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Research paper

A data-driven approach with dynamic load control for efficient demand-side management in residential household across multiple devices

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ABSTRACT

Increasing PV penetration in the residential sector has led to supply demand mismatch in PV in the electricity market, specially during the peak demand hours and peak PV generation hours. Smart grid and smart meters have opened up avenues for designing data driven methodologies to optimize the generation and consumption of energy. In this paper, a dynamic load control mechanism is designed which optimizes the operation of individual appliances (heat pump, electric boiler, battery storage, solar PV and electric car). The optimization algorithm utilizes rolling horizon approach to consider the real time load control. A case of an individual house in Helsinki, Finland is considered to test the developed method. The results of dynamic load control mechanism were compared with operational optimization, wherein dynamic control is not implemented with different building classification and electricity contracts. From the results, it is observed that the optimization with a longer duration offers more benefits as compared to real time control mechanism, but does not reflect a real world scenario. Additionally, consumers having electricity contracts which are variable had the most savings and provides the highest flexibility to the electricity system.

1. Introduction

The energy outlook of the world is completely changing with the rapid increase in incorporating renewable energy sources into the system. This results in a push towards a sustainable energy future to counter the ever-increasing pollution levels and the drastic climate change following it. Countries across the globe have pledged to increase their renewable energy production and limit their emissions in the upcoming decade with the introduction of the Paris Agreement in 2015 (Paris Agreement, 2015). Though the shift towards renewable energy resources is helpful to the environment by reducing emissions arising from energy production, renewable energy production in itself has some associated drawbacks such as the ability to produce only during the presence of the said natural resource e.g., solar energy can be used to provide electricity but only when there is enough solar irradiance and wind energy can be used only when there is sufficient wind speeds which could move the wind turbine to generate substantial amount of electricity.

The total energy consumption within the European Union in 2021 corresponds to nearly 40,000 Terajoules (European Union, 2023c). Within the energy sector, buildings consume more than 40% of the primary energy consumption and within the residential sector, this corresponds to around 75% within the European Union (Cao et al., 2016). Due to such high consumption, there has been significant research regarding the reduction of energy consumption within the residential sector (Guo et al., 2018). The rapid spread of advanced smart meter installations has helped the Distributed Energy Resources (DER) to be integrated into the electricity networks and thus by providing the control to consumers over their consumption. This is possible through the usage of Home Energy Management Systems (HEMS) installed in residential houses. Demand Response (DR) is one potential solution which can help reduce the peak consumption and help the grid in times of need (Sridhar et al., 2022c). With the user-defined comfort settings, a HEMS can schedule shiftable appliances loads within the residential households to minimize peak consumption and save money.

In addition to the increased penetration of smart meter installations within the residential sector, solar Photovoltaic (PV) installation on rooftops of residential households have been gaining a significant share. By 2050, the residential PV installations would correspond to 40% of all solar PV capacity globally (Asmelash and Prakash, 2019). As a result, the consumers of today would become prosumers in the future. With

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Nomenclature

η^{BESS}	Charging and discharging efficiency of BESS
η^{EV}	Charging and discharging efficiency of EV
η_{boiler}	Efficiency of the boiler
$\frac{Q_{loss}^{house}}{\Delta T}$	Overall heat loss coefficient of the house
$\frac{Q_{ventilation}}{\Delta T}$	Ventilation heat loss coefficient of the house
λ_t^{export}	Price of electricity exported from the house to the grid at time t
λ_t^{import}	Price of electricity imported from the grid to the house at time t
A^{boiler}	Area of the boiler
A^{house}	Surface area of the house
C^{house}	Heat capacity of the house
C^{house}	Heat capacity of the house
c_p^{air}	Specific heat of air
c_p^{boiler}	Specific heat of water in the boiler
COP_t^{HP}	Coefficient of performance of the heat pump at time t
E_t^{HP}	Electrical power supplied to the heat pump at time t
n	Air-change rate in the house
P^{boiler}	Electric power needed by the boiler to supply the required thermal power.
P_{CH}^{BESS}	Power to charge the BESS at time t
P_{CH}^{EV}	Power to charge the EV at time t
P_{DS}^{BESS}	Power to discharge the BESS at time t
P_{DS}^{EV}	Power to discharge the EV at time t
P_{max}^{BESS}	Maximum power to charge the BESS
P_{min}^{BESS}	Minimum power to charge the BESS
P_t^{export}	Power exported from the house to the grid at time t
P_t^{import}	Power imported from the grid to the house at time t
P_t^{load}	Power of non-shiftable loads in the household at time t
Q_t^{boiler}	Heat energy from the boiler at time t
$Q_{loss,t}^{boiler}$	Heat lost by the water in the boiler at time t
$Q_{loss,t}^{house}$	Heat lost by the house at time t
Q_t^{HP}	Thermal energy supplied to the heat pump at time t
SoC_t^{BESS}	State of charge of BESS at time t
SoC_t^{EV}	State of charge of EV at time t
SoC_{max}^{BESS}	Maximum state of charge of the BESS
SoC_{max}^{EV}	Maximum state of charge of the BESS
SoC_{max}^{EV}	Maximum state of charge of the EV
SoC_{min}^{BESS}	Minimum state of charge of the BESS
SoC_{min}^{EV}	Minimum state of charge of the BESS
SoC_{min}^{EV}	Minimum state of charge of the EV
$T_{basement}^{house}$	Temperature of the basement in the house where the boiler is situated
T_{max}^{boiler}	Maximum temperature of water in the boiler
T_{max}^{house}	Maximum temperature of the house
T_{min}^{boiler}	Minimum temperature of water in the boiler
T_{min}^{house}	Minimum temperature of the house
T_{ramp}^{house}	Ramping temperature of the house
T_{supply}^{boiler}	Temperature of water supplied to the boiler
$T_t^{ambient}$	Ambient temperature at time t
T_t^{boiler}	Temperature of water in the boiler at time t
T_t^{house}	Temperature of the house at time t
U^{boiler}	Thermal transmittance of the boiler
U^{house}	Thermal transmittance of the house
V^{house}	Volume of the house
$V_{CH,t}^{boiler}$	Volume of water supplied to the boiler at time t
$V_{DS,t}^{boiler}$	Volume of water discharged from the boiler at time t
V_{max}^{boiler}	Maximum volume of water in the boiler
V_{start}^{boiler}	Volume of water in the boiler in the stating
V_t^{boiler}	Volume of water in the boiler at time t
ρ_{air}	Density of air

the increasing retail electricity costs and the decreasing costs of solar PV (Kavlak et al., 2018), grid parity with commercial electricity would be a reality in Europe. On top of this, PV feed-in tariffs have lost their appeal, resulting in consumers choosing to self-consume the produced electricity from their rooftop PV panels, which helps in reducing local voltage swings (Castillo-Cagigal et al., 2011). In addition to the rooftop PV installations in the residential sector, there has been a sharp increase in Electric Vehicle (EV) fleet globally. Within the European Union, there have been nearly 2.85 million of EV fleet in the end of 2021 (ACEA, 2023). The electrification of the transportation sector resulted in increased electricity consumption in the evenings and thus by changing the demand curve with daytime being the lowest demand in the day while mornings and evenings being the high peak hours. This has caused a discrepancy between the PV generation and residential electricity demand (Muenzel et al., 2015).

With the addition of solar PV in the HEMS, consumers have more flexibility to save the energy produced from the PV in a local Battery Energy Storage System (BESS) if available and use it during peak hours resulting in self-consumption and additionally helps in reducing electricity consumption costs. The addition of the BESS addresses the disparity in the PV production and electricity consumption in the households by saving the electricity in the BESS and using it during the times of need. With the addition of BESS in the solar-PV setup, measures like feed-in tariffs, green certifications, and net metering are still required to make such a system profitable (De Boeck et al., 2016). Due to this, shifting the residential loads in homes is one of the ways to extract the maximum potential of BESS to enhance the self-consumption of locally generated electricity through PV panels. Based on the above statements, it can be observed that HEMS can be utilized with rooftop-PV panels and BESS, EV and other shiftable loads in a residential home which can help in reducing the power peaks and shift loads to save electricity buying costs from the electricity supplier through demand response and self-consumption of locally produced electricity.

Hence, in this study, a HEMS was developed to be tested on a residential household to utilize the shiftable loads and optimize the electricity consumption. The objective of this study was to maximize the savings on electricity cost by extracting the maximum potential of the flexible loads and energy storage with dynamic optimization to simulate a real-time operation of the installed HEMS in a typical residential household. Within this study, a typical residential household has been considered with an installed rooftop PV panels, BESS, air-sourced heat pump and boiler for hot water demands. Based on the consumer comfort levels, we analyze the effect of the usage of HEMS on increased savings from the flexibilities in the demand. The study employs a rolling horizon optimization to keep the control strategies of different shiftable loads operating within limits and electricity prices for the upcoming day. The results from this study highlights the different control strategies used within a typical residential household employing HEMS and the potential reductions in electricity costs. Additionally, the study also highlights the impact on self-consumption through the usage of HEMS and the differences through various optimization horizons.

The rest of the paper is organized as follows: Section 2 discusses the existing literature, which is then followed by Section 3 explains the methodology used in this study, considering the different shiftable loads and their respective mathematical equations. Section 4 provides the results obtained in this paper, and the interpretation of the results and the corresponding implications are explained in Section 5. Finally, Section 6 provides the conclusion of this paper.

2. Literature review

The usage of DR in a residential home is not a recent notion, and it has been used widely used in research and some pilot projects across the world. Due to the presence of several studies regarding the control strategies for home energy systems, Rinaldi et al. classified the studies broadly into two different aspects: studies using specific simulation software programs to accurately predict the energy models and the other one where studies use mathematical modeling to analyze and capture the underlying physics of the system (Renaldi et al., 2017). The common traditional simulation programs that use domain specific packages include IDA ICE, Modelica, EnergyPlus and TRNSYS which provide comprehensive results with stochastic information provided to the models (Langer and Volling, 2020). These traditional simulation programs are highly accurate and versatile but cannot be incorporated to work with other forms of systems such as the case of HEMS having heating, EV, PV and BESS systems attached to which a proper control strategy needs to be applied.

In comparison to these, the mathematical models use reduced complexity, which provides a generic but accurate model for analysis. There have been significant literature on HEMS used for DR in residential sectors using different mathematical models. Mixed integer linear programming (MILP) is one such mathematical modeling that is relatively fast and converges quickly and works as one of the ideal algorithms for HEMS (Langer and Volling, 2020).

Based on existing literature, several previous research focus on optimizing the loads of HEMS for a short interval of time. Bruni et al. has studied the effect of shiftable loads in a residential home having rooftop PV panels, fuel-cell energy storage and BESS. The research was tested on a weekly interval for a representative summer and winter week loads in the United States of America (Bruni et al., 2015). Wu and Xia presented a study of using HEMS for DR for a residential building with a diesel generator, rooftop PV panels and BESS. The study analyzed the changes in the electricity consumption of the household using Time of Use tariff programs for a typical summer and a typical winter day (Wu and Xia, 2015). Fernandes et al. has used to schedule different appliances in a residential home using a HEMS during a DR event (Fernandes et al., 2014). The study employs DR in a residential home based on different shiftable loads in a residential household, and the simulation was shown for a couple of hours during which the DR event occurs. Brahman et al. has used cooling, heating power systems, renewable energy sources, and BESS and thermal energy storage within a residential household (Brahman et al., 2015). The results from this study show the scheduling of the different household appliances based on price reduction for a typical day. Dinh and Kim studied a HEMS in a residential household having rooftop PV panels, BESS, and shiftable household loads to be used for DR for energy savings and reduction in peak power while considering consumer's comfort levels (Dinh and Kim, 2021). The study uses different consumer comfort levels and a multi-objective optimization problem to analyze the simulation results for one typical day. Iwafune et al. have studied a home energy management system in a residential household comprising air-conditioning units, electric water heater and floor and space heating in different types of house types such as apartments and detached houses within Japan (Iwafune et al., 2017). The study compares the results by using HEMS for energy savings only during one winter month in two different years. Shakeri et al. has employed an HEMS on a residential building having shiftable appliance loads, rooftop PV and BESS (Shakeri et al., 2017). The results from the study show that the HEMS helps in reducing peaks while not compromising on user comfort levels while simulating the model for a typical winter day in a Time of Use tariff scheme. Wu et al. has developed a HEMS for a residential household having access to a plug-in electric vehicle for DR to reduce electricity costs from buying from the grid while using dynamic price tariffs (Wu et al., 2016). The results from this paper show the savings potential in a household based on different parameters of the EV such as kilometers run throughout the day, minimum requirement of state of charge of the EV during different times, and the available times of the EV for a typical day. Abdalla et al. has employed a HEMS in a residential household considering rooftop PV with BESS and EV for DR for electricity cost reduction (Abdalla et al., 2023). The simulation uses a typical summer and winter months to extract the numerical results. Killian et al. has employed scheduling of household appliances such as heating, freezer, PV panels with BESS, and dishwasher in a residential household (Killian et al., 2018). The study employs the simulation for a typical week and considers occupant's comfort level in the simulation. In comparison to the existing literature, this paper uses the simulation of the HEMS for a full year in an hourly resolution. The existing studies typically used the simulation for a day or a week, which fails to capture the intraday and seasonal variation of PV panel productions, which would affect the results significantly. The intraday variation of the PV production due to cloud coverage is significant in any location, and the seasonal variation is pronounced in locations with four distinctive seasons. Additionally, a full year simulation would not be affected by the initial state of the system, such as the initial state of charge of the BESS.

In terms of pilot project studies, Obinna et al. studied two different pilots of smart home energy management in two cities, one in the Netherlands and another in the United States of America respectively (Obinna et al., 2017). The pilot used rooftop PV, EV, smart thermostats and heat pumps in the HEMS to be shiftable loads. The results from this pilot showed that consumers were willing to shift loads if the shift automatically occurred with information relayed to the consumer beforehand. Tuomela et al. analyzed the consumer consumption data before and after the installation of HEMS (Tuomela et al., 2021). The study analyzed the smart meter data of 10 Finnish households in northern Finland during the winter months of 2018. The HEMS was used to shift only the heating loads of the households having a hot water boiler and an air sourced heat pump in the residential households based on the consumer's level of comfort. The results from this study showed that even when consumers preferred comfort to electricity savings, there was a significant reduction in peak powers and the overall residential loads were reduced when compared to the system without any HEMS with magnitude of changes varying within different households. Vanthournout et al. analyzed a demand response pilot project in Belgium comprising 240 residential households using dishwashers, tumble dryers, and domestic hot water buffers (Vanthournout et al., 2015). The study used the Belgian day–night tariff structure to employ the shiftable appliances in demand response and analyzed the effect of the DR in different months with different participating families.

The existing literature underscores a significant focus on implementing HEMS for DR and self-consumption in residential settings. However, much of this research tends to concentrate on shorter time intervals, overlooking dynamic load scheduling. While previous studies acknowledge the value of annual simulations in capturing intraday and seasonal variations in household heating loads and PV production,

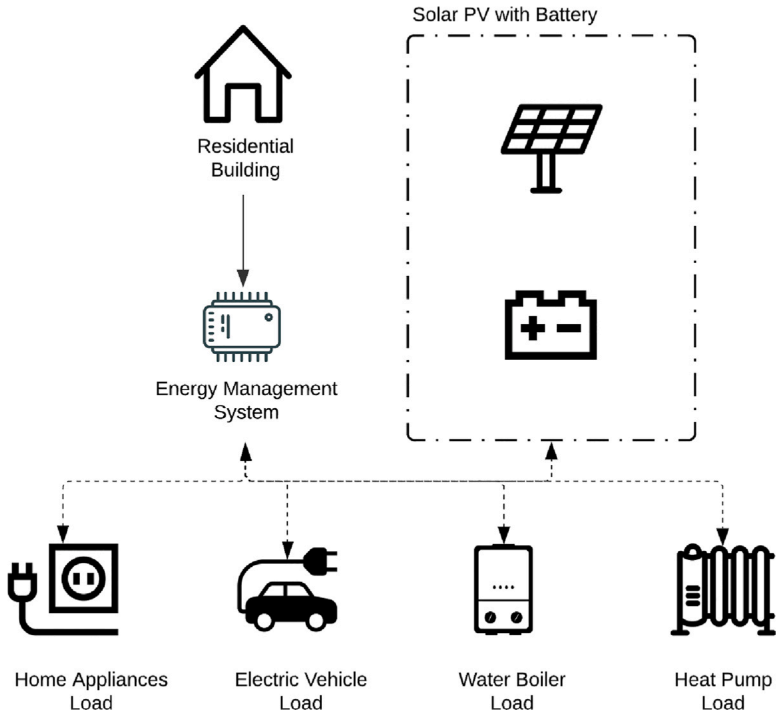

Fig. 1. Home energy flow.

they often remain sensitive to initial conditions. For instance, Salpakari and Lund's work in a Finnish household integrates HEMS with rooftop PV panels, an EV, BESS, and a ground-source heat pump for heating (Salpakari and Lund, 2016). Although they utilize rolling horizon optimization for load scheduling, their focus is primarily on time-of-use pricing, neglecting other pricing mechanisms. Additionally, their emphasis on ground-source heat pumps, despite their lesser prevalence in European residential contexts compared to air-source heat pumps, limits the generalizability of their findings (Menegazzo et al., 2022). Moreover, their study only considers a single building type. In light of these gaps, this study makes the following contributions:

- Develops an optimized scheduling of flexible household loads using MILP while the scheduling horizon is for one full year, thereby implementing rolling horizon optimization which is used to dynamically schedule the loads based on load changes
- The optimization model encompasses diverse building types and electricity pricing options, reflecting variations in heating demand and contract terms.

The results from this study quantify the realized savings achievable through HEMS adoption under different conditions, aiding consumers in decision-making regarding DR participation. Additionally, these findings hold significance for electricity suppliers, aggregators, and policymakers, facilitating the identification of residential consumers ripe for DR enrollment and contributing to the transition towards a sustainable energy future.

In order to address the contributions of this paper, a residential household in Helsinki, Finland is considered. Finland is one of the leaders in the world for sustainable energy production and has set ambitious targets for the upcoming years, making residential DR essential to analyze. Furthermore, there have been several previous studies performed regarding consumer willingness to enroll in DR (Ruokamo et al., 2019; Sridhar et al., 2023). Additionally, the electricity suppliers in Finland provide a various range of choices which would be essential in determining the variation in savings through the usage of HEMS. As a result, it serves as a good example to study the HEMS for Helsinki, Finland.

3. Methodology

In this section, different household appliances and their flexibility are explained along with the different electricity contracts available to choose. In addition the building thermodynamic properties which will be used to analyze the heating loads and the different scenarios which were selected in this paper to analyze the results are discussed.

3.1. Residential house data

To address the gaps in literature, an HEMS was developed to run on a residential household situated in Helsinki, Finland. The house considered for simulation is a residential-detached house in the area of Helsinki, Finland, having 4 occupants. The house has a 100 m^2 floor area with wall areas corresponding to 360 m^2 and windows corresponding to 20 m^2. The non-shiftable loads of the household, which correspond to the usage of lights, appliances, and devices, are adopted from Narayanadhas (2022). A schematic of all the shiftable loads available within the residential household can be viewed in Fig. 1. The non-shiftable loads of the residential household can be observed in Fig. 2.

3.1.1. Photovoltaic panels with battery energy storage system

With the rapid increase in rooftop PV installations in the world, this paper assumes a 5 kW PV panels installed in the rooftops attached to a 20 kWh BESS in the residential home. The PV profile was generated using PV GIS developed by Suri et al. (2008). Crystalline silicone panels were selected along with a 5 kW electricity peak was used to generate the profile and this can be observed in Fig. 3 for a typical year.

3.1.2. Electric vehicles

The household is equipped with an EV and a charging station. The average daily traveled kilometers for passenger cars in Finland is 50 km (Lahtinen, 2019) which corresponds to 10 kWh/day required to charge the EV (Sridhar et al., 2022c). Currently, the size of an EV battery can vary from 15 kWh to more than 100 kWh based on the size of the EV and the power capability. In this paper, the EV car is

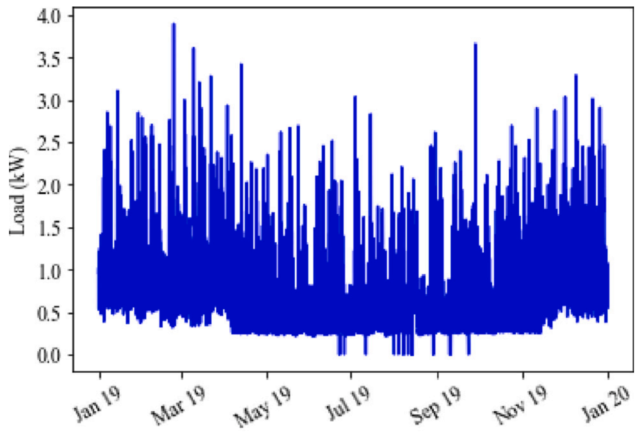

Fig. 2. Non-shiftable loads in the household.

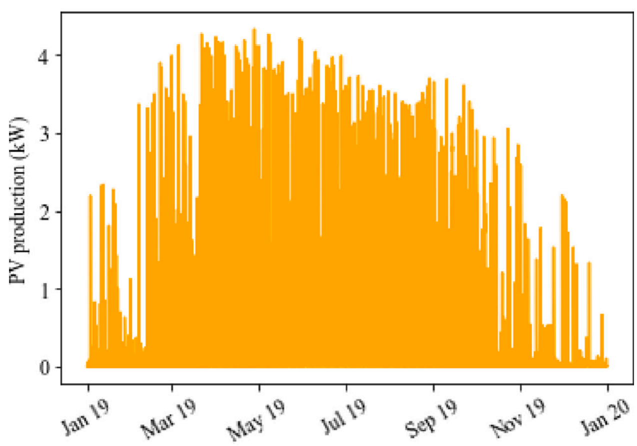

Fig. 3. PV generation.

assumed to have a battery capacity of 65 kWh, and the charging and discharging power is limited to 3.6 kWh/h based on a single phase 16 A EV charger. The EV is expected to be available to charge during 17:00 to 09:00 and not available during the rest of the times during weekdays. For the weekends, the EV is available to charge from 22:00 to 09:00. Currently, there is no electricity sold from the vehicle back to the grid in the analysis.

3.1.3. Heat pump

The household is equipped with an air-sourced heat pump, which can be used to regulate the indoor temperatures within the household. The internal temperature gains from occupants have been neglected in this study due to its minimal impact on the temperature. The indoor temperature has been set to have a lower bound of 19 °C and a higher bound of 23 °C to ensure user comfort within the household based on the study made by Narayanadhas (2022).

3.1.4. Hot water demand

The hot water profile used in this paper was obtained from an open source hot water profile generator: DHWcalc with user defined conditions (Jordan and Vajen, 2005). With the maximum daily water consumption in apartments in Finland being 70 L/person/Day, this study assumes the same for a residential household as the usage of hot water domestically would be similar irrespective of the household (Ahmed et al., 2015). The hot water demand of a typical household can be observed in Fig. 4. The hot water demand is to be fulfilled by the boiler, which is stored in the basement of the house.

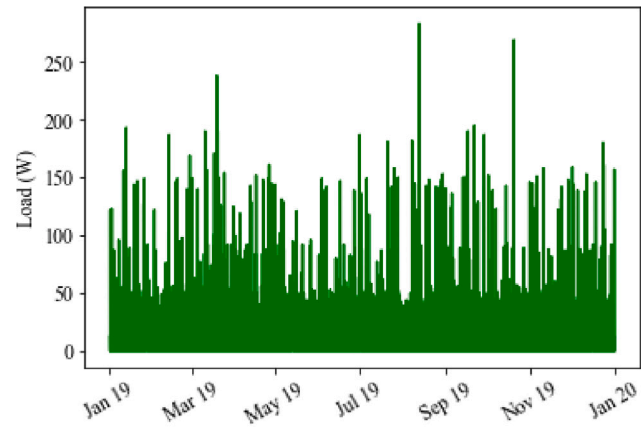

Fig. 4. Hot water demand obtained from DHWcalc for Finland (Jordan and Vajen, 2005).

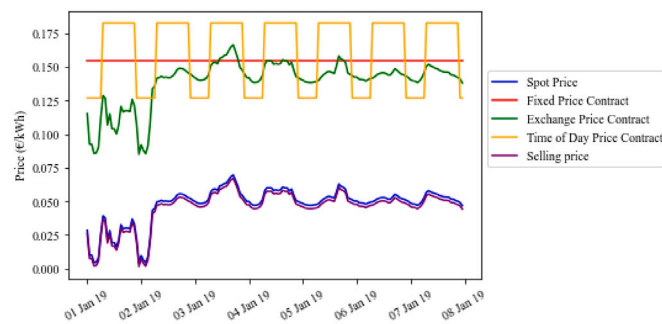

Fig. 5. Electricity contract prices for a typical winter week in Finland provided by Helen Ltd. (Helen Oy, 2023b).

3.2. Electricity contracts

Three different electricity price contracts/retail tariff rates have been included in this study to check the difference in savings for different contracts. The cost of electricity contracts are divided into electricity production and distribution costs. The different electricity contracts available in Helsinki, Finland provided by the electricity supplier Helen (Helen Oy, 2023b) are shown in Table 1.

The variation of the prices for a typical winter week in Finland can be observed in Fig. 5.

The costs associated to electricity distribution for a residential consumer within Helsinki is shown in Table 2 (Helen Sähköverkko, 2023a).

For selling the electricity from the home to the grid, Helen Ltd. buys the produced electricity based on spot prices along with a difference of their commission. Currently, the commission charged by Helen to buy electricity is 0.3 c/kWh, irrespective of the type of electricity contract the consumer has made with the supplier.

3.3. House thermal properties

Based on the different standards of building types within Finland, five different building types have been considered in this study to analyze the results from HEMS simulation based on the Finnish building standards (Laitinen et al., 2014). The associated heat loss coefficient for the different buildings is calculated using Eq. (12). The heat loss through the building property is obtained through the product of thermal transmittance and area of the building. The thermal transmittance is obtained from Laitinen et al. (2014). The ventilation heat

Table 1
Electricity contracts/retail rates in Finland provided by Helen Ltd. Helen Oy (2023b).

Type of contract	Description	Value
Fixed	This type of contract has a fixed cost per until of consumed electricity for 12 months	15.46 c/kWh
Time of Day	This type of contract has one fixed price between 07:00–22:00 and a different fixed price between 22:00–07:00	18.24 c/kWh (07:00–22:00), 12.67 c/kWh (22:00–07:00)
Exchange price	This type of contract has a varying price based on spot market with an additional commission charged by the electricity supplier	(Spot price + 0.38 c/kWh) * 1.24 {To include VAT}

Table 2
Electricity distribution charges from Helen Ltd. Helen Sähköverkko (2023a).

Type of costs	Description	Value
Fixed distribution costs	This is a type of cost which is fixed for all residential consumers registered with Helen as their electricity distribution supplier.	4.07 c/kWh
Taxes	This type of cost is incurred for all residential consumers irrespective of their electricity distribution supplier	2.794 c/kWh
Total costs	Sum of fixed distribution costs and taxes	6.864 c/kWh

Table 3
Building classification considered in the study.

Building classification	Building description	Heat loss coefficient based on building properties (W/K)	Ventilation heat loss coefficient (W/K)	Overall heat loss coefficient (W/K)
A	Building built before 1960	425.4	33.825	459.225
B	Building built between 1960–1979	311.2	33.825	345.025
C	Building built between 1980–2000	222.8	37.95	260.75
D	Building built between 2000–2010	187	33	220
E	Building built after 2010 and fulfilling Finnish building code 2012 Part D5	126.2	41.25	167.45

Table 4
Scenario formulation.

Building type	Tariff type	Scenario
A	Fixed price	A1
	Time of Day	A2
	Exchange price	A3
B	Fixed price	B1
	Time of Day	B2
	Exchange price	B3
C	Fixed price	C1
	Time of Day	C2
	Exchange price	C3
D	Fixed price	D1
	Time of Day	D2
	Exchange price	D3
E	Fixed price	E1
	Time of Day	E2
	Exchange price	E3

loss coefficient is obtained from Eq. (13) where the air-flow rate for different buildings is obtained from Laitinen et al. (2014). The overall heat loss coefficient is the sum of heat loss coefficients by building property and ventilation and can be viewed in Table 3.

3.4. Scenarios

Based on the different thermal properties of the household and the electricity contracts, 15 different scenarios have been formulated to be analyzed in this paper. The different scenarios are shown in Table 4.

In order to extract numerical results, this paper uses the day-ahead prices of Finland (since Finland has one price area for day-ahead prices) and uses the year 2019 for analysis. The reason to choose 2019 was based on eliminating other recent years due to several reasons: 2022 being the year when a huge share of nuclear power got activated in Finland, changing the whole energy landscape of Finland; 2021 was the year of Russian invasion on Ukraine forcing the energy crisis and causing very high prices; 2020 being the year of coronavirus outbreak forcing industries and commercial sector to reduce the operating capacity and thus by affecting the prices.

3.5. Optimization model

The optimization model is designed considering thermal comfort and thermal losses of the residential building. In addition, technical characteristics of boiler like supply temperature, thermal transmittance, area of boiler, heat capacity and efficiency were considered. Similarly, for heat pump, room temperature, density, heat capacity of air, thermal transmittance is considered in the constraints of the model. A residential building's home energy management system with a one-hour temporal resolution is designed. The system consists of a rooftop PV system, a BESS coupled to the PV system, an air-source heat pump, an electric boiler, and a station for charging electric vehicles. The structure is wired into the grid so that extra electricity can be purchased, and extra electricity may be sold. It is anticipated that the model's architecture will be flexible to changes in both the generation of PV electricity and the ambient temperature.

Due to the linear programs being convex in nature and are computationally not expensive and reach convergence faster than other non-linear programs, the HEMS uses linear programming to represent the system (Sridhar et al., 2022a). The Optimization model was modeled as a Mixed-Integer Linear Program (MILP) having various parameters, decision variables, constraints and objective function.

Table 5
BESS parameters.

Parameter	Description	Value
η^{BESS}	Battery charging/discharging efficiency	0.92
SOC^{BESS}_{min}	Minimum state of charge of the BESS	1.6 kWh
SOC^{BESS}_{max}	Maximum state of charge of the BESS	8 kWh
P^{BESS}_{min}	Minimum power to charge/discharge the BESS	0 kW
P^{BESS}_{max}	Maximum power to charge/discharge the BESS	4 kW

Table 6
EV parameters.

Parameter	Description	Value
η^{EV}	Battery charging/discharging efficiency	0.92
SOC^{EV}_{min}	Minimum state of charge of the EV	10 kWh
SOC^{EV}_{max}	Maximum state of charge of the EV	50 kWh
P^{EV}_{min}	Minimum power to charge/discharge the EV	0 kW
P^{EV}_{max}	Maximum power to charge/discharge the EV	3.6 kW

Table 7
Heating parameters.

Parameter	Description	Value
T^{house}_{min}	Minimum indoor temperature of the house	19 °C
T^{house}_{max}	Maximum indoor temperature of the house	23 °C
T^{house}_{ramp}	Ramping indoor temperature limit for the house	2 °C
A^{house}	Surface area of all the walls in the house	300 m^2
V^{house}	Volume the house	250 m^3
h^{house}	Height of the house	2.5 m
ρ_{air}	Density of air	1.007 kJ/kg °C
c^{air}_p	Heat capacity of air	1.2 kg/m^3
U_{house}	Overall thermal transmittance of the house	–
n	Air change rate	–

Table 8
Boiler parameters.

Parameter	Description	Value
T^{boiler}_t	Temperature of water in the boiler	60 °C
T^{boiler}_{supply}	Temperature of water supplied to the boiler	9 °C
V^{boiler}_{start}	Volume of water in the boiler at start	40 L
A^{boiler}	Area of the boiler	2.39 m^2
U^{boiler}	Overall thermal transmittance of the boiler	0.36 W/m^2°C
V^{boiler}_{max}	Maximum volume of water in the boiler	400 L
c^{boiler}_p	Heat capacity of water	4.2 kJ/kg°C
η_{boiler}	Efficiency of the boiler	0.95
$T^{house}_{basement}$	Temperature of basement of house	18 °C

3.5.1. Parameters

Parameters are the variables within the model which stay constant throughout the optimization horizon and are never affected by any decisions made by the model. The parameters for the Battery Energy Storage System (BESS) are listed in Table 5. The parameters for the Electric Vehicle (EV) are detailed in Table 6. The parameters for household space heating are provided in Table 7. The parameters for hot water demand, using a boiler, are shown in Table 8.

3.5.2. Decision variables

Decision variables are the variables within the model which are subjected to vary and are selected by the model based on the objective function. The decision variables for the Battery Energy Storage System (BESS) are presented in Table 9. The decision variables for the Electric Vehicle (EV) are listed in Table 10. The decision variables for space heating are detailed in Table 11. The decision variables for hot water heating using the electric boiler are shown in Table 12.

Table 9
BESS decision variables.

Decision variables	Description
SOC^{BESS}_t	State of charge of BESS at time t
$P^{BESS}_{CH,t}$	Power supplied to charge the BESS at time t
$P^{BESS}_{DS,t}$	Power supplied to discharge the BESS at time t

Table 10
EV decision variables.

Decision variables	Description
SOC^{EV}_t	State of charge of EV at time t
P^{EV}_{CH}	Power supplied to charge the EV at time t
P^{EV}_{DS}	Power supplied to discharge the EVat time t

Table 11
Space heating decision variables.

Decision variables	Description
T^{house}_t	Indoor temperature of the house at time t
$Q^{house}_{loss,t}$	The heat lost by the house at time t
P^{HP}_t	Electrical power supplied to the heat pump at time t
Q^{HP}_t	Thermal energy supplied by the heat pump at time t

Table 12
Boiler decision variables.

Decision variables	Description
T^{boiler}_t	Temperature of the water in the boiler at time t
$Q^{boiler}_{loss,t}$	The heat lost by the boiler at time t
P^{boiler}_t	Electrical power supplied to the boiler at time t
Q^{boiler}_t	Thermal energy supplied by the boiler at time t
V^{boiler}_t	Volume of water in the boiler at time t
V^{boiler}_{CH}	Volume of water supplied to the boiler at time t
V^{boiler}_{DS}	Volume of water discharged from the boiler at time t

3.5.3. Constraints

Constraints are the equations which limit the decision variables and act as a boundary layer for decision variables. They are essential to mimic the actual physics of the system and help the system converge to the best result.

The following BESS constraints are used in this study:

$$SoC^{BESS}_t = SoC^{BESS}_{t-1} + (P^{BESS}_{CH,t} * \eta^{BESS}) - (P^{BESS}_{DS,t}/\eta^{BESS}) \tag{1}$$

The state of charge of the BESS is defined by the state of charge of the BESS in the previous hour, along with the potential charging and discharging happening in the current hour.

$$SoC^{BESS}_{min} \leq SoC^{BESS}_t \leq SoC^{BESS}_{max} \tag{2}$$

The state of charge of the BESS should never go below the lower limit and never go higher than the upper limit.

$$P^{BESS}_{min} \leq P^{BESS}_{CH,t} \leq P^{BESS}_{max} \tag{3}$$

$$P^{BESS}_{min} \leq P^{BESS}_{DS,t} \leq P^{BESS}_{max} \tag{4}$$

The charging and discharging of the BESS should not be higher than the maximum power possible to charge and discharge the BESS, and not lower than the minimum power possible to charge and discharge the BESS.

Similar to the BESS constraints, the following EV constraints are used in this study:

$$SoC^{EV}_t = SoC^{EV}_{t-1} + (P^{EV}_{CH} * \eta^{EV}) - (P^{EV}_{DS} * \eta^{EV}) \tag{5}$$

The state of charge of the EV is defined by the state of charge of the EV in the previous hour along with the potential charging and discharging happening in the current hour.

$$SoC^{EV}_{min} \leq SoC^{EV}_{t} \leq SoC^{EV}_{max} \tag{6}$$

The state of charge of the EV should never go below the lower limit and never go higher than the upper limit.

$$P^{EV}_{min} \leq P^{EV}_{CH,t} \leq P^{EV}_{max} \tag{7}$$

$$P^{EV}_{min} \leq P^{EV}_{DS} \leq P^{EV}_{max} \tag{8}$$

The charging and discharging of the EV should not be higher than the maximum power possible to charge and discharge the EV, and not be lower than the minimum power possible to charge and discharge the EV.

The constraints which help to mimic the physical reality of working of a heat pump is obtained from Ryan (2020) and it is as follows:

$$T^{house}_{min} \leq T^{house}_{t} \leq T^{house}_{max} \tag{9}$$

The temperature of the house should be within the accepted temperature limit based on user comfort levels.

$$-(T^{house}_{ramp}) \leq (T^{house}_{t} - T^{house}_{t-1}) \leq T^{house}_{ramp} \tag{10}$$

The changes in indoor temperature should not be more than 1 °C based on user comfort.

$$C^{house} = V^{house} * \rho_{air} * c^{air}_{p} \tag{11}$$

The heat capacity of the house is defined as the product of volume of the house, density of air and the specific heat of air.

$$\frac{Q^{house}_{loss}}{\Delta T} = U^{house} * A^{house} + \frac{Q_{ventilation}}{\Delta T} \tag{12}$$

The ratio of heat loss coefficient of the house is defined as the sum of heat loss coefficient of the house due to ventilation and due to building thermodynamic property, i.e., the product of thermal transmittance of the house and surface area of the house.

$$\frac{Q_{ventilation}}{\Delta T} = 0.33 * n * V^{house} \tag{13}$$

The ratio of heat loss of the house due to ventilation to the change in temperature is defined as the product of 0.33, air-change rate in the house and the volume of the house.

$$Q^{house}_{loss,t} = (T^{house}_{t} - T^{ambient}_{t}) * \frac{Q^{house}_{loss}}{\Delta T} \tag{14}$$

The heat lost by the house in a specific time is provided by the product of the difference between indoor temperature and the ambient temperature and the ratio of heat loss of the house to the change in temperature defined in Eq. (12).

$$T^{house}_{t} = T^{house}_{t-1} - \frac{Q^{house}_{loss,t}}{C^{house}} + \frac{Q^{HP}_{t}}{C^{house}} \tag{15}$$

The indoor temperature of the house at the current time is provided by the indoor temperature of the house in the previous hour and the ratio of heat lost by the house to the heat capacity of the house and the ratio of heat provided by the heat pump to the heat capacity of the house.

$$P^{HP}_{t} = \frac{Q^{HP}_{t}}{COP^{HP}_{t}} \tag{16}$$

The electrical power supplied to the heat pump is defined as the ratio of thermal energy supplied by the heat pump to the coefficient of performance of the heat pump.

$$COP^{HP}_{t} = 3.25 + 0.0875 * T^{ambient}_{t} \tag{17}$$

The coefficient of performance of the heat pump is defined as a function of the ambient temperature provided by Quintel (2023d).

The constraints associated to the hot water boiler are as follows:

$$T^{boiler}_{min} \leq T^{boiler}_{t} \leq T^{boiler}_{max} \tag{18}$$

The temperature of water within the boiler should be within the minimum and the maximum limits allowed as per Table 8.

$$V^{boiler}_{t} = V^{boiler}_{start} + V^{boiler}_{CH,t} - V^{boiler}_{DS,t} \tag{19}$$

The volume of water in the boiler is defined as the sum of volume of water in the boiler in the beginning and the volume added to the boiler and the difference of the volume discharge from the boiler which corresponds to the hot water demand as observed in Fig. 4.

$$Q^{boiler}_{loss,t} = U^{boiler} * A^{boiler} * \frac{V^{boiler}_{t}}{V^{boiler}_{max}} * (T^{boiler}_{t} - T^{house}_{basement}) \tag{20}$$

The heat lost by the water in the boiler can be defined as the product of thermal transmittance of the boiler, area of the boiler, ratio of water in the boiler and the difference in temperature between outside and inside the boiler.

$$Q^{boiler}_{t} = V^{boiler}_{CH} * c^{boiler}_{p} * (T^{boiler}_{t} - T^{boiler}_{supply}) + Q^{boiler}_{loss,t} \tag{21}$$

The heat energy needed by the boiler can be defined as the product of volume of water entering the boiler, the specific heat of water in the boiler, the difference in change in temperature of the boiler and the boiler losses needs to be added to this to compensate for the thermodynamic losses.

$$P^{boiler}_{t} = Q^{boiler}_{t} / \eta_{boiler} \tag{22}$$

The electrical power supplied to the boiler is defined as the ratio of the thermal energy supplied by the boiler to the efficiency of the boiler. The energy flow constraints for the HEMS are as follows:

$$P^{HP}_{t} + P^{export}_{t} + P^{load}_{t} + P^{boiler}_{t} + P^{EV}_{CH,t} + P^{BESS}_{CH,t} = P^{import}_{t} + P^{PV}_{t} + P^{EV}_{DS,t} + P^{BESS}_{DS,t} \tag{23}$$

The sum of overall power supplied to the heat pump, exported to the grid, load, boiler, charging EV and BESS should be equal to the sum of power imported from the grid, energy obtained from PV panels and the discharging power of EV and BESS.

3.5.4. Objective function

The objective function is the equation in the model with which is set to be optimized based on the constraints, parameters, and the decision variables. The objective of the HEMS is to minimize the overall electricity costs and is calculated as shown below

$$\min \sum_{t=1}^{8760} P^{import}_{t} * \lambda^{import}_{t} - P^{export}_{t} * \lambda^{export}_{t} \tag{24}$$

3.6. Rolling horizon optimization

In the context of a Home Energy Management System (HEMS), rolling horizon optimization emerges as a strategic computational approach to efficiently allocate and manage energy resources over time. Rather than attempting to optimize the entire energy consumption plan for an extended period, the rolling horizon method divides the planning horizon into shorter intervals. This can be observed in Fig. 6.

Within each interval, the HEMS leverages optimization algorithms to determine the most optimal energy consumption strategy based on current data, such as electricity prices, household demand, and renewable energy availability. This short-term plan is then implemented, and the optimization process is repeated as the system progresses. This iterative approach allows the HEMS to adapt dynamically to fluctuations in energy prices, variations in user behavior, and changes in renewable energy production, ensuring a responsive and adaptive energy management strategy that aligns with the evolving needs and conditions within a home environment. The working of the overall HEMS can be observed in Fig. 7.

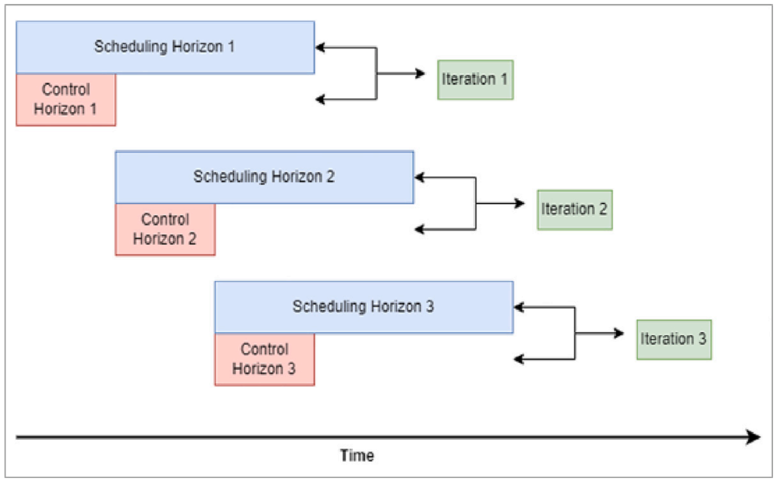

Fig. 6. Working of rolling horizon.

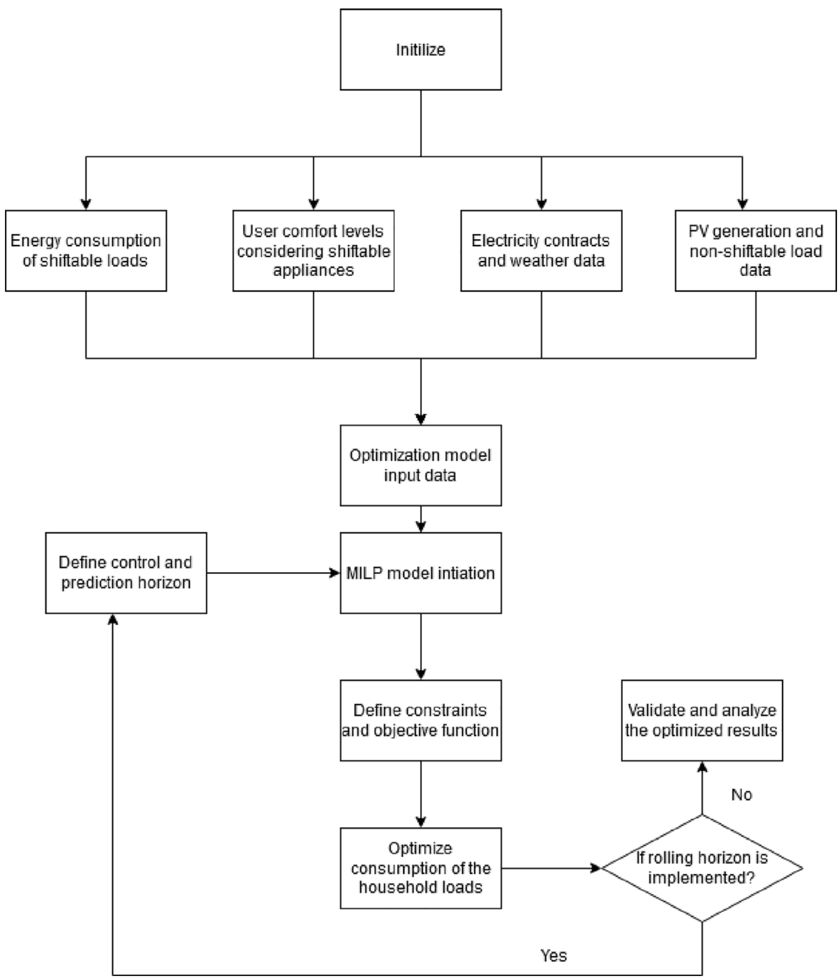

Fig. 7. Working of the HEMS with rolling horizon optimization.

4. Results

In order to assess the working of the HEMS on the residential household, one specific building type is used with different electricity tariff structures. The results for using building type 'C' using fixed price contracts can be observed in Figs. 8 and 9.

In Fig. 8, it can be observed that there have been a significant grid imports coming to the residential household and there have been no export to the grid. Additionally, it can be seen that the heat pump loads are more or less constant throughout the day as there is no price volatility to shift the loads in lower hours to increase savings. The EV charging also happens in the evening times when the EV is available to charge.

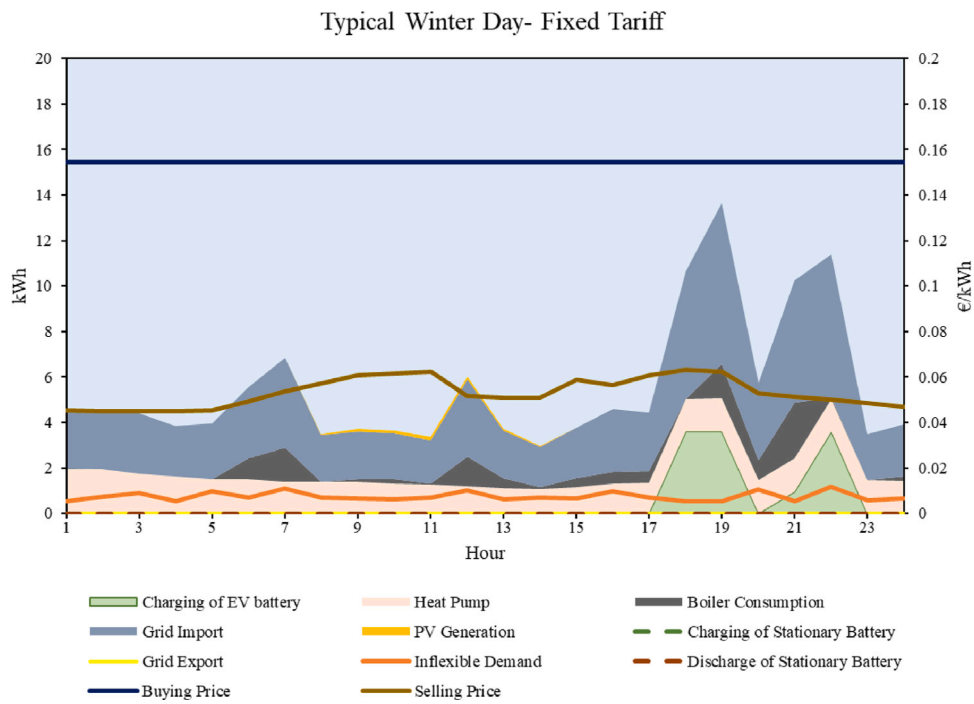

Fig. 8. Typical winter weekday — fixed tariffs.

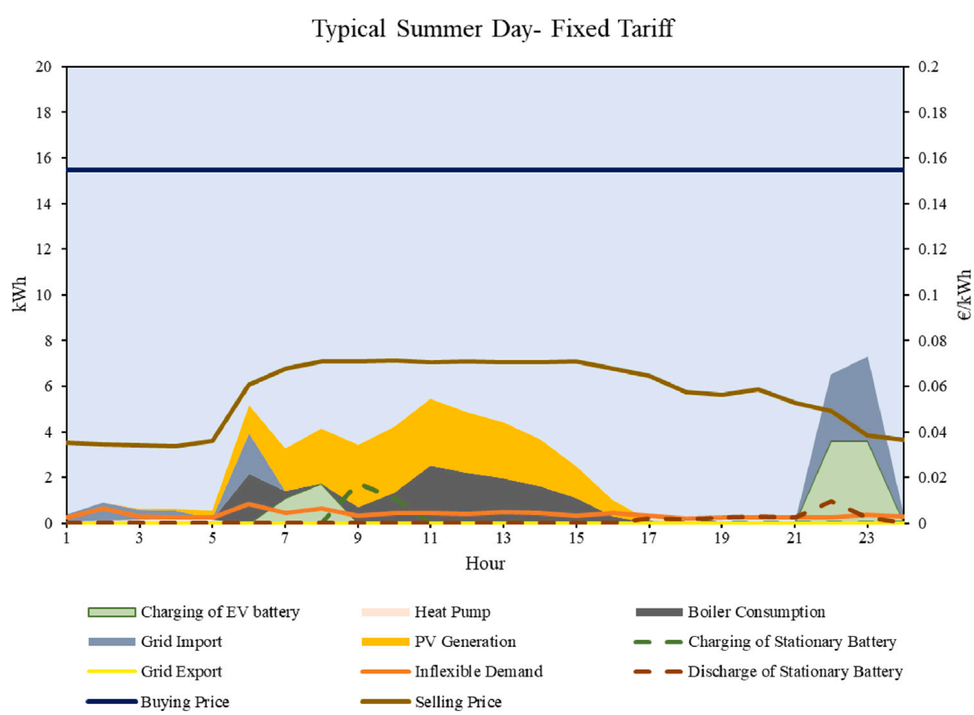

Fig. 9. Typical summer day — fixed tariffs.

Similar to the winter weekday, Fig. 8 shows the working of the HEMS in fixed price tariffs in a typical summer weekday. In contrast to the winter months, the heat pump is not activated here due to the high ambient temperature and the EV has been charging in the available times. In both Figs. 8 and 9, there has been no export to the grid due to the low export costs and the high import costs, which are fixed throughout the day. Due to this, there have been very minimal flexibility possible in this system with the usage of HEMS.

The results for using building type 'C' using time of day contracts can be observed in Figs. 10 and 11.

In Fig. 10, the working of HEMS can be clearly seen. With the changes in electricity prices during different times of the day, the HEMS shifts the loads to try to reduce the cost of electricity imported from the grid. This can be seen by the usage of the BESS to charge during low price hours. Similar to this, the EV is charged accordingly in the low price hours.

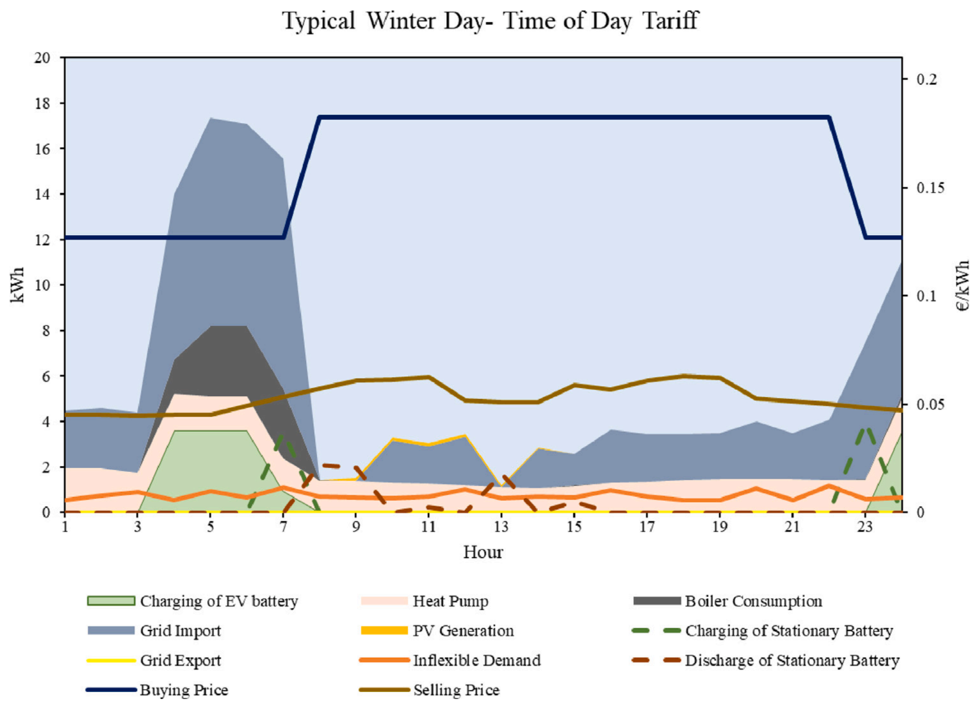

Fig. 10. Typical winter weekday — time of day tariffs.

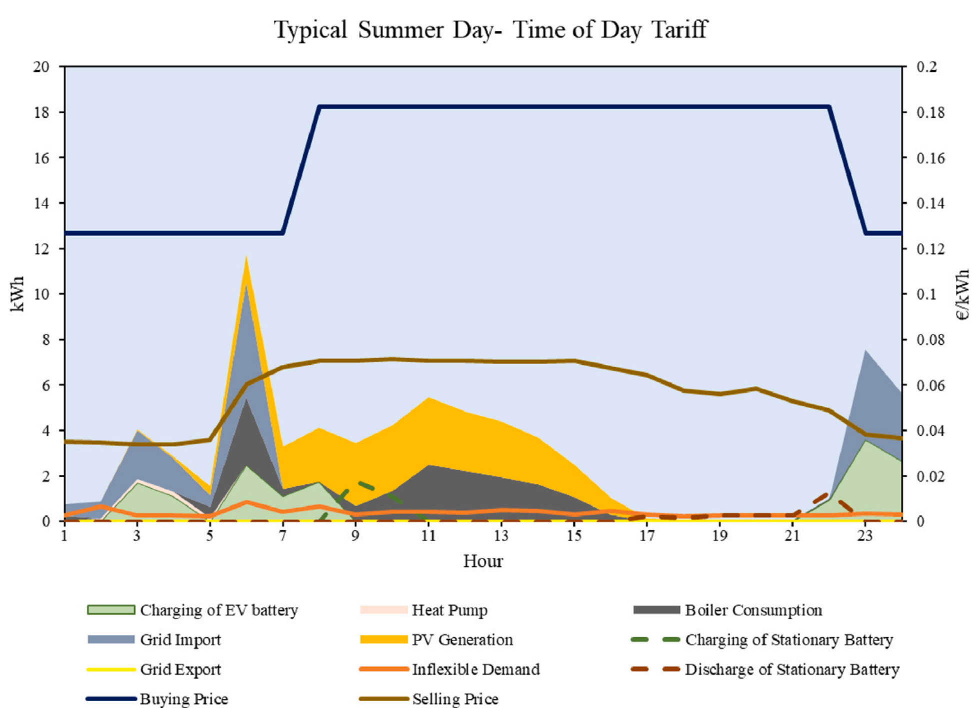

Fig. 11. Typical summer weekday — time of day tariffs.

The operation of the HEMS in the household during a typical summer workday can be observed in Fig. 11. Similar to the previous cases, there is no heat pump load during the day and the EV and BESS are charged during the low price hours to increase the savings in electricity bills.

The results for using building type 'C' using exchange price contracts can be observed in Figs. 12 and 13.

Further, the working of HEMS in the residential household in a winter day using exchange price tariffs can be observed in Fig. 12. For the time of day tariffs, the HEMS charges the EV during the low price hours, which occur during early morning hours in the day. There is no

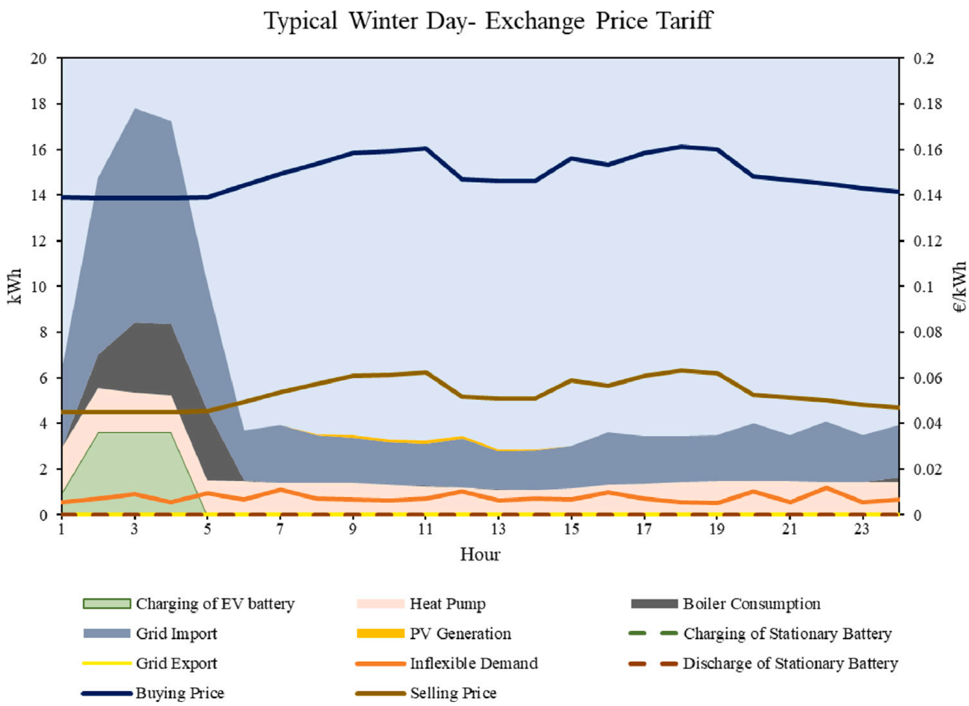

Fig. 12. Typical winter weekday — exchange price tariffs.

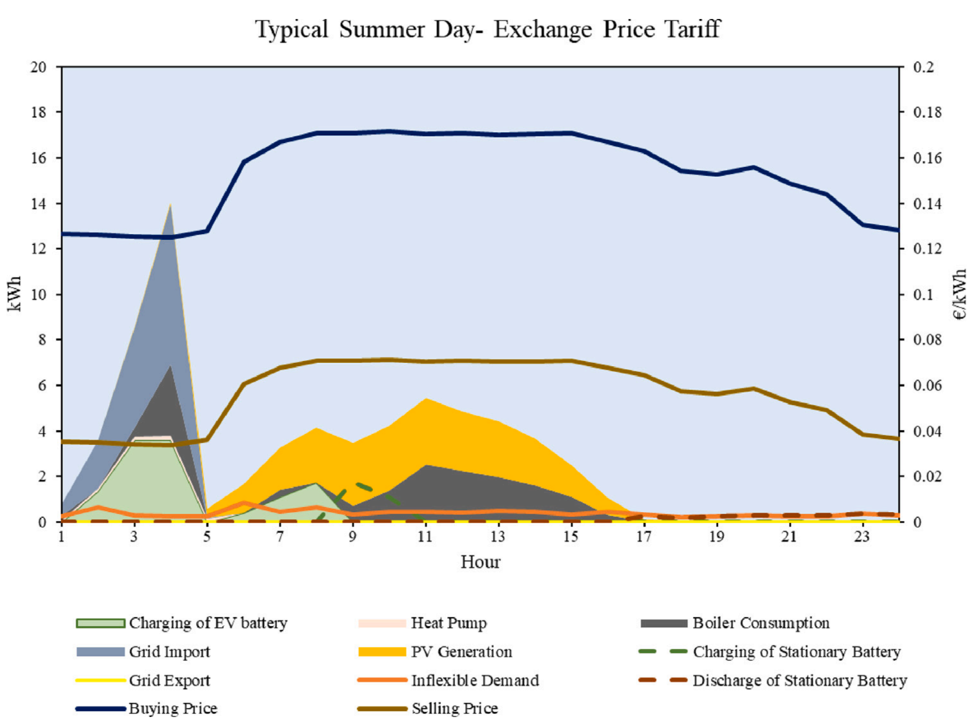

Fig. 13. Typical summer weekday — exchange price tariffs.

charging of the BESS, as the difference in prices throughout the day is not enough to cover for the charging and discharging losses for the BESS.

The working of HEMS in the residential building in a typical summer day can be observed in Fig. 13. Similar to the previous cases, the EV charges when there are low prices, which occurs during early morning hours and there is no heat pump loads in the summer. But unlike the previous cases, there is the charging of the BESS in this case due to the price volatility being higher than the efficiency losses due to charge and discharge from the BESS.

Table 13
Results for different scenarios and electricity contracts.

Scenario	Annual cost of electricity (€/annum)		Self consumption (%)	
	Annual optimization	Real-time rolling horizon optimization	Annual optimization	Real-time rolling horizon optimization
A1	3883.49	3887.18	99.9	99.3
A2	3625.16	3627.80	99.7	99.1
A3	3274.88	3295.15	99.3	98.9
B1	3338.55	3342.32	99.9	99.2
B2	3077.50	3080.28	99.7	99.1
B3	2792.11	2812.61	99.3	98.9
C1	2942.95	2947.28	99.8	99.2
C2	2682.03	2684.93	99.7	99
C3	2442.24	2463.00	99.3	98.7
D1	2754.71	2759.14	99.8	99.2
D2	2494.51	2497.52	99.7	99
D3	2275.76	2296.55	99.3	98.8
E1	2515.33	2519.98	99.8	99.1
E2	2256.84	2259.93	99.7	99.2
E3	2064.21	2085.19	99.3	98.7

The results from using the different building classification types and different electricity savings can be observed in Table 13. From the table, it is evident that the effect of different building types is directly affecting the annual costs of electricity. The building type A corresponds to very old buildings which does not have thermal insulation within the household. As a result, the heating losses are higher, thus by increasing the heat pump consumption throughout the year. As the thermal insulation is increased for the other building types, the annual costs are lower when compared to building type A. Similarly, building type B has a higher cost than C, D and E, and type C has higher costs than types D and E. Compared to all the building types, building type E had the lowest annual costs. In terms of different electricity contracts, the fixed price contract had the highest annual costs and the exchange price contracts had the lowest annual costs. This is explained by the fact that there is more volatility of prices in exchange price contracts, making the HEMS to optimize flexible loads to reduce the electricity costs. The time of day prices has a similar annual costs as exchange price contracts but still lower. In terms of self-consumption, the values are always close to 99% due to the fact that there is almost close to zero excess electricity which can be sold back to the grid to gain sufficient profits. Within the different electricity contracts, the self consumption for fixed price contracts is higher than the rest, which is then followed by time of day contracts. This can be attributed to the low volatility in the prices among these contracts, making the self consumption a more viable option than selling it back to the grid due to low selling prices.

Through the usage of real-time rolling horizon optimization, the optimization algorithm is updated based on real-time operational feedback, thus by providing results that are close to real world. The difference in annual costs among different building types based on annual optimization and rolling horizon is that as the building insulation level increases (as we move from A to E), the energy requirements for heating the living space decreases, which results in increase of the differences in annual costs. This is attributed to the fact that the required energy by the household is lower, making the utilization of PV generation to meet other loads of the household and to store in BESS. This is also validated by checking the self-consumption value for different buildings. As the insulation increases, the self consumption decreases, increasing excess PV production after meeting the load requirements. Additionally, the increase in volatility of the prices adds more savings to the household. As a result, the usage of real-time rolling horizon for buildings with exchange price contracts shows a higher saving potential compared to other types of electricity contracts.

5. Discussion

Based on the above results, the paper provides five key insights which would be essential for electricity suppliers, residential consumers, aggregators, policy-makers and researchers:

First, the rare usage of BESS for arbitrage or self-consumption can be clearly seen in the household. The BESS in the residential household had a charging/discharging efficiency of 92%. As a result, for arbitrage if the price spread is not more than 15% (round trip charging and discharging efficiency = 92*92/1000), the BESS would not be extensively utilized in the HEMS. In case of self-consumption, only when there is excess PV generation after meeting the load, will be stored in the BESS, which is minimal in the considered use case. Considering the different electricity tariffs, the BESS would be ideal mainly for time of day tariffs throughout the year, which guarantees a constant change in price over a day. Using this tariff type would utilize the BESS to its full capacity, which can help in energy savings, but can also lead to faster degradation of the BESS. Due to the uncertain future and the lack of accurately predicting the future prices, it is only logical to utilize the BESS as and when there is enough volatility in the prices to justify the charging and discharging of the BESS. The utilization of BESS in fixed price is not possible due to no volatility, and the utilization in exchange price tariff is only profitable when there is sufficient volatility in the day-ahead prices.

Second, the impact of different housing classification on the annual energy costs is evident. With Helsinki, Finland being in a sub-arctic temperature zone, heating corresponds to a major energy share. The possibility of having residential consumers flexible with their heating consumption in itself would help augment the electricity savings. The consumers having a higher insulation level has a lower annual costs than consumers living in older buildings with lower insulation levels. The consumers in newer buildings also have a lower self consumption share from PV as their heating loads are lower, making the PV to be utilized elsewhere needed.

Third, the impact of having different electricity tariffs can have a direct correlation in the annual energy savings. It is evident from the fact that the usage of fixed tariff structure would have the least annual savings, which is the maximum electricity cost. This tariff structure did not capitalize on the presence of BESS in the household, which acts as a huge flexibility asset. This is due as the cost of energy loss in the BESS is higher than the spreads available between the variation of electricity prices. Considering this, the time of day contracts and exchange price contracts utilizes the BESS only when the price spread is higher and the fixed price contracts never utilizes the BESS. Within the two variable price contracts, exchange price contracts have a higher utilization of BESS, making it ideal for consumers to choose to maximize their annual savings.

Fourth, the current schemes for exporting electricity back to the grid is not profitable. The current export prices in Finland are based on the day-ahead prices and a small commission back to the energy supplier. In this current contract type, the possibility of selling electricity back to the supplier is not profitable and as a result, the majority of the renewable generation is typically saved in the BESS and is later utilized for the building's consumption. This is evident from the high self-consumption values shown in Table 13.

Fifth, the effect of rolling horizon optimization can be clearly observed in the changes in result like annual cost of electricity compared to the simulation results from the annual optimization of residential building. In the rolling horizon optimization, the availability of range of data for the model is limited to the optimization horizon, which limits the model to plan in long term with limitations in decision-making. While in the annual optimization, the model has access to the data of the whole year to make the best decision. This results in the rolling horizon optimization model to have a lower savings/ higher electricity costs, making this approach as close as to real-world operation.

In addition to the above-mentioned points, there are some limitation in this study which needs to be acknowledged to support the results and insights from this paper. In this study, the initial costs of all the appliances are not considered. Currently, the installations of rooftop PV panels are significantly increasing and costs of BESS have been decreasing over the previous years. In addition to this, the majority of analysis in this study employs only G2V (grid to electric vehicle) and not V2G (electric vehicle to grid). As a result, the energy savings would be higher than what was observed in this study. Currently due to technical difficulties and a lack of clear pricing strategy for the same, it has been omitted in this study. Finally, the study uses data from 2019 for day-ahead prices where the price volatility is less pronounced, thereby reducing the savings through the usage of exchange price contracts. The increasing penetration of renewable energy will lead to increased volatility, which enhances overall annual savings through the use of HEMS (Sridhar et al., 2022a). Hence, the results from this paper provides a baseline to understand the savings through exchange price contract, which will more likely be increased in the future.

6. Conclusion

The increasing renewable energy generation due to the rapid increase of rooftop PV installations have made an average consumer of today, a prosumer in the future. With the rapid increase of renewable production in the energy system the volatility in the electricity price has increased leading to the need for flexibility an utmost importance for a stable functioning of the energy system. Within this study, the usage of HEMS for different building types and electricity contracts available within Finland has been analyzed. Five different building classifications and three different electricity contracts have been used to simulate the usage of HEMS for a residential household situated in Helsinki, Finland. The annual costs are directly correlated to the buildings' insulation level and the electricity contract. The newer buildings had a higher savings in comparison with the older buildings, and exchange price contracts proved to be the best in extracting the flexibility of the household. On top of this, a real-time rolling horizon optimization was performed to represent the performance of HEMS in real world scenario. Using this, the HEMS gets updated based on real-time operational feedback and this changes the annual costs incurred to the consumer. The consumers with exchange price contracts experienced the highest savings in comparison to other electricity contracts, and the overall costs were lower than what was obtained for annual optimization. The results from this study shows that consumers with exchange price contracts and having a good building insulation has the lowest annual costs, making them ideal prosumers for the future.

CRediT authorship contribution statement

Araavind Sridhar: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Jagruti Thakur:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Ashish Guhan Baskar:** Validation, Methodology, Formal analysis, Conceptualization.

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

Data will be made available on request.

References

Abdalla, M.A.A., Min, W., Bing, W., Ishag, A.M., Saleh, B., 2023. Double-layer home energy management strategy for increasing PV self-consumption and cost reduction through appliances scheduling, EV, and storage. Energy Rep. 10, 3494–3518.

ACEA, 2023. Vehicles in use Europe 2023.

Ahmed, K., Pylsy, P., Kurnitski, J., 2015. Monthly domestic hot water profiles for energy calculation in finnish apartment buildings. Energy Build. 97, 77–85.

Asmelash, E., Prakash, G., 2019. Future of Solar Photovoltaic: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects. International Renewable Energy Agency, Abu Dhabi.

Brahman, F., Honarmand, M., Jadid, S., 2015. Optimal electrical and thermal energy management of a residential energy hub, integrating demand response and energy storage system. Energy Build. 90, 65–75.

Bruni, G., Cordiner, S., Mulone, V., Rocco, V., Spagnolo, F., 2015. A study on the energy management in domestic micro-grids based on model predictive control strategies. Energy Convers. Manage. 102, 50–58.

Cao, X., Dai, X., Liu, J., 2016. Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade. Energy Build. 128, 198–213.

Castillo-Cagigal, M., Caamaño-Martín, E., Matallanas, E., Masa-Bote, D., Gutiérrez, Á., Monasterio-Huelin, F., Jiménez-Leube, J., 2011. PV self-consumption optimization with storage and Active DSM for the residential sector. Solar Energy 85 (9), 2338–2348.

De Boeck, L., Van Asch, S., De Bruecker, P., Audenaert, A., 2016. Comparison of support policies for residential photovoltaic systems in the major EU markets through investment profitability. Renew. Energy 87, 42–53.

Dinh, H.T., Kim, D., 2021. An optimal energy-saving home energy management supporting user comfort and electricity selling with different prices. IEEE Access 9, 9235–9249.

European Union, 2023c. Energy statistics: an overview. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_statistics_-_an_overview#Final_energy_consumption. (Accessed 24 December 2023).

Fernandes, F., Morais, H., Vale, Z., Ramos, C., 2014. Dynamic load management in a smart home to participate in demand response events. Energy Build. 82, 592–606.

Guo, F., Akenji, L., Schroeder, P., Bengtsson, M., 2018. Static analysis of technical and economic energy-saving potential in the residential sector of xiamen city. Energy 142, 373–383.

Helen Oy, 2023b. Electricity products and prices. https://www.helen.fi/en/electricity/electricity-products-and-prices. (Accessed 24 December 2023).

Helen Sähköverkko, 2023a. Electricity distribution tariffs. https://www.helensahkoverkko.fi/globalassets/hinnastot-ja-sopimusehdot/hsv---enkku/Distribution-tariffs.pdf. (Accessed 24 December 2023).

Iwafune, Y., Mori, Y., Kawai, T., Yagita, Y., 2017. Energy-saving effect of automatic home energy report utilizing home energy management system data in Japan. Energy 125, 382–392.

Jordan, U., Vajen, K., 2005. DHWcalc: Program to generate domestic hot water profiles with statistical means for user defined conditions. In: Proceedings of the ISES Solar World Congress, Orlando, FL, USA. 12.

Kavlak, G., McNerney, J., Trancik, J.E., 2018. Evaluating the causes of cost reduction in photovoltaic modules. Energy Policy 123, 700–710.

Killian, M., Zauner, M., Kozek, M., 2018. Comprehensive smart home energy management system using mixed-integer quadratic-programming. Appl. Energy 222, 662–672.

Lahtinen, S., 2019. Number of kilometres driven with cars in 2019 unchanged from the year before – kilometres for heavy vehicles decreased. URL: https://www.stat.fi/til/tiet/2019/tiet_2019_2020-04-15_tie_001_en.html#:~:text=According%20to%20the%20road%20traffic,were%20driven%20with%20passenger%20cars.

Laitinen, A., Tuominen, P., Holopainen, R., Tuomaala, P., Jokisalo, J., Eskola, L., Sirén, K., 2014. Renewable energy production of finnish heat pumps. VTT Technical Research Center of Finland. Final Report of the SPF project.

Langer, L., Volling, T., 2020. An optimal home energy management system for modulating heat pumps and photovoltaic systems. Appl. Energy 278, 115661.

Menegazzo, D., Lombardo, G., Bobbo, S., De Carli, M., Fedele, L., 2022. State of the art, perspective and obstacles of ground-source heat pump technology in the European building sector: A review. Energies 15 (7), 2685.

Muenzel, V., Mareels, I., de Hoog, J., Vishwanath, A., Kalyanaraman, S., Gort, A., 2015. PV generation and demand mismatch: Evaluating the potential of residential storage. In: 2015 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference. ISGT, IEEE, pp. 1–5.

Narayanadhas, T., 2022. Dynamic management of schedulable household assets for solar self-consumption maximization with demand side management.

Obinna, U., Joore, P., Wauben, L., Reinders, A., 2017. Comparison of two residential smart grid pilots in the netherlands and in the USA, focusing on energy performance and user experiences. Appl. Energy 191, 264–275. http://dx.doi.org/10.1016/j.apenergy.2017.01.086, URL: https://www.sciencedirect.com/science/article/pii/S030626191730096X.

Paris Agreement, 2015. Paris agreement. In: Report of the Conference of the Parties To the United Nations Framework Convention on Climate Change (21st Session, 2015: Paris). HeinOnline, Retrived 4 December 2017.

Quintel, 2023d. Heat pumps. https://docs.energytransitionmodel.com/main/heat-pumps/. (Accessed 24 December 2023).

Renaldi, R., Kiprakis, A., Friedrich, D., 2017. An optimisation framework for thermal energy storage integration in a residential heat pump heating system. Appl. Energy 186, 520–529.

Ruokamo, E., Kopsakangas-Savolainen, M., Meriläinen, T., Svento, R., 2019. Towards flexible energy demand–Preferences for dynamic contracts, services and emissions reductions. Energy Econ. 84, 104522.

Ryan, T., 2020. In harmony: Virtual power plants: Predicting, optimising and leveraging residential electrical flexibility for local and global benefit.

Salpakari, J., Lund, P., 2016. Optimal and rule-based control strategies for energy flexibility in buildings with PV. Appl. Energy 161, 425–436.

Shakeri, M., Shayestegan, M., Abunima, H., Reza, S.S., Akhtaruzzaman, M., Alamoud, A., Sopian, K., Amin, N., 2017. An intelligent system architecture in home energy management systems (HEMS) for efficient demand response in smart grid. Energy Build. 138, 154–164.

Sridhar, A., Baskar, A.G., Thakur, J., 2022a. Energy storage integration with run of river power plants to mitigate operational environmental constraints: Case study of Sweden. J. Energy Storage 56, 105899. http://dx.doi.org/10.1016/j.est.2022.105899, URL: https://www.sciencedirect.com/science/article/pii/S2352152X22018874.

Sridhar, A., Honkapuro, S., Ruiz, F., Annala, S., Wolff, A., 2022c. Assessing the economic and environmental benefits of residential demand response: A finnish case study. In: 2022 18th International Conference on the European Energy Market. EEM, IEEE, pp. 1–6.

Sridhar, A., Honkapuro, S., Ruiz, F., Stoklasa, J., Annala, S., Wolff, A., Rautiainen, A., 2023. Toward residential flexibility—Consumer willingness to enroll household loads in demand response. Appl. Energy 342, 121204.

Suri, M., Huld, T., Cebecauer, T., Dunlop, E.D., 2008. Geographic aspects of photovoltaics in europe: contribution of the PVGIS website. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 1 (1), 34–41.

Tuomela, S., de Castro Tomé, M., Iivari, N., Svento, R., 2021. Impacts of home energy management systems on electricity consumption. Appl. Energy 299, 117310.

Vanthournout, K., Dupont, B., Foubert, W., Stuckens, C., Claessens, S., 2015. An automated residential demand response pilot experiment, based on day-ahead dynamic pricing. Appl. Energy 155, 195–203. http://dx.doi.org/10.1016/j.apenergy.2015.05.100, URL: https://www.sciencedirect.com/science/article/pii/S0306261915007333.

Wu, X., Hu, X., Yin, X., Moura, S.J., 2016. Stochastic optimal energy management of smart home with PEV energy storage. IEEE Trans. Smart Grid 9 (3), 2065–2075.

Wu, Z., Xia, X., 2015. Optimal switching renewable energy system for demand side management. Sol. Energy 114, 278–288.