. Besides good thermal insulation in the building design, energy-intensive routines of residents need to be considered when estimating their carbon footprint. Net-zero and even net-positive—i.e., the total energy production exceeds total energy demand annually—neighbourhoods that benefit from increased penetration of RES at the end-user level, together with digital smart home technologies (SHT) that can help implement energy conservation practices [1], are being implemented in different parts of Europe and UK. In this paper, we focus not on the design of net-positive residential communities but rather on the energy-centric evaluation of how truly net-positive a building is when considering the energy practices of its residents and how these are affected by SHTs, low carbon technologies and a dynamic electricity pricing system.

A range of energy efficiency solutions and policy incentives, tailored towards energy conservation and mitigating the effects of climate change and reducing the economic cost to end-users, have been intensified following the Paris agreement in response to the ever increasing emissions of greenhouse gases (GHGs) in combination with the turmoil in the energy markets. The impact of these solutions in the European Union (EU) can be seen in the report of the International Energy Agency (IEA) [2] where an annual decrease of 3.5%, equivalent to 94.9 teraWatt hours, of energy consumption in the EU was observed in 2022, leading to a reduction of 202 megatonnes of carbon emissions, compared to the global average increase of 1.9% in total energy consumption equivalent to 168 megatonnes of carbon emissions. In addition to the introduction of energy-efficient appliances and incentives, according to the 2023 Consumer Conditions Scoreboard published by the European Commission [3], 72% of respondents believe that they need to personally do more to tackle climate change and 57% are consider their environmental impact when purchasing goods and services.

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https://doi.org/10.1016/j.apenergy.2024.123404
Received 15 January 2024; Received in revised form 22 April 2024; Accepted 3 May 2024
Available online 11 May 2024

List of Abbreviations

ADAM	Adaptive moment estimation
CM	Coffee machine
DHW	Domestic hot water
DW	Dishwasher
EU	European Union
EV	Electric vehicle
FRD	Fridge
FRZ	Freezer
GAN	Generator gradient weight
GDPR	General data protection regulation
GHG	Greenhouse gases
HB	Electric hob
HT	Heating appliance
IEA	International Energy Agency
IHD	In-home displays
KET	Kettle
ML	Machine learning
MW	Microwave
NOK	Norsk Krone
OV	Electric oven
PED	Positive energy districts
PHEV	Plug-in hybrid electric vehicle
PV	Photovoltaic
REF	Fridge-freezer
RES	Renewable energy sources
SGD	Stochastic gradient descent
SHT	Smart home technologies
TD	Tumble dryer
WD	Washer-dryer
WM	Washing machine

Nomenclature

α	The plane incident angle
α_p	The solar panel azimuth
α_s	The solar azimuth
α_t	The solar panel tilt
$\bar{p}_{high}$	The average electricity price during the exporting period
$\bar{p}_{low}$	The average electricity price during the lower tariff hours
a	The surface albedo
a_i	The state of the i–th appliance
B	The total energy bill
$b(t)$	The energy import price vector per kWh
c	The grid supply compensation
$C(t)$	The energy cost vector
E_i	The energy vector of the i–th appliance
$E_{bal}(t)$	The energy balance vector
$E_c(t)$	The energy consumption vector
$E_p(t)$	The energy production vector
$E_{shifted}$	The energy that is not self-consumed but exported to the grid during higher energy price periods and later re-imported during lower energy price periods
g	The grid fees
G_{arb}	The partial average arbitrage gain
h	The angular elevation of the solar disc above the horizontal plane
$I_{dif,h}$	The global diffuse irradiance
$I_{dif,p}$	The diffuse plane irradiance
$I_{dir,h}$	The global direct irradiance
$I_{dir,p}$	The direct plane irradiance
l	The length of the smart meter data gap
n	The number of the appliances
$p(t)$	The energy price vector per kWh
QI	Quality Index
$s(t)$	The energy export price vector per kWh
$S_{expected}$	The total number of samples that are expected
$S_{missing}$	The total number of consecutive samples that are missing with a duration less than l
T	The total monitored period
VAT	The value added tax
$w(t)$	The energy import or export price vector

Furthermore, in the aforementioned report, it was shown that 71% of the EU population, including Norway and Iceland, changed their habits to save energy in line with the soaring energy prices, with Norway being one of the countries exceeding the average of the EU. A similar observation about the engagement of people in climate policy actions is echoed in [4], where it was concluded that although there was a rise in negative sentiment following popular policy events such as the Paris Agreement, positive sentiment was more prominent in social media.

The reduction of CO_2 emissions through the rapid electrification of future urban buildings has been highlighted as an area of paramount importance for future study in [5] and of equal importance to the decarbonisation of the power sector with net-zero and even net-positive buildings being introduced throughout Europe. However, although these houses are designed to reduce energy usage and carbon emissions, the actual energy consumption of the households is often higher than designed. The increased demand for energy services, such as high indoor temperature, is the direct result of energy efficiency measures, such as better insulation. Consequently, people can afford to have higher temperatures due to the efficiency of their living spaces or because they become less attentive to savings because they are aware that their household is more efficient. In some more rare cases, the increase in energy demand can also be said to relate to users' interaction with technology, such as the user interface and socio-technical mismatch effects. The first occurs when households replace their appliance with a smarter one and do not know how to use it, adjusting the device poorly and consuming more energy. The second occurs when the technologies work efficiently only when they are operated as designed; however, they do not fit with households' everyday lives. Indeed, the energy performance gap [6], between actual energy requirements of lived-in buildings compared to expected energy consumption—according to standards such as ISO 16343:2013 [7]—has been attributed to different factors, including unrealistic occupants' behavioural assumptions and unpredictable usage habits [8].

Therefore, it is imperative to understand and quantify the deviation between actual and predicted energy consumption and to explore energy efficiency approaches that take into account the practices and routines of the end user. Such approaches include more accurate predictions of expected energy consumption and lead to solutions that can help end-users reduce their energy bills and carbon footprint through flexibility in their routines. This can take the simple form of shifting flexible loads to maximise RES generation and decongest the grid at peak demand, which in turn reduces wholesale prices and dependency on non-renewable generators to meet demand. Flexible load shifting curtails the peak demand, avoiding the use of fossil fuels to supplement renewables; for example, climate change has forced UK emergency coal power plants to be used with hot [9] and cold [10] temperature, mostly led by the extravagance of using heating and cooling appliances even if the temperature is not extreme [11].

While the understanding and prediction of energy consumption in households has been the subject of numerous studies [12], these generally focus on qualitative [13] or quantitative [14] data analysis. In a review of different approaches for energy research design methods [15], the importance of bridging qualitative analysis—which can offer great detail and high explanation but with limited capabilities in scaling—with quantitative analysis—which can easily scale up but may lack in explanatory power—is highlighted. Following a critical review [16] of how building energy efficiency is affected by occupant behavioural patterns (considering occupational behaviour, energy efficiency, conservation, and consumption analysis), it was concluded that in most research, holistic approaches are not employed but tend to be focused on a singular area of interest such as ventilation and heating. Similarly, a review of over 200 articles, of which about 83.48% focused on quantitative data with predominant usage of basic statistical approaches on energy behaviour of households [17], highlighted the need for mixed-methods research on building energy consumption to provide insights not only on "what" is being consumed but also "how" and "why". These review articles make the case that energy-related mixed-methods approaches are needed but still in their infancy, with no specific framework in place to better analyse occupant lifestyles that can lead to better understanding of user profiles and routines, and hence improved energy efficiency recommendations.

Mixed-methods research, that is, combining quantitative and qualitative data collection and analysis in one study, was introduced as a means to reduce bias—as a result of only quantitative or qualitative research—and improve the robustness and depth of research findings by neutralising the weaknesses of each type of data [18], and can be categorised as: (i) exploratory sequential mixed-methods, where the research first focuses on the qualitative analysis and the quantitative data are used in order to provide more detailed explanations; (ii) explanatory sequential mixed-methods, where the research first focuses on the quantitative analysis and the qualitative research is used to provide more detailed explanations; (iii) convergent mixed-methods, where quantitative and qualitative data—that are collected approximately at the same time—are merged as a way to analyse a problem; (iv) complex designs with embedded core designs, where a primarily quantitative or qualitative design can be intersected with a secondary method, or a mixed-methods can be intersected within another methodology or within a theoretical framework. This paper adopts a complex mixed-methods approach to propose a framework to jointly understand the "what", "how" and "why" of energy consumption in net-positive dwellings. We briefly review mixed-methods approaches in the literature next and identify gaps that we address via our proposed framework.

A mixed-methods clustering approach for energy data using quantitative survey data—variables related to energy and socioeconomics—and qualitative codes associated with transcripts from interview data was proposed in [19], whereby a two-step process was followed. First, quantitative and qualitative data were clustered separately and secondly, links between the clusters were identified. Clear links were identified that can unlock findings that would not have been possible analysing only quantitative or qualitative data, such as households that exhibit the same energy consumption but have completely different socio-economic characteristics and different levels of awareness about clean energy. In [20], via case studies in Spain and in the Benelux, a mixed-methods design process was proposed integrating occupant behaviour and attitudes towards energy use and indoor conditions. Although quantitative parameters such as temperature, relative humidity, CO_2 levels, and parameters such as sound, light, and movement were used, actual energy consumption was not analysed. Based on the practices of the occupants, profiles were generated and compared with the average profiles used in simulations and energy regulations using an embedded design in order to explain and validate quantitative analysis through qualitative data. The importance of occupant comfort and "convenience and time" was highlighted as a major parameter that affects actual energy use in a household.

Different approaches have been proposed in providing activity load consumption and feedback to end users, with the majority of them jointly analysing qualitative smart meter/submetered data and qualitative socio-demographic data to produce more meaningful feedback through in-home displays or mobile apps. In [21], a mixed-methods convergence approach, using qualitative electrical energy measurements from sub-metering devices and smart meters together with demographic data, was proposed to quantify the energy intensity and temporal routines of occupant activities, leveraging on quantitative non-intrusive load monitoring research and qualitative practice theory research. In [22], different methodological approaches including analysis of large databases, surveys, qualitative interviews, indoor measurements and electricity readings, combined with surveys and qualitative interviews, showed that people's intentions are not mandated by the amount of energy they consume, but by the domestic activities they engage in, such as regulating indoor climate, cooking and laundry. An exploratory mixed-methods approach was implemented to understand energy consumption after in-home displays (IHD) installation in [23], with quantitative analysis performed first with the objective of quantifying the change in energy consumption before and after IHD installation. Qualitative analysis was then performed to understand the reasoning behind the reduced energy consumption identified through the energy data and, therefore, to explain why energy consumption was statistically significantly lower than before IHD introduction.

Though previous work reviewed above has demonstrated the value of mixed-methods approaches to reduce bias in findings of pure qualitative or quantitative research for understanding energy demand, there is still a gap in the literature from explaining energy consumption patterns in homes to using this understanding to improve energy efficiency measures. Indeed, most prior work reports occupant energy use patterns, occupant-building interactions, and uncovering relationships between behaviour and influencing factors, without relating to explain the "why" and "how". Therefore, in this paper, we hypothesise that mixed-methods analysis would provide the tools to explain from the "what" to the "how" and "why" of end-user energy consumption to directly inform energy efficiency initiatives. To this end, the main contribution of the paper is a complex mixed-methods methodology intersecting quantitative load disaggregation methods from granular smart meter data, quantitative cost reduction analysis from dynamic pricing profiles and qualitative analysis of interviews and questionnaire data from state-of-the-art net-positive/plus buildings. Specially, the methodology answers the following:

1. "what" is of the energy gap between energy consumption and RES production of plus-home living spaces and "why" this gap arises;
2. "what" is the deviation between actual energy consumption and net-positive energy balance and "how" this can be explained through the lens of household routines;
3. "what" is the deviation between actual and expected energy bills, "why" net-positive houses exposed to dynamic electricity pricing do not always have a zero bill, and "how" this can be explained through time of use tariffs in relation to their energy-intensive activities; and,
4. "what" are the insights gained on user-centric load shifting potential, "why" they are suited to the user based on their routines, and "how" load shifting is actionable when aligning with dynamic energy pricing, as a means to reduce CO_2 emissions.

The rest of the manuscript is organised as follows. In Section 2 the complex mixed-methods approach is explained, comprising quantitative and qualitative data collection process, the estimation of renewable energy production, the disaggregation of the activities and the exploitation of the energy price information. This is followed by Section 3

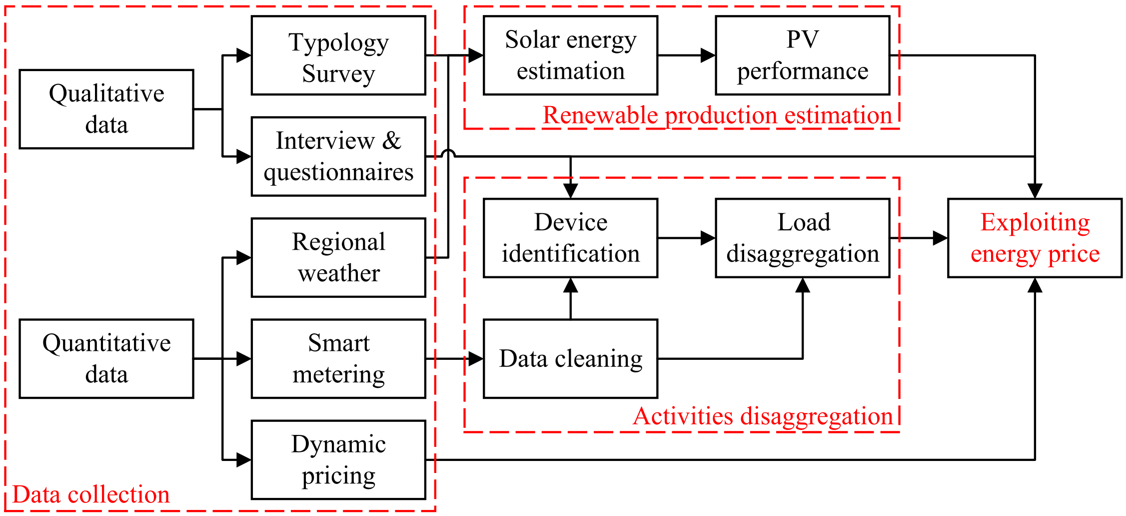


Fig. 1. Mixed-methods approach flowchart showing building blocks of the overall methodology adopted.

where the mixed-methods evaluation approach and the key findings are presented as per the above four questions. Lastly, in Section 4, the key conclusions including limitations of the study and future work directions are discussed.

2. Methodology

In order to quantify the energy gap between energy consumption and production in net-positive dwelling, explain the deviation through the lens of disaggregated activities and deviation between actual and expected energy bills, we follow the overall methodology of Fig. 1, where each of the blocks are described below.

2.1. Data collection

Quantitative and qualitative data were simultaneously collected from a pilot project within the framework of Positive Energy Districts (PED) in the region of Eastern Norway (Østlandet) that houses approximately 70 families. The buildings were built between 2018 and 2019 consisting of detached, semi-detached and flat-apartments targeted at middle-income families. The houses were designed to meet all their energy demands through electricity and in an environmentally friendly manner, meeting passive house standards, equipped with solar panels, ground source heat pumps for space heating and domestic hot water (DHW), and smart home technology, including a smart energy management system. In this smart district, in contrast to standard practice, the solar panel installer buys the energy surplus without deducting the network tax that is being paid to supply the grid with power. Thus, each homeowner has their consumption settled against their share of the production and, therefore, they are getting paid the actual amount of money that their panels produce. Further to that, all households have an EV or a plug-in hybrid vehicle (PHEV). Some households have a dedicated EV fast charger, while others rely on generic 3-pin chargers due to the additional costs of installing a dedicated chargepoint.

2.1.1. Qualitative & quantitative data

During April 2022, 9 in-depth, semi-structured, face-to-face interviews on energy practices assisted by smart home technologies were conducted with one or more householders—in one specific case including the presence of teenagers during the interview. The 9 households vary in terms of demographic characteristics—i.e., age, sex, educational background, and occupation. Interviews were recorded, transcribed and analysed through traditional coding and content analysis techniques [24]. As described in [25], which uses the same data as this paper to explore social practices with respect to energy use, the recruitment process was carried out through door-to-door canvassing, in which data saturation was swiftly achieved for three main reasons. First, semi-structure interviews enable the exploration of the same questions with all participants. Second, the homogeneity of the sample in terms of housing characteristics, appliances type, make and availability, access to smart technologies and EVs as well as prosumer scheme. Third, the qualitative and quantitative data triangulation strengthen the reliability and validity of the study. Adhering to the general data protection regulation (GDPR) guidelines, participants' consent declaration was obtained for interviews as well as for the aggregate readings from smart meters through their energy provider for a period of 2 months, stretching from mid-February to mid-April 2022.

The monitoring period was selected as it is during spring and spans almost evenly before and after the northward equinox, with daylight ranging from approximately 8 to 14 h for the whole monitoring period. As the district of Eastern Norway is located north from the Tropic of Cancer and in close proximity to the Arctic Circle, it exhibits very short days during the winter period—as low as 2 h per day—and on the other hand, extremely lengthy days during summer—exceeding 18 h.

It is challenging to assess net consumption and solar energy production only from a 2-month sample. However, in the monitoring period the solar irradiation and the temperature are neither extremely low, as would have been the case around the southern solstice, nor extremely high, as would have been the case around the northern solstice. As can be observed in Fig. 2 the monitored period spans in the linear area of optimal solar production, and the monitored period average deviates by approx. 5% of the yearly average. Further to that, the temperature during the two-month period varied between −8 °C and 19 °C with the yearly variation being between −15 °C and 30 °C and the average temperatures between −4 °C and 17 °C for the whole year. Therefore, the temperature range during the monitored period is close to the yearly average. Since heating and hot water demand are correlated with outdoor temperature, a monitoring period close to the yearly average, provides a realistic estimate of the yearly consumption. In addition, the monitored period contains both periods of normal working days and a week of school holidays—during February—which usually affects the energy consumption as people tend to travel during breaks. Therefore, the monitored period can be considered a representative sample both for production and consumption.

Three-phase power supply is installed in all households and therefore the smart metering data—sampled at 10-second intervals—contain information about the total active and reactive power as well as the voltage and the current consumption on a per-phase basis. In addition to these readings, an hourly sample of the aggregate active and reactive

Table 1
Summary of households.

ID	Type	Area	Floors	Rooms	PV [kWp]	Occupancy (age)
1	Detached	148 m^2	3	4	4.8	2 adults (>60) & 1 dog
3	Detached	193 m^2	3	4	6.4	2 adults (≈34) & 1 child
5	Semi-detached	90 m^2	2	2/3	14	2 adults (≈30) & 2 children
6	Detached	148 m^2	3	4	4.8	2 adults (>60) & 1 teenager
7	Semi-detached	90 m^2	2	2/3	14	2 adults (>38) & 2 teenagers
9	Semi-detached	131 m^2	2	3	9.6	2 adults (≈32) & 1 child

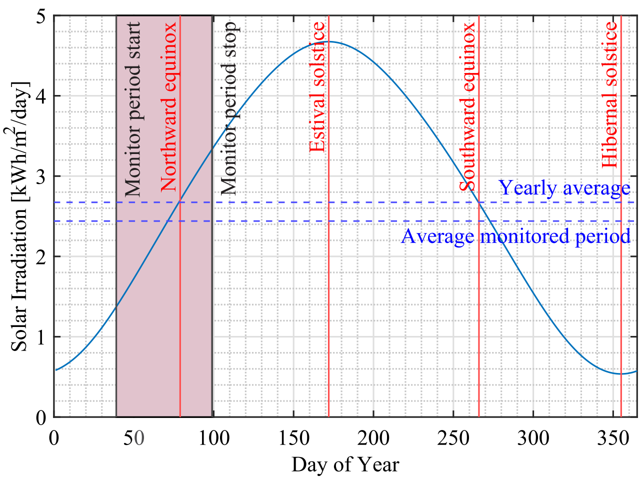


Fig. 2. Average maximum solar irradiation on the PV panels located on the roofs of the buildings of the neighbourhood under study, calculated as described in Section 2.2. Longitude and latitude considered are limited to satellite data granularity (0.5 × 0.5 km) with the coverage of the neighbourhood (0.130 × 0.325 km). PV panels are installed in a circular pattern with different tilt per house relative to the sun position.

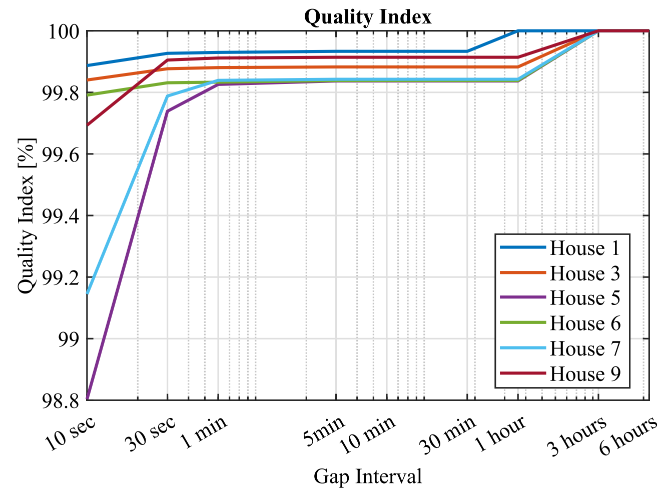


Fig. 3. Quality index of continuous smart meter data samples for each of the 6 households included in the study, highlighting gap intervals that needed to be filled before calculating energy consumption.

power was also provided for billing purposes. The hourly price vectors for the import and export of electricity were also provided by the energy provider. Due to technical issues, it was only possible to collect smart meter data from 6 households. A questionnaire on appliance time-of-use, based on [26], was supplied via email to two households, selected due to extreme cases of ratio of production to consumption. This detailed information on households' energy-consuming routines and habits in relation to appliances contributed to map hourly usage patterns and validate load disaggregation results on these households. The knowledge was then transferred to other households under study. A summary of the houses involved in the study is presented in Table 1. The description of the occupant profiles is based on the way that the homeowners self-identified during the aforementioned in-person interviews.

2.1.2. *Cleaning of smart meter readings*

Collected meter readings occasionally suffer from gaps, which need to be filled. To facilitate the interpolation process and estimate the quality of the data, a Quality Index was calculated based on the length of the gaps. The Quality Index (QI) is given by:

$$QI(l) = \frac{S_{expected} - S_{missing}(l)}{S_{expected}}, \tag{1}$$

where $S_{expected}$ are the total number of samples expected (10-sec samples for a period of 2 months, i.e., 509,400 samples) in the dataset and $S_{missing}$ are the total number of consecutive samples that are missing with a duration less than l, where l is the length of the gap. Fig. 3 represents the Quality Index (Eq. (1)) for the 6 households with smart metering data. For each household, the number of missing samples that exceeded a certain duration was calculated. This step is considered necessary as the quality of the activity disaggregation results are related with the quality of the submetered data. Gaps in the data that spanned less than 1 h were replicated using the nearest-neighbour interpolation method under the constraint that the total consumption during that hour should be equal to the difference between the two billing measurements, i.e., the total energy consumed during that hour. Gaps that spanned for more than one hour were filled based on average historical data, i.e., the average of the consumption on the same day of the previous weeks—using again the constraint that the total energy consumption per hour should be equal to the billing energy power.

2.2. *Estimation of renewable production per house*

As the solar production data was not available from the meter readings, an estimate of solar energy production was performed using weather data, as well as building-specific data. Global solar irradiance in that specific area, measured by [27] was collected every hour. Data were collected on an hourly basis as market clearance occurs once every hour. Based on the installed capacity of photovoltaics (PVs), as well as on the orientation and tilt of the solar panels installed on the rooftop—assuming a fixed azimuth and tilt angle—an hourly estimate of the energy produced through the PVs was calculated based on the widely used and cited Global Solar Energy Estimator (GSEE) simulation model of [28]. The direct plane irradiance is then given by (as in [28], Eq. (2)):

$$I_{dir,p} = \frac{I_{dir,h} \times cos(\alpha)}{cos\left(\pi/2 - \alpha_s\right)}, \tag{2}$$

where α is the plane incident angle given by (as in [28], Eq. (1)):

$$\alpha = arcocos\left[sin(h) \times cos(\alpha_t) + cos(h) \times sin(\alpha_t) + cos(\alpha_p - \alpha_s)\right], \tag{3}$$

and the diffuse plane irradiance by (as in [28], Eq. (3)):

$$I_{dif,p} = I_{dif,h} \times \frac{1 + cos(\alpha_t)}{2} + a \times \left(I_{dir,h} + I_{dif,h}\right) \times \frac{1 - cos(\alpha_t)}{2}, \tag{4}$$

with $I_{dir,h}$ and $I_{dif,h}$ being the global direct and diffuse irradiance respectively, a being the albedo, h being the angular elevation of the centre of the solar disc above the horizontal plane, α_p being the solar panel azimuth, α_t being the solar panel tilt and lastly α_s being the solar azimuth, i.e., the angle between the projection of Sun's centre onto the horizontal plane and due south direction. Lastly, based on the work in [28] and the PV performance model presented in [29] panel efficiency was calculated based on temperature-dependent parameters.

2.3. Disaggregation of activities from smart meter readings through transfer learning

Sub-metering devices used to measure energy consumption at the appliance level were not installed in the monitored households. Therefore, energy consumption on a per-appliance basis is estimated based on the total energy consumption and validated through soft labels from the qualitative data analysis—i.e., interviews and surveys—as well as through the quantitative data. For example, Sofie (house 9) discussed her vehicle's charging patterns:

> I guess it would usually probably be around late afternoon evening is when we would be charging it. When we are going out for the day. (Sofie, 32-years old, house 9)

a fact that was cross-validated from the questionnaire and the actual load data. Different machine learning (ML) models have been shown to perform well for the load disaggregation problem [30]. A sequence-to-subsequence model [31,32] and a WaveNet model [33] were shown to effectively perform load disaggregation task by transfer learning from publicly available datasets, and are used for disaggregation of appliances of the households under study.

As the aforementioned models are based on supervised learning, training data are required to develop the models. Therefore, publicly available data sets were used to train load disaggregation models. Based on the interview data and questionnaires, the installed appliances were identified and the most adequate datasets, which contain similar appliances, were selected. More specifically, ECO [34], REFIT [35] and PECAN [36] datasets as well as the EV consumption dataset in [37] were used. ECO dataset contains three-phase residential smart meter data as well as sub-metering of 6 households for a period of 6 months with a sampling frequency of 1 Hz. The ECO dataset was considered adequate, as it contains similar installations—i.e., three-phased ones—and similar appliances to the ones targeted in our research. A summary of data availability in the ECO dataset is presented in [32]. The REFIT dataset [38] contains smart meter data as well as sub-metering of 20 households for a period of 21 months with a sampling frequency of 1/8 Hz. As with the ECO dataset, the REFIT dataset was considered adequate as it contained a variety of different households with several different appliances that were similar to the ones targeted. PECAN dataset includes EV loads from several households in Texas and New York area with a sampling rate of 1 Hz. Finally, the dataset in [37] contains data from one year of a household in Germany where a high-power EV charger—i.e. 11kW—is installed with a sampling rate of 1/60 Hz, which coincides with the presence of similar EV chargepoints in the smart neighbourhood that is being studied.

Publicly available datasets were re-sampled at the same sampling rate as collected data. As the targeted households had a sampling rate of 1/10 Hz, the other datasets used were down-sampled or up-sampled to the same rate. As ECO [34] and PECAN [36] were sampled in 1-second intervals, downsampling was performed by aggregating the energy consumed during each 10-second period. REFIT [38] dataset, which had a sampling rate of 1/8 Hz, could not be directly resampled as the data are required to be down-sampled by a non-integer. Therefore, data were resampled at the new lower rate by interpolating the values. Finally, the EV dataset in [37], which has a sampling rate of 1/60 Hz, was up-sampled by assuming the same power level throughout the 60-sec period.

As EV charging events are generally characterised by relatively high power and long duration, they can be more easily disaggregated compared to low-power and complex loads. The sequence-to-subsequence model, which benefits from higher convergence speed when compared to sequence-to-sequence models—due to the fact that it targets the middle of a time-series—as well as from lower computational costs compared to a sequence-to-point model—was used to disaggregate the EV load. Based on the work in [31], the parameters of the network were selected as follows: (i) window size: 512 samples; (ii) loss: L1; (iii) discriminator filter optimiser: Stochastic gradient descent (SGD); (iv) generator filter optimiser: ADAM; (v) initial learning rate (SGD) 0.001; (vi) initial learning rate (ADAM): 0.0005; (vii) ADAM momentum term: 0.5; (viii) generator gradient weight (L1): 100; (ix) generator gradient weight (GAN): 1; (x) number of layers: 7; (xi) discriminator filters (1st layer): 32; (xii) generator filters (1st layer): 32 and (xiii) epochs: 120.

Based on the interview data, households were split into two categories, the ones that had a high power EV charger—i.e., a dedicated charger with a nominal power of 11kW—and the others that used a portable EV charger (3 kW) that plugs into a standard residential socket (esp. for PHEV). More specifically, regarding their charging routines, Brian (house 1) stated that a dedicated charger capable of being programmed is installed in his household:

> Yes! I have programmed my charger to start at 1 o'clock at night because it's when the energy is cheaper. So, I always charge my car at night. (Brian, 61-years old, house 1)

On the other hand, Sofie (house 9) stated that they have a PHEV:

> We have plugin hybrid [...][1] 50 Kilometres. Mm-hmm. And then after that it goes on to gas. But we do not really use gas that much cause we do not go very far. (Sofie, 32-years old, house 9)

with a standard 3-pin socket system installed in their property due to the cost of getting a dedicated charger:

> I was looking into that one. The prices were starting to get expensive, then they became expensive all the time instead... (Sofie, 32-years old, house 9)

Two different models were used for these two groups. The same procedure as in [31] was followed for the training of the models. The model used for the disaggregation of high-power EV charger loads was trained on the household from [37] as it showed a similar load profile. On the other hand, the disaggregation of the rest of the EVs was based on a model trained on a selection of households from the PECAN dataset [36] that exhibited a similar low-power charging level, i.e., houses 661, 1642, 4373, 6139, 8156 from Austin and house 27 from New York.

As the rest of the household appliances exhibit a more complex signal, a WaveNet network was used to estimate their load. The training data set consisted of a mixture of different households from the REFIT [38] and ECO [34] data sets that contained the same appliances. The targeted appliances were the most commonly used high consumers—as identified through the questionnaire: (i) heating appliances (HT); (ii) washing machines (WM); (iii) tumble-dryers (TD); (iv) washer-dryers (WD); (v) dishwashers (DW); (vi) electric hobs (HB); (vii) electric ovens (OV); (viii) coffee machines (CM); (ix) kettles (KET); (x) microwaves (MW); (xi) fridge (FRD); (xii) freezers (FRZ) and (xiii)

[1] Note that [...] is the ellipsis symbol that denotes an intentional omission of a word, sentence, or whole section from a quotation from interview data without altering its original meaning.

fridge-freezers (REF). More specifically, from the REFIT dataset the following houses were used for training the models: house 1 (WM, TD, DW, HET), house 6 (FRZ, MW, KET, WM, DW), house 8 (FRD, FRZ, KET, WM, DW), house 9 (MW, KET, WM, WD, DW, HET), house 16 (HET) and house 18 (FRD, FRZ, REF, MW, WM, WD, DW). From the ECO dataset the following houses were used: house 1 (CM, TD, REF, FRZ, KET, WM), house 2 (DW, REF, FRZ, KET, HB, OV), house 3 (CM, REF, FRZ, KET), house 4 (MW), house 5 (CM, KET, MW) and house 6 (CM, KET).

Based on the interviews collected in households, as well as the appliance availability and time-of-use survey, the appliances were grouped into different routines, taking into account different activation times. Energy-intensive activities were taken into account and grouped into the following categories: breakfast, lunch, dinner, laundry, cleaning, heating, refrigeration, and vehicle charging. Breakfast, lunch, and dinner were further grouped into the cooking practices activity, and laundry and cleaning were also grouped into a single category.

The identified routines, with the corresponding time windows and appliances were: (i) EV charging (EV): all-day; (ii) heating (HT): all-day; (iii) refrigeration (FRD, FRZ, REF): all-day; (iv) laundry/cleaning (WM, TD, WD, DW): all-day; (v) breakfast (KET, CM): 05:00–10:00; (vi) lunch (HB, OV, MW): 10:00–15:00 and (vii) dinner (HB, OV, MW): 15:00–21:00. Appliances that can be used during different activities were grouped based on time-of-use. The amount of energy consumed in a household that was not a result of the aforementioned appliances/activities is considered as a non-disaggregated load and presented as a separate activity, namely “Other”. Through the combination of quantitative data analysis and the interviews energy consumption on a per-activity basis was further explained. For example, heating practices of the homeowners were explored, with Brian (house 1), compared to Sofie & Arthur (house 9), discussed his high thermal comfort expectations:

> In these rooms, the daily living rooms we prefer to have it around 22/23 degrees, ah, in the winter (emphasis), and in the bathroom we prefer around 24/25 (Brian, 61-year-old, house 1).

During the activity-level disaggregation process, electrical heating load was observed only at some households, as others were able to cover all of their heating needs through the ground source heat-pump system. The methodology was validated through the soft labels on houses 1 and 9, and rolled out across all other houses in the study. As time-of-use surveys were not available for houses 3, 5, 6 & 7, validation of the disaggregated loads was performed through manual inspection of the electricity load profiles by an energy expert.

2.4. Exploiting energy price information

In Norway, the energy market is cleared on an hourly basis. The hourly balance of import minus export is calculated, and then the customer is either debited or credited the equivalent amount. The hourly energy price per kWh—import and export—is communicated to the customer one day in advance. The import cost of energy per kWh—denoted as $b(t)$ [NOK/kWh]—is the sum of the price per kWh—denoted as $p(t)$ [NOK/kWh], the Value Added Tax (VAT)—denoted as VAT and currently 25%—, and the grid fees—denoted as g [NOK/kWh]—which were approx. 0.4 NOK/kWh for the monitored period. Therefore, the hourly import cost in [kWh] is given by:

$$b(t) = p(t) \times (1 + VAT) + g. \tag{5}$$

On the other hand, the export gain per kWh—denoted by $s(t)$ [NOK/kWh]—is the sum of the price per kWh,[2] (without the addition of VAT) plus a small compensation for supplying the grid—denoted as c [NOK/kWh]—which is approx. 0.1 NOK/kWh. Therefore, the hourly export gain per kWh is given by:

$$s(t) = p(t) + c. \tag{6}$$

The energy balance, i.e., the energy exported subtracted from the energy imported per time slot and denoted as $E_{bal}(t)$ can be expressed as:

$$E_{bal}(t) = E_c(t) - E_p(t), \tag{7}$$

with $E_c(t)$ and $E_p(t)$ being the energy consumed from the appliances and the energy produced (from the solar panels) at time t, respectively. $E_p(t)$ was estimated through the solar insolation data and the installed capacity as described in Section 2.2 through the methodology provided in [28]. The appliances energy consumption, $E_c(t)$, can be expressed as:

$$E_c(t) = \sum_{i=1}^{n} a_i(t) \times E_i \tag{8}$$

where a_i is the state of the i–th appliance out of a total of n appliances and E_i is the energy vector of the i–th appliance. Therefore the energy cost per time-slot can be expressed as:

$$C(t) = E_{bal}(t) \times w(t) \tag{9}$$

where $w(t)$ is set to $b(t)$ or $s(t)$ if energy is imported or exported, respectively. By combining the above equations the energy cost per time-slot can be written as:

$$C(t) = \begin{cases} \left(\sum_{i=1}^{n} a_i(t) \times E_i - E_p(t) \right) \times (p(t) \times (1 + VAT) + g) & E_{bal}(t) \geq 0 \\ \left(\sum_{i=1}^{n} a_i(t) \times E_i - E_p(t) \right) \times (p(t) + c) & E_{bal}(t) < 0 \end{cases} \tag{10}$$

and the total energy bill as:

$$B = \sum_{t=1}^{T} C(t) \tag{11}$$

where T is the total monitoring period.

The financial gain obtained through load shifting is capped by the maximum amount of flexibility that each user is willing to accept on a per-activity basis. Therefore, the maximum financial gain will be obtained when B is minimum, under the constraints that a continuous event cannot be split, i.e., an appliance activation cannot be intermitted and split into sub-activations, that certain appliance activation are bounded by the activation of another appliance, i.e., certain appliances' loads are dependent on previous appliances loads—e.g., the tumble dryer and the washing machine—and that activation constraints are imposed by the requirements of the end-users.

As inferred from the empirical study and validated through the smart meter data, several users selected to export their solar energy (instead of self-consuming) during the solar production hours as the energy price was higher and then import energy from the grid during cheaper energy hours. The partial average arbitrage gain through this strategy can be obtained by combining Eq. (5) & (6) and can be expressed for each household as:

$$G_{arb} = E_{shifted} \times \left(\overline{p}_{high} \times (1 + VAT) - \overline{p}_{low} + g - c \right), \tag{12}$$

where $E_{shifted}$ is the amount of energy that is not self-consumed but exported to the grid during higher energy price periods and later re-imported during lower energy price periods, $\overline{p}_{high}$ is the average electricity price during the exporting period and $\overline{p}_{low}$ is the average electricity price during the lower tariff hours.

[2] In Norway, during the monitoring period, as already mentioned in Section 2.1 the energy produced is sold at the same price as the energy imported from the grid (without including VAT).

3. Mixed-methods evaluation approach and key findings

Energy plus-home neighbourhoods are expected to exhibit an energy net-positive balance, i.e., the total energy produced should exceed the total energy consumed. Following the qualitative methodology (empirical study) of the households in this study, it was concluded that those who moved into this energy-plus neighbourhood had expectations of close to zero/negative energy bills. However, after about two years of living in their new homes, the residents agreed during a community meeting with the real estate and energy supply companies that their energy bills were much higher than they had anticipated. Therefore, initial enthusiasm from being able to reduce the bills and achieve net-positive energy balance was replaced with anger and disappointment in the new builds. This motivated our study to determine a systematic methodology for evaluating net-positive and net-zero buildings in terms of energy consumption taking into account occupant behaviour such that they are meaningful to the building occupants and therefore actionable through flexibilities in their domestic routines. We demonstrate our methodology through a case study on a net-positive community in Norway from six participating households, summarised in Table 1, all equipped with a smart meter.

3.1. Explaining the energy gap between energy consumption and production in net-positive dwellings

We first determine the ratio of estimated solar PV energy production (see Section 2.2) to measured energy consumption from smart meter data. A ratio of total production to total consumption greater than 1 indicates true net-positive and the smaller than 1 ratio indicates higher consumption with respect to production. This is shown for our case study, monitored over a period of two months, in the third row of Table 2. Only house 9 is net-positive, followed closely by houses 5 and 7 with a close to 1 ratio.

This can be visualised in Fig. 4, which shows the total energy consumption and production of each household. As can be observed in Table 2 and Fig. 4, houses 5, 7 and 9 have a ratio close to 1, with energy consumption almost matching production. However, houses 1, 3 and 6 have over twice more consumption than production with ratios much less than 0.5 with houses 1 and 6 consuming approximately five times the energy produced. Houses 1, 3 and 6 are completely detached houses, with larger living areas and comparably less production capacity—less space for solar panels (see Table 1) on the rooftop due to a roof patio. On the other hand, houses 5 and 7 are semi-detached/terraced houses with smaller living area and thus lower energy consumption, which is almost compensated by the higher PV production capacity—larger number of solar panels installed on the rooftops (see Table 1). Therefore, the actual topology of a building and the limitations that this may introduce in terms of installation capacity of renewables, greatly affect the net-balance of future home livings spaces and need to be taken into consideration at design stage. However, in order to do so, it is important to accurately quantify the consumption needs of the inhabitants of these dwelling, which can only be done through the lens of household routines and activities, as discussed next.

3.2. Explaining the deviation through the lens of disaggregated activities

As shown in [21], understanding households consumption through the lens of occupant activities or daily routines offers better actionable insights than aggregate-level smart meter consumption. Following the proposed quantitative methodology of load disaggregation together with qualitative empirical research described in Section 2.3 for the same two-month period, the actual consumption of essential energy-intensive routines of heating, cooking, laundry/cleaning, EV charging together with refrigeration consumption are determined and shown in the fourth to eighth rows of Table 2. We can explain over 50% of the consumption for all households in the study. From the empirical study, these "Other" loads can be attributed to smart devices that are running all day, including automation for ventilation/purification of the household, auto blinds and robot vacuums that are charging all day.

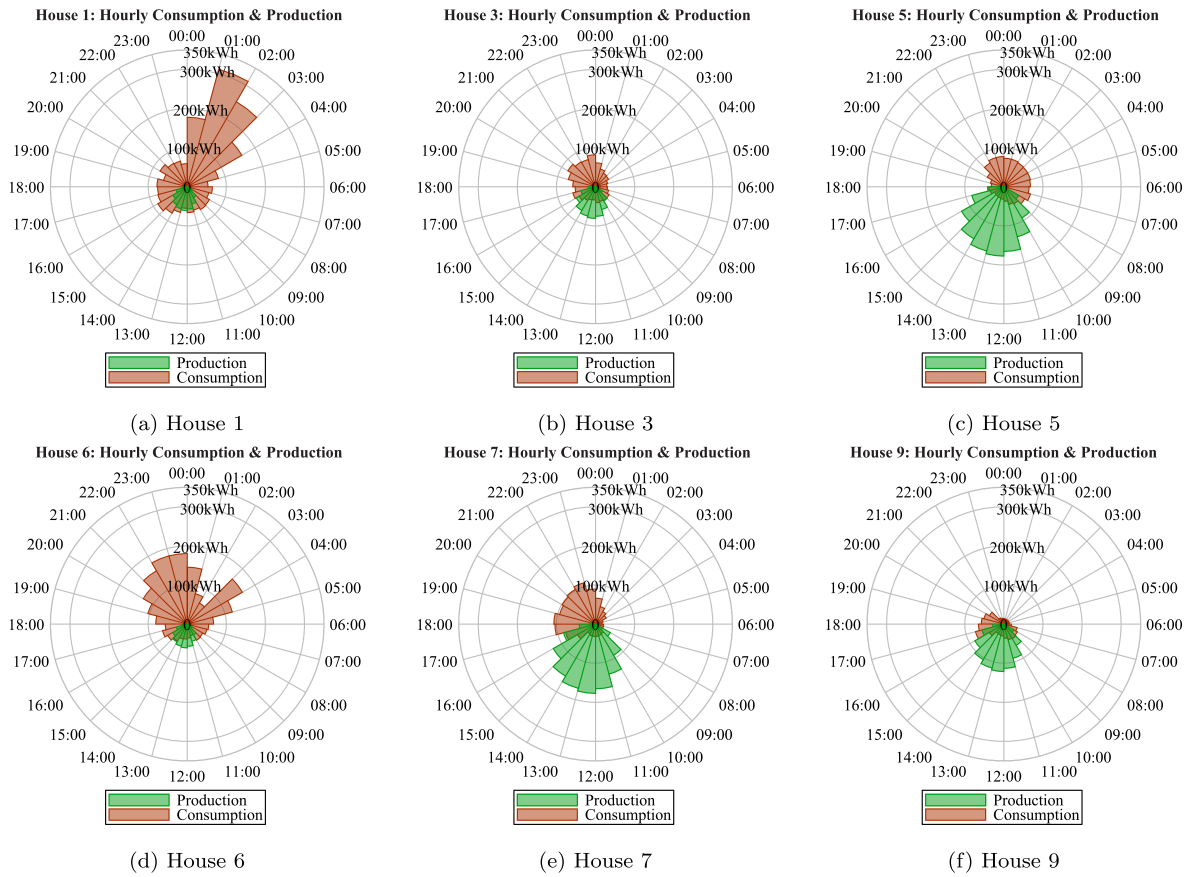
Heating energy consumption corresponds to the additional energy consumed for space heating when the ground source heat pumps cannot meet the demand. All detached households (houses 1, 3 and 6) and only one of the semi-detached households (house 7) do not meet their heating requirements solely through the ground source heat pumps but need additional energy to achieve their thermal comfort levels, a fact that can be attributed to the higher than expected heating expectations as highlighted by the empirical study. Cooking activities across all houses are responsible for the same percentage of the total bill (in the range of 3%–6%) whereas laundry and cleaning activities greatly vary across the participating households. From the empirical study and occupation as per Table 1, as expected, households with more occupants (house 7) and households with young children (houses 3 & 9) tend to consume more energy for their laundry/cleaning practices due to the increased demand laundry, tumble drying and dishwashing. An exception to this pattern is house 5, which although occupied by two adults and 2 children, has a lower laundry/cleaning consumption due to the reduced usage of the tumble dryer, concluded from load disaggregation methodology (see Section 2.3). EV charging greatly varied across the households due to the transportation requirements of the homeowners. As the data correspond to the post-COVID period, from interview data, households 3 & 9 mostly work from home and therefore their transportation needs are lower. On the other hand, households 1, 5, 6 & 7 commute on a daily basis, charging every single day, resulting in their EV charging consumption contributing to almost 60% of their total energy consumption. Lastly, refrigeration also varied across the different households, with detached houses 1, 3 and 6 having higher consumption than semi-detached houses 5, 7 and 9. Indeed, refrigeration of house 9 consumes 1.5 times more than that of house 1. All houses were already furnished with A-rated white goods when sold—semi-detached house 9 had a fridge-freezer whilst detached house 1 had two refrigerating appliances.

Finally, all essential cooking, laundry and refrigeration related loads for all houses are covered by solar PV production. As discussed previously, additional heating was not expected due to communal ground source heating provision and explains deviation from net-positive. Although EV charging provision in terms of infrastructure was planned, expected charging patterns and consumption are much lower than actual, especially for houses 1, 3 and 6, whose PV capacity can clearly not meet EV charging together with essential cooking, laundry and refrigeration. This has serious implications for electrification of transportation as residential charging is growing and planning net-positive dwelling must take this into account with better models informed from studies such as ours.

3.3. Explaining deviation between actual and expected energy bills

The estimated electricity balance for each household shown in Table 2 was calculated based on Eq. (11), taking into account the hourly energy consumption and production and the hourly pricing vector. A key observation from the last row in Table 2 is that, despite being close to or net-positive, houses 5, 7 and 9, do not have a zero bill, although production should be meeting consumption costs. We explain this deviation next through the energy pricing strategy in Norway, with similar approaches being followed by the majority of countries participating in the Nord Pool [39], where energy prices vary hourly and consumers/prosumers are directly exposed to the price variability for both energy import and export, with billing tied to the day-ahead market price.

As observed in Fig. 5(a), although the electricity price was relatively stable before the end of February 2022, from that point on the price exhibits high variability due to the turmoil in the energy market as



(a) House 1 (b) House 3 (c) House 5

(d) House 6 (e) House 7 (f) House 9

Fig. 4. Differing levels of hourly discrepancy between energy consumption and production, totalled over the monitoring period, for each of the 6 households.

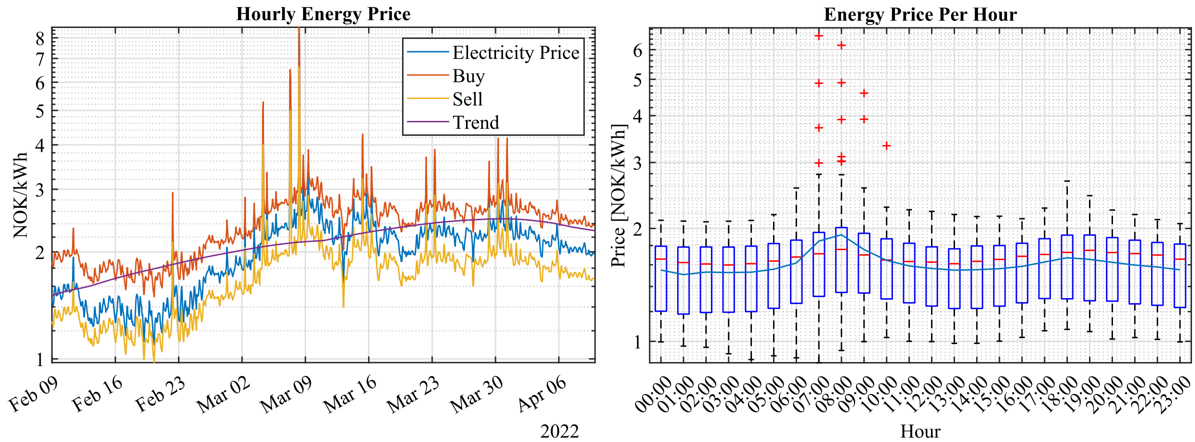
Table 2
Energy breakdown and estimated electricity cost balance.

	House 1	House 3	House 5	House 6	House 7	House 9
Consumption [kWh]	2276	1181	1289	2045	1300	762
Production [kWh]	414	552	1208	414	1209	826
Ratio	0.18	0.47	0.93	0.20	0.93	1.09
Heating [kWh]	630 (28%)	149 (13%)	0 (0%)	318 (16%)	134 (10%)	0 (0%)
Cooking [kWh]	90 (4%)	77 (6%)	46 (4%)	53 (3%)	64 (5%)	48 (6%)
Laun./Clean. [kWh]	74 (3%)	174 (15%)	81 (6%)	131 (6%)	178 (14%)	186 (24%)
EV [kWh]	718 (32%)	258 (22%)	799 (62%)	1061 (52%)	627 (48%)	95 (12%)
Refrigeration [kWh]	138 (6%)	159 (13%)	94 (7%)	144 (7%)	91 (7%)	92 (12%)
Other [kWh]	626 (27%)	364 (31%)	267 (21%)	338 (16%)	206 (16%)	341 (43%)
Bill (B) [NOK]	4429	1649	770	3951	785	185

a result of the embargo of Russian fuels in several parts of the world following Russian invasion of parts of Ukraine [2]. As can also be seen through the trend line in Fig. 5(a), the price of electricity appears to be increasing throughout March 2022, with a small decline during April due to better weather conditions, decreased energy demand, and stabilisation of the energy market. In Fig. 5(b) the high variance of hourly electricity prices can be observed (on logarithmic scale), especially during the peak morning hours. Outliers during the period from 07:00–09:00 reached 7 NOK/kWh an almost 4-fold increase from the average. Energy end-users were directly impacted by the hourly variance of the energy price vector, with our households under study commenting on their unexpectedly high energy bills.

> [...] but we have an extremely expensive energy in Norway this year. ... we are used to pay under 50 øre [~0.047 euro] for a kWh, and this year we have paid 4–5 krone [~0.45 euro] for a kWh, so it is extremely. So, many people in Norway are broke, and the government is going to take some of the bill for us. (Brian, 61-years old, house 1)

Looking at Figs. 4 and 5(b), we observe that energy production mostly occurs during 10:00–15:00 when the electricity prices exhibit a local minimum, whereas the energy consumption occurs mostly during the early morning hours and the late afternoon/early evening hours when the average hourly electricity price exhibit two local maxima. This partially explains the deviation from zero bills for houses 5, 7 and 9, which although close to or net-positive, experience a significant bill. The bills can partly be compensated by arbitraging—through load shifting and solar energy exports—due to the energy price model: the local minimum during the midday, when the majority of the solar production takes place, has a median export tariff obtained through Eq. (6) of 1.58 NOK, which is higher than the global minimum during the night hours, with a median import tariff obtained through Eq. (5) of 1.53 NOK. On the other hand, the import tariff during early morning and early evening hours are 1.92 NOK and 1.67 NOK, respectively. Therefore, by applying Eq. (12), for all households a small gain in



(a) Energy price hourly vector.

(b) Hourly energy price variance over the monitoring period.

Fig. 5. High energy price fluctuation during the monitored period with evident spikes after the start of the energy crisis.

the range of approx. 4%–8% is achieved. All houses, except house 1, partially consume what they are producing exporting the majority to the grid, as observed in Fig. 4. House 1, although importing the majority of its energy during the night hours when the tariffs are cheaper, due to exceptionally high import (as observed in brown in Fig. 4(a)) relative to export, incurs the largest bill. Houses 3, 6, 7 & 9 import a significant part of their consumption during evening when, in general, the electricity prices exhibits a local maximum. House 6, like house 1, has a disproportionally higher consumption than production, with the majority of the energy consumed being concentrated between the early morning hours and the late evening hours when the energy price exhibit maxima. House 3, although partly self-consuming, exports a significant amount of energy to the grid, which is later re-imported between late-afternoon and late-evening when again the energy prices are higher. Net-positive house 9 has a non-zero bill because is consuming the majority of the electricity during the two local maxima (morning and early evening) when the energy prices are highest and energy production is low. Similarly, house 7, which is close to net-zero consumes the majority of energy during evening when the energy prices are higher. House 5, which although following an arbitrage strategy (see Eq. (12)) by exporting almost all of the produced energy and importing back from the grid during the night hours, still import a significant amount of energy consumption during late evening and early morning hours when there is no solar production and the energy prices are higher.

From the empirical study it was concluded that although the energy price was communicated to the end-users in advance, households did not engage with the daily fluctuating energy prices (see Fig. 5(a)) but rather assumed approximate periods when the energy price was cheaper or more expensive based on their past experience and therefore the actual incurred costs were higher than expected. This is evident for house 1, especially for EV charging, where the household incorrectly assumed it was cheaper to always charge at 01:00 and is further explored in Section 3.4 in relation to flexibility along the energy price model to reduce the energy bill.

3.4. Load shifting potential demonstrated by a case study

From the previous findings in Sections 3.2 and 3.3 and the empirical study, it is clear, householders do not fully benefit from different energy feedback apps and automation systems present in their smart homes due to the non-optimal scheduling of the load consumption, mandated by flexible and non-flexible energy consuming practices, as well as due to the inherent complexity of following and scheduling their daily activities based on the live fluctuating energy prices. In order to further analyse the energy cost on a per activity basis using the local energy price, stacked plots of the total hourly cost, broken-down on a per-activity basis were created to inform household demand flexibilities taking both time of use and the local fluctuating energy price into account. Refrigeration, as is the case for the other always-on loads, is considered non-flexible since it cannot be shifted. Furthermore, based on the interview data, routines that are mandated due to external factors, such as the sequence of certain events, e.g., the usage of the tumble dryer after the washing machine, or transport patterns, e.g., the requirement to have the EV charged by a certain time in the morning, and dishwasher followed by cooking, were constraints considered in the rest of the analysis. We demonstrate how we approach the load shifting potential of a household, using house 1 as a case study since it had the smallest production to consumption ratio explained by activities such as heating and EV charging not covered by production, and it had the highest energy bill, as discussed in Sections 3.2 and 3.3, despite actively trying to shift loads to cheaper tariff times:

> [. . .] we charge the car at night, we do not do the dishwasher in the morning or when we are making food for dinner, because it is when we have a high price, so we usually turn on the dishwasher when we go to bed because it is when the energy is cheaper. (Brian, 61-years old, house 1)

While Section 3.2 quantified (in Table 2) and discussed the activity-level energy consumption, it did not show the temporal dimension of when these activities occur in order to analyse flexibilities. Fig. 6 visualises the relative energy consumption of activities at different times for house 1. Cooking is a non-flexible activity, as stated by the household. On the other hand, EV charging occurs between 01:00 and 04:00, and laundry and dishwashing occur during morning and evening hours—as per the empirical study, these activities are intentionally carried out to coincide with cheaper energy tariffs and are also flexible.

For comparison purposes, we also consider net-positive house 9. House 9, while open to doing their bit for the environment, they are not convinced load shifting will make a difference, as per their interview when asked about load shifting:

> No, and like I know that a lot of people, or I think some people will maybe wait to do laundry or something, but to be honest, I do not want to do that. [. . .] I do not wanna change what, any daily activities according to energy prices or energy usage because, well, I mean, these houses are great with energy, with the solar panels and everything, but I guess with home and my comforts,

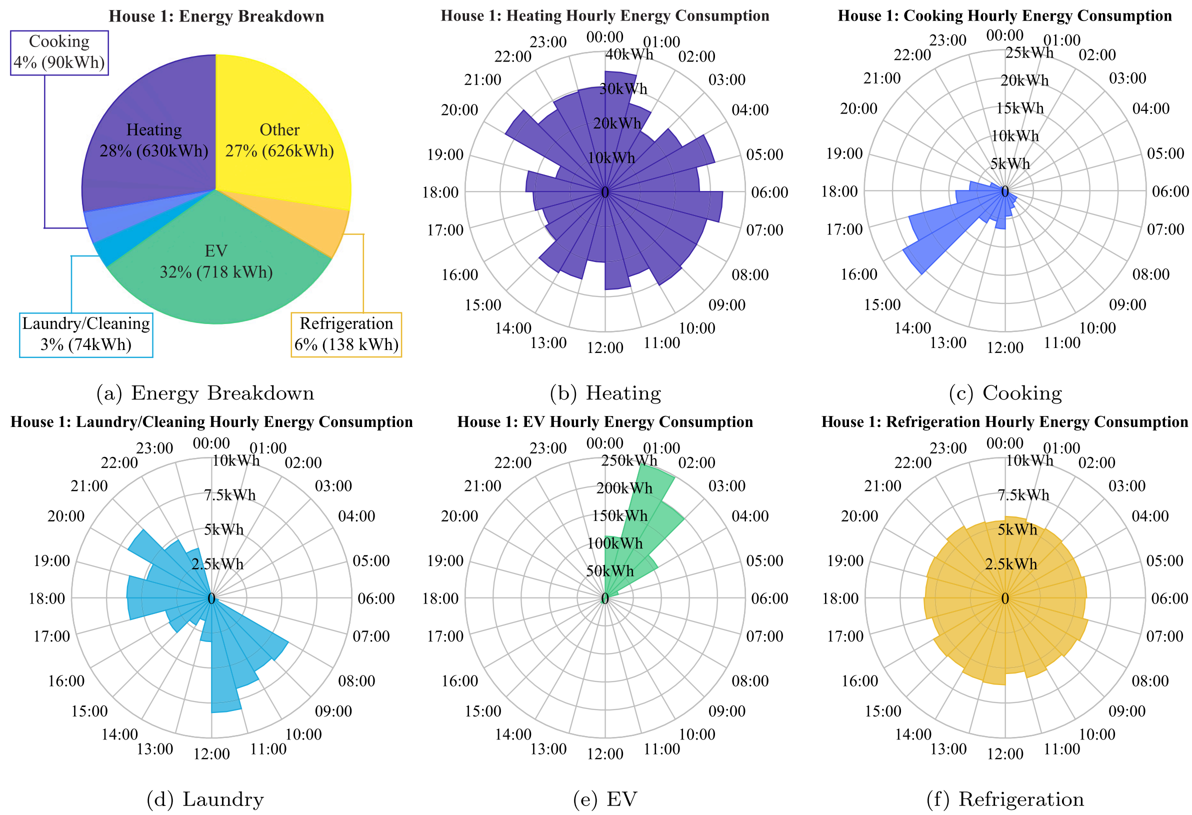


Fig. 6. House 1: Total energy consumption breakdown of heating, cooking, laundry/cleaning, EV charging and refrigeration over the monitoring period.

> I do not wanna change anything because I just wanna be comfortable so, and maybe it is selfish. [. . .] So if I could do some things to save energy and, you know, every, you hear every 10 min of how global warming in the environment we need to do our part and to, and things like that. but I do not think, not doing laundry at six in the evening is going to really make a major change with anything. (Sofie, 32-years old, house 9)

As can be observed through Figs. 7(b), 7(c) and 7(d) and from the empirical study, energy-intensive activities occur primarily during evening hours, after work for house 9. As expected, house 9 with an infant, has higher laundry and dishwashing needs, with over twice the energy consumption compared to house 1, and contributes to 24% of their consumption, as observed in Figs. 7(a) and 7(c). Qualitative analysis of the interview data indicated that house 9 uses their washing machine more often than dishwasher, tends to do laundry both in the morning and evening, but dishwashing is mostly in the evening after dinner.

Figs. 8(a) & 8(b) present the total hourly costs on a per-activity basis for houses 1 & 9, respectively. This is in agreement with the previous observation that EV charging is the main contributor to energy bills, followed by heating. Similarly, in house 9, the main contributor is laundry activity and EV charging to a lesser extent at relatively expensive import tariff periods. Potential for load shifting was estimated per activity, the results of which are presented in terms of total cost reduction and savings per-activity given a certain level of maximum accepted flexibility under the constraints imposed either by end-users' practices or intangible loads. A graph that correlates the accepted flexibility by end-users and the resulting reduction of the cost on a per-activity basis is presented. In addition to the cost reduction graph, a separate graph is produced that enables end-users to understand their per-activity savings when accepting a certain level of flexibility.

Flexibility analysis was performed in house 1 for heating, though not specified as flexible by the occupant, as the inherent inertia of the building materials can compensate the temperature drop that would occur by moving a heating load. Figs. 8(c) & 8(e) depict the maximum possible cost reduction, and therefore savings, per activity for house 1. As can be seen, laundry has the highest potential for cost reduction (up to 10%) in terms of percentage compared to the rest of the activities. However, since laundry routines are not responsible for a high share of the total energy bill (see Fig. 8(b)) the total savings of laundry are marginal, that is, up to 30 NOK. Cooking activities also demonstrate a very low capability for cost reduction and savings, mainly due to their low participation in the total bill and their non-flexible nature. On the other hand, EV and heating, which are the most consuming loads (see Fig. 6(a)), have a high load shifting potential. Although Brian (house 1) can monitor the energy price through the energy price app and subsequently schedule his vehicle charger, he does not use it as he does not find that convenient and because he believes that he has already understood—more or less—the price fluctuation. According to Fig. 8(c) although the maximum cost reduction achievable by following the energy prices is approx. 2%, due to the fact that the EV is responsible for a considerable amount of the bill, this reduction can be translated into savings of more than 60 NOK. Lastly, taking into account the inertia of the building materials, heating can be shifted out of the main peak hours—i.e., 07:00–09:00 and 17:00–19:00 and therefore achieve the maximum possible savings—up to 150 NOK—without sacrificing comfort levels.

Although house 9 did not state that their laundry practices are flexible, flexibility analysis was performed in order to investigate the potential savings. Results for house 9, differ from those of house 1, mainly due to the lower amount of energy used, as well as due to the fact that Sofie and Arthur (house 9) are not actively monitoring and shifting their activities based on energy prices. Unlike house 1, where EV shifting has a very low percentage of improvement, in house 9, EV charging scheduling can lead to a reduction of up to 3.9% of the total costs of the EV. Furthermore, cooking activities can also greatly benefit from load shifting, even for low levels of accepted flexibility

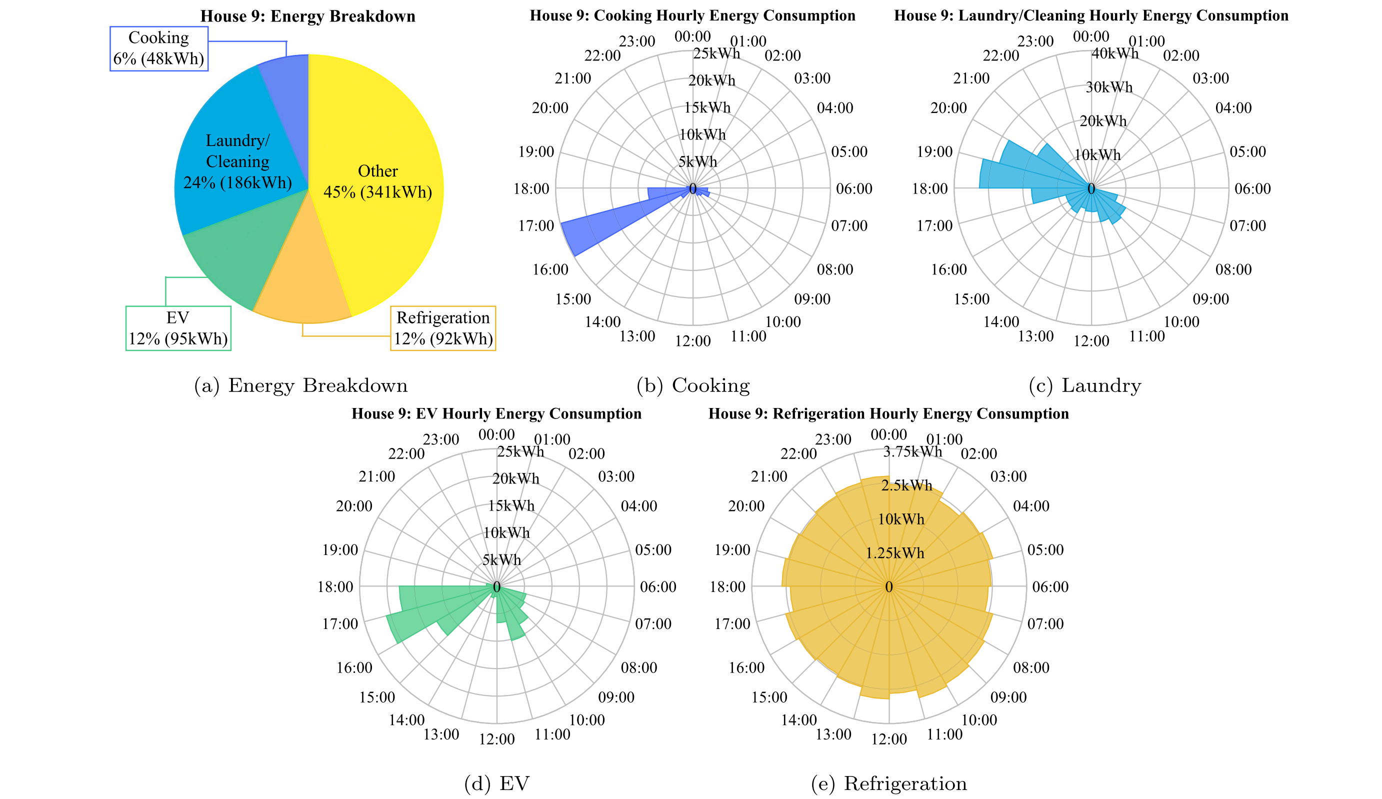


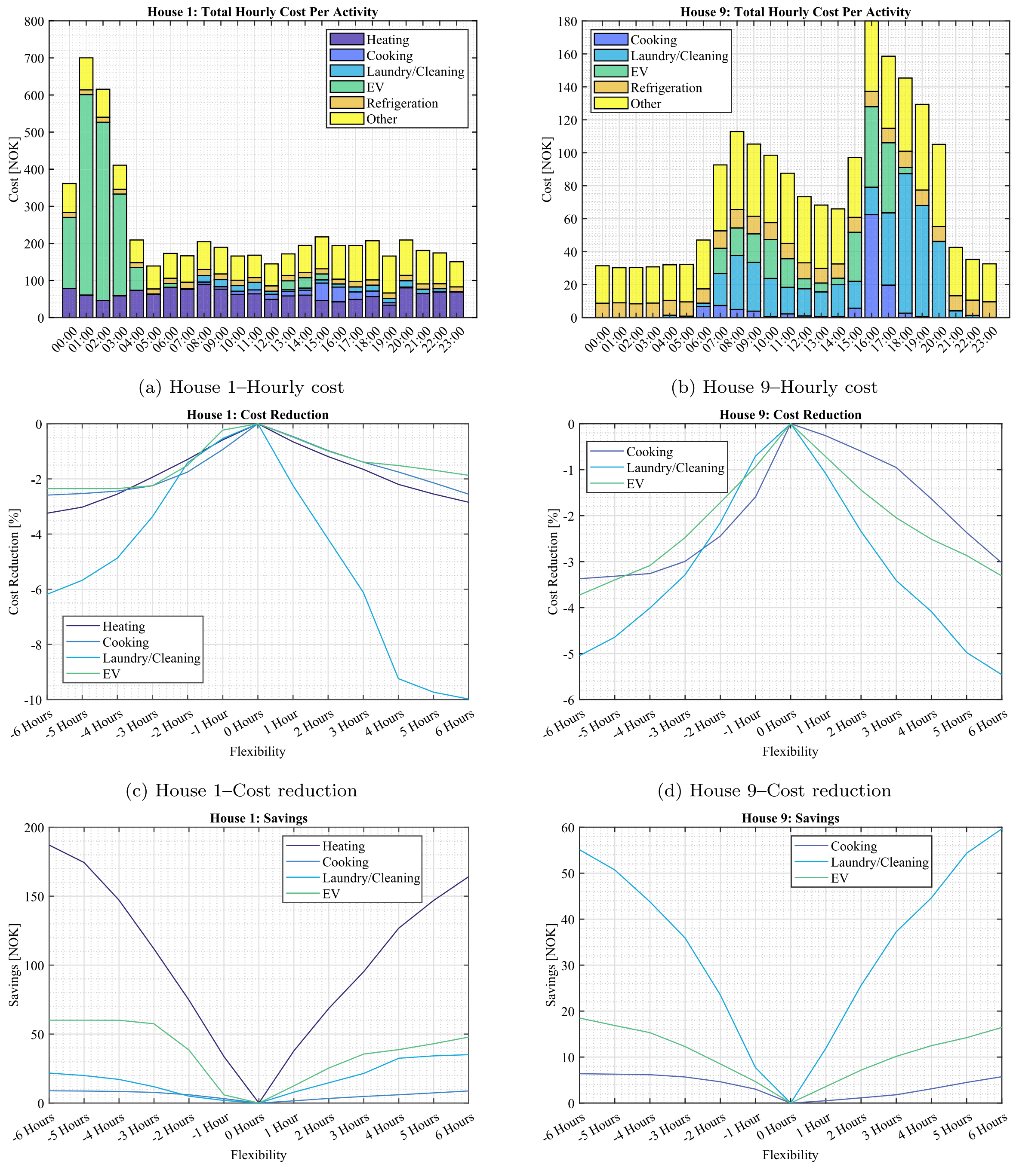
Fig. 7. House 9: Total energy consumption breakdown of cooking, laundry/cleaning, EV charging and refrigeration over the monitoring period.

with a maximum possible reduction of up to 3.4%. Lastly, laundry practices, which represent a considerable amount of the total energy used in house 9 as shown in Fig. 7, can greatly benefit from load shifting with cost reduction of up to 5.5%, i.e. approx 60 NOK. Although house 9 does not expect to make any difference by shifting their activities throughout the day, the flexibility analysis combining Table 2 and Fig. 8(f), demonstrated that a reduction of more than 50% of the total bill (and reduced pressure on the grid, and overall more eco-friendly) can be achieved by shifting the daily activities and therefore almost achieving a net-zero utility bill balance.

4. Conclusion

The proposed approach to evaluating the net-positive lived-in housing stock is especially timely given the construction of several, designed, net-zero and even net-positive developments throughout the world to reduce the carbon footprint. The built environment is being developed to comply with regulation and not necessarily for actual performance. Jointly considering qualitative data and methods in relation to end-users routines as well as dynamic energy pricing and measured consumption and renewable production during design and modelling of the housing stock to inform policy and regulation should be prioritised as assumptions being made during the construction of a building do not always represent the reality. As a consequence, designed "plus" homes, during their usage, fail to achieve their goal. This was demonstrated in this study through evaluation of a smart neighbourhood in Norway where, although all houses were designed based on current net-positive standards, they actually failed to achieve that goal. Furthermore, as highlighted through the actual data gathered, in dwellings where the end-user has little understanding of energy production from on-site renewables and dynamic pricing models, end-users who are actively flexible with their energy consumption or expect zero bills are disappointed. We propose a mixed-methods approach-based evaluation of the housing stock that helps pinpoint where assumptions do not meet reality taking into account household routines and dynamic energy pricing. These insights can action additional PV panel installation as well as load shifting potential of households to achieve net-zero.

The proposed mixed-methods approach bridges the gap between social science qualitative analyses—which can offer great detail and high explanation but with limited scope in scaling and high cost—with engineering quantitative analyses—which can scale up but can lack explanatory power through abstraction and generalisation of traditional energy data analysis design methods. Although our proposed mixed-methods methodology is shown to more accurately evaluate and explain energy demand of net-positive dwellings by incorporating the diversity of occupants and their practices, the reliance on qualitative data—that could lack accuracy—and the subsequent errors in load disaggregation that embed this qualitative data could affect the accuracy of the overall methodology. Therefore, the main key limitations of the study would lie in the scalability due to the reliance on qualitative data and the accuracy of the methodology due to occupants not providing, intentionally (due to privacy concerns) or not (they can genuinely forget some aspects of their energy-intensive activities), accurate responses in home surveys and interviews. The latter is mitigated in our study through the triangulation and the cross-validation of the qualitative and quantitative data as proposed in the Methodology section. The proposed methodology can directly be applied to other net-positive dwellings where required quantitative and qualitative data can be collected (smart meter data, PV size and orientation, tariff information, participation in the interviews). Absence of some of the data used in this study could limit the accuracy and type of findings. Different mixed-methods approaches can be compared by using a different method for one of more of the building blocks of our overall proposed methodology, showing in Fig. 1. For example, these could be different NILM approaches for the estimation of the load consumption of individual activities, different PV and solar models for the calculation of the energy production and different models for estimating energy cost based on user feedback or appliance sub-metering.



(a) House 1–Hourly cost (b) House 9–Hourly cost

(c) House 1–Cost reduction (d) House 9–Cost reduction

(e) House 1–Savings (f) House 9–Savings

Fig. 8. Total actual hourly cost and potential cost reduction and savings over the monitoring period, per activity, given different levels of demand flexibility.

Funding

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 955422.

CRediT authorship contribution statement

Apostolos Vavouris: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Fernanda Guasselli:** Investigation, Formal analysis, Data curation, Writing – review & editing. **Lina Stankovic:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Conceptualization. **Vladimir Stankovic:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Validation. **Kirsten Gram-Hanssen:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Sébastien Didierjean:** Writing – review & editing, Supervision, Resources.

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.

Data availability

The curated qualitative and quantitative data will be made available under CC-BY licence via the University of Strathclyde repository.

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