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Towards sustainable urban living: A holistic energy strategy for electric vehicle and heat pump adoption in residential communities

Abdullah Dik [a,b,*], Cagri Kutlu [a], Hao Sun [a], John Kaiser Calautit [a], Rabah Boukhanouf [a], Siddig Omer [a,**]

[a] *Faculty of Engineering, The University of Nottingham, Nottingham, UK*
[b] *Faculty of Engineering, Iskenderun Technical University, Hatay, Türkiye*

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ABSTRACT

Electric vehicles (EVs) and heat pumps (HPs) are key in reducing carbon emissions from transportation and domestic heating, yet their adoption may increase peak load demands on electrical networks. One of the aims of this research is to assess the potential impact of uncontrolled EV charging on community-scale distribution networks, exploring how this could stress the existing electrical infrastructure. It also explores the role of EVs in Vehicle-to-Grid (V2G) and smart charging applications, aiming to enhance community distribution systems. The study investigates the maximum stabilisation level achievable under various scenarios, highlighting the importance of smart energy management in integrating renewable energy and addressing uncertainties in the modelling process. Additionally, this study discusses the proposed systems' scalability, consumer behaviours' impact on the suggested energy solutions, and the potential implications of recent technological advancements for simulated communities. The research employs a sophisticated, integrative approach, combining stochastic methods with several robust energy software. Key findings suggest that uncontrolled EV charging can lead to grid capacity issues at high EV penetration levels, particularly during colder months. While smart charging and V2G technologies can moderate peak loads in many scenarios, achieving 100 % sustainable technology integration requires enhanced energy management or increased network capacity, especially in winter. Wind and solar power integration demonstrates strategic complementarity, particularly in winter, enhancing the reliability and stability of the community grid. It is also observed that peak solar generation hours misalign with the community's highest demand times, posing challenges for solar energy utilisation in EV charging in residential-based areas.

1. Introduction and literature review

The International Energy Agency (IEA) (International Energy Agency (IEA) 2023) reported that fossil-based sources were still responsible for 60 % of the global electricity market at the end of 2022. The IEA also added that restrictions on natural gas have led to an increase in coal-based electricity production, and CO_2 emissions from electricity production have reached a record level of 14.8 Gt CO_2. The UK has made significant progress in reducing carbon emissions from electricity generation. Compared to 1990, the UK's carbon emissions from electricity generation have been reduced by almost three-quarters, to the current level of 53.7 Mt of carbon emissions annually (Department for Energy Security and Net Zero (DESNZ) 2023).

Renewable energy sources (RESs) are considered a key solution to grid decarbonisation and climate change mitigation (Sinsel et al., 2020). IEA (International Energy Agency (IEA) 2023) estimated that by the end of 2023, the global renewable energy market will experience its highest annual increase, exceeding 440 GW, with solar photovoltaics (PVs) accounting for two-thirds of this increase. The UK has also achieved substantial progress in the field of renewable energy (RE) integration. While RES were responsible for 2 % of the UK energy market in 1991, RES accounted for 43 % of the production in the market and surpassing fossil production for the first time in 2020 (National Grid, 2023). In 2023, wind energy accounted for 29.4 % of total electricity production, while solar energy made up 4.9 % of the renewable energy market (National Grid, 2023). Significant increases in wind and solar energy production

* Corresponding author.
** Co-Corresponding author.
E-mail addresses: abdullah.dik@nottingham.ac.uk (A. Dik), siddig.omer@nottingham.ac.uk (S. Omer).

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are expected in the UK in the coming years. By 2030, offshore wind generation is expected to increase to 50 GW, and solar PV capacity is expected to increase to 70 GW (National Grid, 2023). Moreover, within the scope of 2050 zero carbon targets, 90 % of the electrical energy produced should be from renewable sources, and 70 % of this renewable energy supply should be provided by wind and solar energy (Bouckaert et al., 2021).

In the UK the transportation sector is the largest contributor to carbon emissions, contributing 34 % of UK carbon emissions in 2022 (Department for Energy Security and Net Zero (DESNZ) 2023). The decarbonisation of this sector is well underway through the gradual introduction of EVs (Arowolo & Perez, 2023). EV sales in the UK have continued their growing trend in 2023. Statistics from ZAPMAP (Zap--Map, 2023) indicated that, as of September 2023, there are 1489,000 units of EVs on UK roads (920,000 BEV and 560,000 PHEV). Even compared to 2019, EVs have grown by approximately 450 %. The infrastructure for EV charging is one of the most critical factors for the adaptation of EVs. The UK has achieved significant progress in its EV charging infrastructure. A recent report by the UK government (HM Government, 2022) reveals that the UK has 29,600 public chargers, including 5400 fast sockets. More specifically, considering England motorways and major A roads, no EV is now further than 25 miles from the fast charge point. Additionally, the UK government estimates that 300,000 charging stations will be installed by 2030 to align with the decision to ban ICE vehicles by that year. The government also anticipated that this figure could reach 700,000 with the potential high adoption of on-street chargers (HM Government, 2022). Looking ahead, the UK government detailed the timeline of the transition to EVs, with plans such as requiring zero-emission vehicles in 2035, eliminating charging station infrastructure concerns, and introducing various support packages within the scope of the Road to Zero targets (Department for Transport (DfT) 2021). Furthermore, all major automakers have agreed to shift towards EVs to electrify their vehicle fleets (Dik et al., 2022). However, the complete phasing out of internal combustion engine cars may take several decades, and the transition will vary by market and vehicle type. Equally important, National Grid (National Grid ESO, 2023) has updated their 2040 EV number estimates to approximately 30 million based on a rapid decarbonisation scenario and 23 million based on a non-target scenario in the UK. This update marks a significant development, as a reliable power grid is fundamental to supporting the growth of the EV market and achieving zero-emission targets (Dik et al., 2022; Held et al., 2019). However, a recent UK government report (HM Government, 2022) emphasised that EV charging operations will significantly impact the power network. The report acknowledges the lack of data to assist decision-making, especially the unknown future demand modelling.

Similarly, the decarbonisation of heat in buildings, which accounts for over 17 % of total carbon emissions, is another target of the UK government to achieve net zero emissions (Department for Energy Security and Net Zero (DESNZ) 2023). Hence, in the UK and many developed countries, there are concerted efforts, towards replacing carbon-based gas boilers with electrically driven heat pump (HP) systems. According to a report from the UK Parliament, while HPs possess significant growth potential in the UK, political uncertainties have impeded their growth rate (Harris & Walker, 2023). The report also stated that 72,000 HP units were installed in the UK in 2022 and emphasised the UK government's target to increase annual HP installations to 600,000 units by 2028. Given this target, it is reasonable to anticipate a significant increase in the number of HPs in the UK in the near future. However, according to current HP statistics, HPs have been installed in only 1 % of UK home stock so far, and it is predicted that HP will be required in almost 80 % of homes to meet net zero targets (Harris & Walker, 2023). Globally, it is estimated that 600 million HP will need to be actively operated by 2030 to achieve global net zero targets, but with this current growth rate, only 40 % of the target might be achieved (Heat Pumps London, 2023). However, at this point, it is known that global investments will increase to 160 billion dollars by 2030 to increase HP adoption within the scope of 2050 targets. In the UK, ASHPs and GSHPs are the most commonly used types of HPs. Although the exact rate of adoption of these two types in the UK is unknown, ASHPs are responsible for 60 % of global HP sales, while GSHPs account for only 2.5 % of HP installations in the European Union (EU) (Heat Pumps London, 2023). While there are no specific statistics on SAHPs, it is projected that their market value, estimated at 4523 billion dollars in 2022, will increase to 8732 billion dollars by 2030, with a 7.53 % compound annual growth rate (Research and Markets, 2023). The UK Parliament report (Harris & Walker, 2023) underscored that many people are unfamiliar with heat pumps and that there is a shortage of qualified installers. The report (Harris & Walker, 2023) also noted the absence of clear long-term strategies for utilising heat pumps to reduce carbon emissions in domestic heating.

Based on these efforts and the introduction of various technologies and strategies, a concept known as 'sustainable community' has emerged. It is an increasingly important concept to support countries' carbon targets by combining several decarbonisation measures. Today, independent communities from the grid, which produce and consume their own energy, are attracting significant attention. For example, Swansea Community Energy and Enterprise Scheme, and Awel Co-op, are real-world projects supporting the sustainable community concept in the UK and more details about them can be found in (Wales Government, 2023) and (Wales Government, 2023), respectively. However, it might be beneficial to know that the communities involving unpredictably complex dynamics because of decentralised high-capacity PV and wind energy production, EV charging and discharge operations, and HP high-performance requirements should be examined with random-based approaches.

A growing body of literature recognises the importance of sustainable communities equipped with low-carbon technologies (Abbasi et al., 2023; Han et al., 2022; Tostado-Véliz et al., 2022). A detailed comparative analysis between the current study and the most recent related research is shown in Table 1.

The table summarises key parameters analysed in recent community-based energy management studies, particularly the past two years. The explanation of each given aspect or parameter is as follows:

The current study offers a foundational context by analysing the UK's grid system, incorporating considerations of the existing distribution system's capacities for real-world applications. In addition, as shown in the table, the study evaluates the country's sustainable targets in the near and distant future with the national carbon neutrality progress assessment and provides a perspective in different time zones with penetration scenarios at different scales. Additionally, the study incorporates an analysis of housing and vehicle stock, factoring in power network capacity. This approach allows for a more nuanced analysis of energy demand, recognising the direct impact of the number of houses and EVs on consumption patterns.

Furthermore, energy demand seasonality analysis is important in such modelling to capture the fluctuations in energy needs, whether caused by thermal systems or EV charging. Examining EV and charger trends can reveal technological advancements in the market. Furthermore, a detailed analysis of electric vehicle types and charger needs underscores the diversity in the electric vehicle market and its effect on grid demand. Comprehensive insights into EV scheduling and driving pattern variability are essential to better predict grid behaviour on an hourly basis. These insights allow for more precise energy supply planning, especially given the variability across different day types. The importance of stochastic EV charge demand calculation is its ability to consider randomness and uncertainties, thereby enabling a more sensitive approach to charge demand calculation for robust grid management strategies. Lastly, the integration and effective management of renewable energy sources and heat pump technologies, as observed in RES integration analysis and HP technology integration, respectively, underscore the need to diversify and incorporate varying sustainable

Table 1
Comparative analysis of some features between the current study and related research.

Aspects/Parameters	This Study	(Mohammadi et al., 2022)	(Han et al., 2022)	(Lo et al., 2023)	(Doroudchi et al., 2018)	(Abbasi et al., 2023)	(Zhu et al., 2023)	(Dorotić et al., 2019)	(Tostado-Véliz et al., 2022)	(Liu et al., 2022)
Grid System Analysis (Country Codes)	GB	–	GB	–	–	PK	–	HR	–	CN
National Carbon Neutrality Progress Assessment	✓	–	–	–	–	–	–	✓	–	–
Housing Stock Analysis (No. of houses)	384	4	384	1	1	40	Scale-based	2424	6	Scale-based
Vehicle Stock Analysis (No. of EVs)	461	4	465	23	1	2	200	5630	2	200
Seasonality Analysis for Thermal (T) and EV Charging (V) Demands	✓	–	T	–	✓	V	–	T	–	T
EV (V) and Charger (C) Market Trends	✓	–	–	V	–	–	–	–	V	–
Comprehensive EV Type Analysis for Charging Needs	✓	–	–	✓	–	–	✓	–	✓	–
Comprehensive EV Charger Analysis for Charging Needs	✓	–	–	–	–	–	✓	–	–	–
Comprehensive EV Scheduling Insights	✓	–	–	✓	✓	–	✓	–	–	–
Driving Pattern Variability in EVs Based on Day Type	✓	–	✓	–	✓	–	✓	–	–	–
Stochastic EV Charge Demand Calculation	✓	–	–	–	✓	–	✓	–	–	–
RES Integration Analysis	PV and Wind	PV	PV	PV	PV	PV	PV and Wind	PV and Wind	PV	PV
Heat Pump Technology Integration	ASHP, GSHP and SAHP	–	GSHP	–	GSHP	–	–	–	–	ASHP
Seasonal & Hourly HP Efficiency Variation	✓	–	–	–	–	–	–	–	–	–

*Abbreviations: GB - Great Britain, PK - Pakistan, HR - Croatia, CN - China, T - Thermal-related, V - EV-related, C - Charger-related, PV - Solar Photovoltaic, ASHP - Air Source Heat Pump, GSHP - Ground Source Heat Pump, SAHP - Solar Assisted Heat Pump.

solutions for a balanced and decarbonised grid system.

1.1. Research novelty, aims and objectives

A general review of recent literature reveals promising findings regarding the integration of renewable energy sources, particularly solar PVs. However, there's a notable gap in studies that holistically centre on locating EVs as instrumental tools to enhance large-scale RESs such as solar PVs and wind turbines. Additionally, a major problem with such an application is capturing the complex details of combining different elements like grid and EV status and dynamic local renewable source outputs, while also dealing with natural uncertainties such as fluctuating weather conditions and varying EV charging/discharging patterns influenced by user behaviours. This present study performs an advanced, multi-staged and comprehensive stochastic model to discover and optimise the possible benefit of EVs in supporting the community grid and improving PVs and wind turbine integration to make an essential contribution to the field.

According to the UK government's road map, there is a growing interest in HPs (Harris & Walker, 2023). However, rather than considering the penetration of EVs and integration of different types of HPs as solely sustainable solutions, our study collectively considers the potential stress pressures on the grid due to the electricity needs of these technologies and explores the inherent complexities of electricity consumption patterns. The multi-stage analysis in this investigation is designed to address various uncertainties, ranging from the impact of seasonal changes to the unpredictability of market trends. This is achieved by combining environmental variabilities with probabilistic modelling techniques. While the study's comprehensive design introduces a realistic simulation of the developing energy ecosystem in the near and long future, it also provides valuable insight to many stakeholders, from households to network operators.

Finally, this investigation builds upon our previous paper (Dik et al., 2023), which provides a fundamental understanding of the synergy between EVs, HPs and the grid at the individual household level. In this paper, the analysis was carried out for scaling to a community level and integrating large-scale RES, HPs, and EVs may provide a realistic simulation of the real world. Undoubtedly, the building up of such a system, however, also brings numerous uncertainties, ranging from localised energy generation to varying demand patterns in heating and EV charging throughout the year. This study offers a robust approach to navigating these uncertainties by performing an advanced multistage stochastic model. In this way, a comprehensive methodology is presented to evaluate the effectiveness of EVs with V2G technology and smart charging to stabilise community distribution systems and decarbonise distribution networks by enhancing renewable energy usage within an uncertain environment.

2. Methodology

2.1. Study concept and defined scenarios

Undoubtedly, technological developments and incentives based on carbon reduction targets contribute to an increase in EVs and HPs. However, both technologies can potentially change the amount of energy demanded from the distribution grid. Given the necessity to maintain a balance between energy generation and consumption in the system, the adaptation of these technologies into the network should be examined in detail.

This prospective study was first designed to analyse the impact of technologies such as EVs and HPs by including possible uncertainty and randomness. This research also examines the emerging role of V2G in the context of power network balancing on the community scale. The last purpose of this study is to discover the synergy between EVs, HPs, and renewables to manage the distribution networks of electrified communities safely and enhance large-scale renewable energy integration.

Fig. 1 shows the conceptual design of the simulated community. Nottingham/UK has been selected as the project location. Nottingham is a large city in the UK's East Midlands at 52.58 latitudes and −1.08 longitudes. SOLARGIS (SOLARGIS, 2023) and MET Office (MetOffice, 2023) estimated that Nottingham received 1137.5 kWh of solar irradiation annually and 3.6 m/s average wind speed.

Today, there are approximately 30 million homes in the UK, contributing to 21 % of the country's total carbon emissions (Department for Energy Security and Net Zero DESNZ and Department for Business, Energy & Industrial Strategy BEIS, 2021). Experts have noted that over 80 % of the residences that are occupied by about 67 million UK citizens by 2050 have already been built in the UK (Energy Saving Trust, 2021). Given this, the 1930s semi-detached model house, representing over 3 million homes in the current UK housing stock, was selected as the representative house type for this simulation to accurately mirror the current housing stock in the UK (The University of Nottingham, 2023). The E.ON research house, a three-bedroom semi--detached replica of a 1930s home located at the University of Nottingham, was the primary reference for the community's proposed house design. E.ON house, which is located at the University of Nottingham and is a two-story building with a total interior floor area of 153 m^2 (76.5 m^2 for each floor), is taken as a reference to the design of the community. The image of the E.ON house can be seen in Appendix 1 [33]. Dimensions of the building were also taken from the original blueprints, ensuring adherence to the actual measurement values.

In addition to domestic home technologies, the study considers the possible integration of EV chargers, Air Source Heat Pumps (ASHPs), Ground Source Heat Pumps (GSHPs), and Solar-Assisted Heat Pumps (SAHPs) into houses in the community. Furthermore, the community is equipped with on-grid solar photovoltaic (PV) and wind energy facilities, which are connected to the distribution grid and contribute to the community's energy supply.

A comprehensive flowchart illustrating the present research method is presented in Fig. 2. The analysis begins with an assessment of the community power network's operational and peak capacities, a crucial step for understanding its ability to integrate sustainable technologies and manage the dynamic demands of modern energy consumption. This assessment is crucial for capturing the operational dynamics of the community power network. Subsequent analysis focuses on the residential energy usage patterns, utilising literature statistics to develop an electro-domestic energy consumption profile. Additionally, the Monte Carlo Simulation method is utilised to estimate EV charging needs within the community, demonstrating a comprehensive approach to energy demand assessment. Following that, the Integrated Environmental Solutions Virtual Environment (IES VE) software is then applied to calculate thermal energy requirements for household heating and domestic hot water. IES VE was chosen here because of its demonstrated reliability in literature and widespread usage in dynamically simulating and optimising building thermal conditions, offering comprehensive modelling capabilities and real-time data integration (IES, 2024; Shahzad et al., 2020; Wei et al., 2022). Further, MATLAB is employed to analyse the energy consumption of different heat pump configurations, including ASHPs, GSHPs, and SAHPs. These are assessed with the goal of efficiently meeting thermal demands. An initial assessment then takes place, which involves an analysis of the community network without the integration of any management strategy. This foundational analysis establishes the baseline operational parameters of the network, evaluating how the current infrastructure performs under both typical and possible future load conditions in the absence of management strategies that could modulate demand or supply. As the analysis advances, smart charging and V2G algorithms are integrated to optimise EV charging and discharging processes, aiming to improve the efficiency and stability of the community's energy system. In the next step, the HOMER Pro-software is utilised to calculate the community's potential outputs from solar and wind integration over the years. HOMER Pro-which is renowned in literature and recommended by experts was also chosen here because of its ability to efficiently analyse and optimise hybrid renewable energy systems, excelling in grid integration (Allouhi et al., 2022; Ekren et al., 2021; HOMER 2023; Rahmat et al., 2022). In the final step, the research conducts a new assessment that illustrates the outputs of renewable energy systems and the impact of smart charging and V2G strategies on network performance. The evaluation focuses on the network's capacity to meet future energy demands and maintain stability, and it offers insights into the network's readiness for sustainable energy practices in the future.

To carry out the simulation, the given assumptions are considered in the study:

- The simulated community, which is solely comprised of homes, is equipped with EV chargers, ASHP, GSHP, and SAHP based on scenarios. It's supported by an on-grid solar PV and wind energy system, adhering to the sustainable community concept.
- The EVs and conventional vehicles have similar daily travel patterns.
- Charge and discharge operations are performed between 20 % and 80 % SOC. Preferred SOC after discharge operations varies between 60 % and 80 %. Additionally, vehicles are promptly connected to the charger upon their arrival.
- The necessary technology is available at the grid operators and EVs, enabling Smart Charging and V2G discharging.
- The EV user's home has the necessary infrastructure for allowing discharging.

Fig. 1. Schematic diagram of the proposed system.

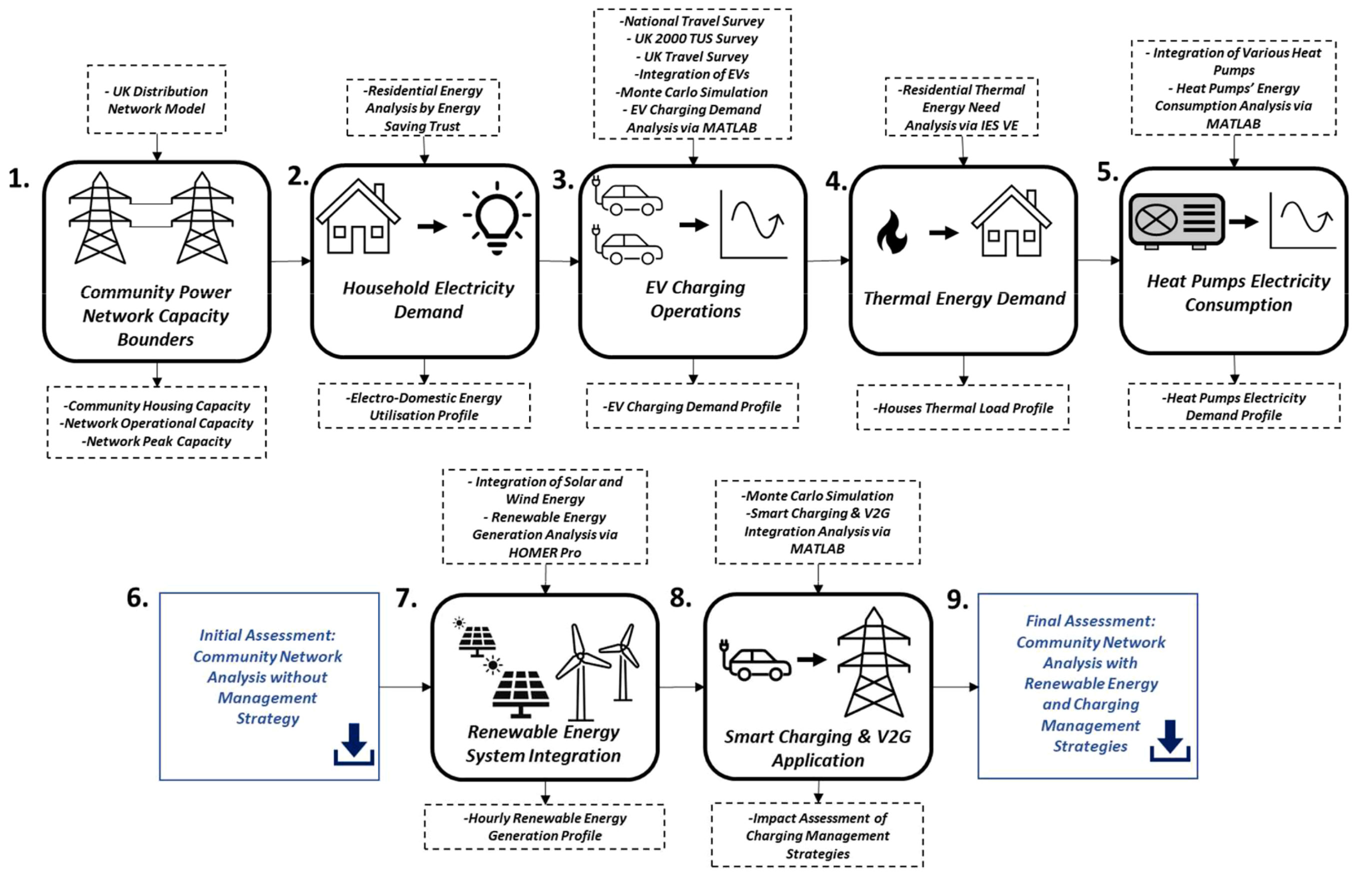

Fig. 2. The methodological framework of the research.

The research assumptions can be supported by the practical implementations observed in European demonstrator projects across Denmark, the Netherlands, and Poland, as highlighted in the SERENE H2020 project (SERENE, 2024). These projects exemplify the integration of HPs, renewable energy self-consumption through smart controls, and EV charging infrastructures within residential communities. The Danish case's transition from fossil fuels to electric heating, supplemented by smart renewable energy management, directly validates this present study model's theory of a sustainable community supported by renewable sources and advanced technologies. The Dutch and Polish cases further reinforce the feasibility of this research's assumptions by focusing on smart energy systems, community-based renewable integration, and V2G capabilities. Further substantiation for the current paper's assumptions comes from the literature. The similarity in daily travel patterns between EVs and conventional vehicles is supported by (Daina et al., 2017), who demonstrate that using conventional driving patterns to model EV usage is a common approach, aligning with the assumptions of this paper. The SOC range for charging and discharging operations, which enhances battery lifespan and ensures cost savings, is supported by the literature [((Bayram & Tajer, 2017; Department for transport (DfT) 2022; Koncar & Bayram, 2021; Kostopoulos et al., 2020; Ramadan et al., 2017))] and further detailed in the methodology section of this current investigation. Lastly, the availability of technology for smart charging and V2G discharging at both grid operators and in EV users' homes is supported by Hoehne and Chester's research (Hoehne & Chester, 2016).

A detailed discussion can be found in the following sub-sections. Additionally, the applied methodological procedure in the investigation is outlined as follows: 1- Formulation of the scenarios, 2- Identification of the community power network, 3- Calculation of the conventional energy consumption in the community, 4- Modelling of Monte Carlo Simulation (MCS) for EVs' charging demand and discharging operations, 5- Modelling of thermal energy demand, 6- Modelling of the HPs for heating and domestic hot water, and 7- Designing of off-grid solar and wind energy stations.

2.2. Scenario description and reasoning

Reflecting on the statistics and future projections presented in the Introduction section of this paper, an increase in the integration of RES, notably solar PVs and wind turbines, is expected in the UK. The adoption of low-carbon technologies, especially EVs and HPs, is also projected to rise in line with national sustainability policies. These trends support the development of the scenarios within this research, where a gradual yet significant increase in the uptake of EVs and HPs is anticipated, therefore advancing local renewable production capabilities. The scenarios are designed to reflect the varying degrees of technology penetration from the short to the long term, capturing the evolution of community energy frameworks as they transition towards sustainable practices. The adoption rates, informed by empirical data discussed in the Introduction and aligned with governmental targets, form the basis for assessing the implications of these technologies on the power network's infrastructure and the network's capacity to meet future energy demands.

In the study, five different penetration scenarios are examined. The study aims to reflect possible scenarios ranging from 25 % to 100 % sustainable technology adaptation that might be encountered in a UK community, covering short-term to long-term time horizons. A summary of the five case scenarios explored in the study is provided in Table 2.

Table 2 summarises the five scenarios explored in this study, each representing a different level of sustainable technology penetration within a UK community, from the short-term to the long-term. These scenarios are constructed based on anticipated increases in RES integration and adopting low-carbon technologies, reflecting national sustainability goals. The following details provide a deeper insight into

Table 2
The proposed scenarios for community-based energy management with EVs.

Scenarios	Time Horizon	EV Penetration [%]	HP Penetration [%]	Conventional Supply [%]	Renewable Supply (Solar PV/Wind) [%]
S1	Short-term	25	25	75	25 [60 %/40 %]
S2	Medium-term	50	50	50	50 [50 %/50 %]
S3	Alternative Medium-term	75	75	50	50 [50 %/50 %]
S4	Long-term	100	100	25	75 [40 %/60%]
S5	Alternative Long-Term	100	100	25	75 [60 %/40 %]

each scenario's unique characteristics and their implications for community-based energy management.

S1 - Short-term scenario: At this stage, the community begins to adopt EVs and HPs, though their use is not yet widespread. The energy supply is predominantly from the grid, with an early inclination towards adopting solar panels due to their ease of installation, fewer regulatory hurdles, and cost-effectiveness.

S2 - Medium-term scenario: The community attempts a balanced mix of renewable energy, taking advantage of both solar and wind energy due to improved infrastructure. While solar energy maintains its significance, the focus also shifts towards maximizing the UK's wind energy potential, accompanied by a steady increase in the adoption of EVs and HPs.

S3 - Alternative medium-term scenario: This variation reflects a faster integration of EVs and HPs, as some regions might more readily embrace these technologies due to supportive, sustainable policies and incentives.

S4 - Long-term scenario: The community's long-term goal is to enhance wind energy generation, tapping into the UK's vast wind potential to achieve zero carbon targets. With the maturing renewable infrastructure, the interest in wind energy surges alongside the complete integration of low-carbon technologies.

S5 - Alternative long-term scenario: Similar to the long-term vision of scenario S4, this scenario explores the full adoption of EVs and HPs. However, it distinguishes itself by illustrating a scenario where solar PV integration in the community grid is prioritised over wind energy.

2.3. Determining system boundaries and capacities in power distribution network

This section evaluates the operational boundaries and capacity of community power systems. It aims to examine the existing distribution network's capability to manage the evolving demands of modern energy consumption by EVs and HPs and generation from RESs. Central to the analysis is identifying the network's operational and peak capacities, which serve as benchmarks for the present research model. This assessment attempts to highlight the network sufficiency and strategies for adopting low-carbon technologies such as EVs, HPs and RESs.

The UK power grid system consists of an integrated generation, transmission and distribution networks. The National Grid transmission network operators (TNOs) operate the high-voltage transmission network, while the Distribution Network Operators (DNOs) manage the low-voltage distribution networks that supply electricity to consumers. Additionally, the Office of Gas and Electricity Markets (OFGEM) provides independent market regulation of these grid network operators.

The existing grid system, is a legacy of the traditional one direction flow of electricity from large, centralised power generators to the consumer. As a result, these networks may not provide the opertaional flexibility to cope with the dynamic fluctuation of renewables, high demand from additional consumer loads to facilitate the decarbonisation of the heat and transport sectors (Fachrizal, 2020). Therefore, it is essential to thoroughly investigate the network's hosting capacity before making any connections to distribution systems (UKEVSE n.d.). Hosting capacity refers to the maximum load and production capacity that can be added to the network without necessitating upgrades (Bollen & Rönnberg, 2017). Western Power Distribution (Western Power Distribution (WPD) 2020) stated that exceeding the hosting capacity value in distribution networks can cause many problems, such as heating in cables, reverse power flow to transmission lines, formation of fault levels (extreme current levels) due to high currents, and voltage fluctuation. For this reason, this study considers the distribution system's peak and operational power capacities, which are directly related to the hosting capacity.

In this study, the assessment of system capacity within the power distribution network utilised a model representative of a typical UK residential distribution network, as illustrated in Fig. 3. The typical UK distribution mechanism forms the basis of a 33/11 kV substation with two 15 MVA transformers each. The 11-kV substation supplies the power to six 11-kV feeders. Each 11 kV feeder distributes power to eight 11/0.433 kV substations with 500 kVA capacity, and each of these substations then transmits power to 384 households via 4 different feeders (Ingram et al., 2003). The designed capacity of the distribution networks enabled the determination of the community's housing capacity, which amounts to a total of 384 units. Furthermore, Han et al. (Han et al., 2022) have identified that the maximum and operational capacities of community networks in the UK typically reach 500 kW and 400 kW, respectively. Consequently, these values have been adopted as the peak and operational capacities for the proposed residential community power distribution network model.

This evaluation of the operational boundaries and capacities within the UK's power distribution network establishes a foundational framework for the research model developed in this study. The identified housing capacity of 384 units, along with the peak and operational capacities of 500 kW and 400 kW, respectively, serve as critical inputs for modelling the integration of sustainable technologies—namely, EVs, HPs, and RESs—into the simulated residential community. These capacity values are instrumental in planning the integration of these systems and in analysing the potential overloading problems that such integration may result into the network. An understanding of system capacities not only highlights potential operational constraints but also provides a realistic basis for developing solutions that enhance the network's hosting capacity.

2.4. Electro-Domestic energy consumption trends and analysis

The energy consumption data published by National Statistics (Department for Energy Security & Net Zero DESNZ and Department for Business, 2022) showed that the annual energy demand for UK domestic use has been increasing in recent years. The gathered data for domestic electrical energy demand and the number of households in the UK is represented and compared in Fig. 4. As shown in Fig. 4, the electrical energy demand had an upward trend between 2000 and 2005, then there has been a gradual fall until 2019 and starts to rise again. This inverse proportion between electricity demand and population may be a result of the increased energy efficiency and implementation of demand side management (DSM) strategies.

In buildings, electrical energy is typically demanded for three primary purposes: operating electronic home appliances (electro-domestic load), charging EVs, and heating. This part of the study discusses the conventional electrical load profile consumed in homes, except for EV charging and heating demands.

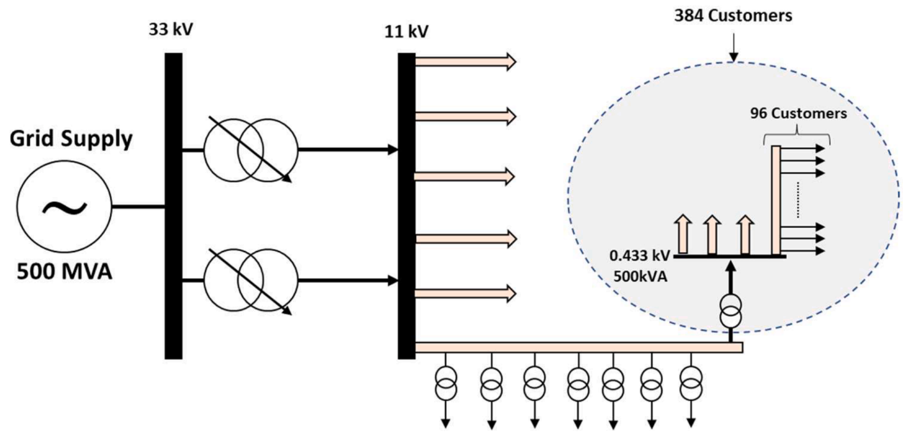

Fig. 3. Overview of the UK distribution mechanism.

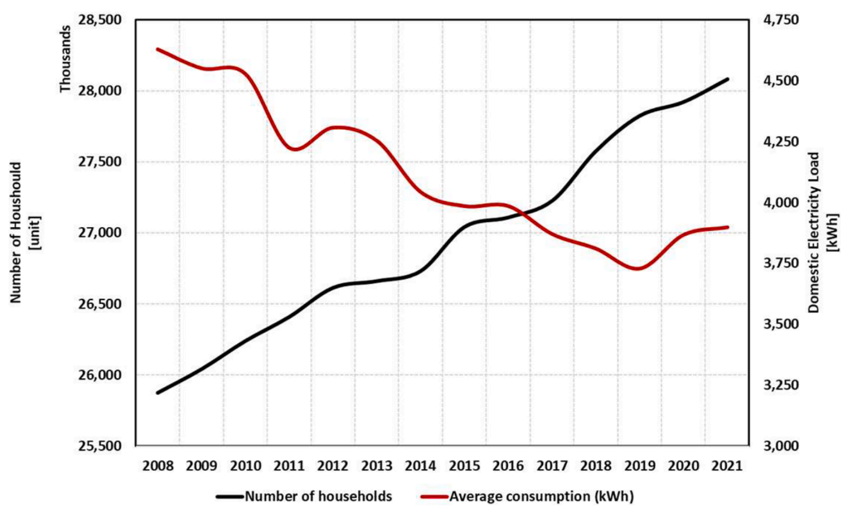

Fig. 4. Interrelation between the number of households and domestic electricity consumption in the UK.

In the present investigation, an energy analysis which was conducted by the Energy Saving Trust (EST), the Department of Energy and Climate Change (DECC), and the Department for Environment, Food and Rural Affairs (DEFRA) (Owen & Foreman, 2012) was used as a reference in the modelling of conventional load demand. Their analysis was based on long-term electric metre monitoring. They was determined home electricity consumption habits and the amount of the load in the UK. For the analysis, 251 houses were monitored in the UK, and the average hourly electricity load pattern was analysed by gathering the data in 2- and 10-minute intervals.

2.5. Approach for modelling electric vehicle charging and discharging

EV charging might be a fundamental factor that affects the decarbonisation of networks EVs, as regular electricity consumers, draw electrical energy to meet travel needs, with the increasing number of EVs directly raising the electrical energy demand for charging. This suggests that EVs could significantly stress the network in the future (Dik et al., 2022). To anticipate potential overloading issues and to implement necessary precautions, it is crucial to thoroughly discuss the capacities of the distribution networks and the potential load demands of future EV batteries.

Studies over the past two decades have provided important information about the modelling of EV charging. Deterministic and stochastic approaches are the most widely used methods to estimate the charging demand of EVs (Gholami et al., 2022; Kavousi-Fard & Khodaei, 2016). However, deterministic approaches, which often involve constant assumptions regarding battery capacity, State of Charge (SOC), charger power range, efficiency, and the EV types, may lead to severe limitation in charging load calculations. This is due to the variability of these factors in real-world applications, contrary to the fixed assumptions made. Modelling that excludes any probabilistic factors can cause serious network problems and unnecessary excessive network investments (Kim & Hur, 2020). Consequently, incorporating stochastic approaches that consider all parameters is critical for the accurate modelling of EV charging demands. This study seeks to tackle uncertainty and possibility factors in charging load estimation by developing a model with advanced stochasticity. For this purpose, in this study, a Monte Carlo Simulation (MCS) was modelled in MATLAB to dynamically simulate the uncertainties in the vehicle and charger variety, day-dependency, vehicles' arrival and departure times, temperature effect and daily travel habits. All these factors are detailed below.

The National Travel Survey (NTS) (Department for Transport (DfT) 2022) serves as one of the primary reference sources for this study's methodology. NTS is an annual survey study with 7000 households and 16,000 people from all age groups in England. The main purpose of the survey is to establish personal travel patterns. The average number of vehicles per household and per person by year using NTS data in 2021 is presented in Fig. 5. It might be essential to know that the presented data includes only people over 17 years old. It is observed that the number of vehicles per household and per person in England has increased slightly over the years. More specifically, the number of vehicles per household

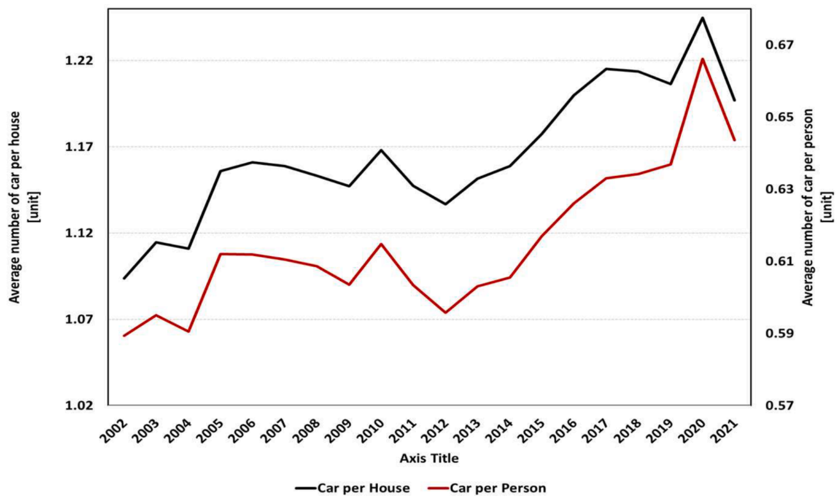

Fig. 5. The average number of vehicles per person and per household in the UK by years.

in 2021 has been determined to be 1.2. In the present study, since the number of households in the simulated community is 384, the total number of EVs in the community is determined as 461 in a fully EV adaptation scenario such as Scenario 4&5.

Vehicle variety is a critical parameter that should be evaluated in predicting the charging demand for EVs. The International Energy Agency (IEA) (International Energy Agency (IEA) 2023) highlighted that globally, 500 electric car models were available at the end of 2022, with around 150 models available in the UK. This diversity indicates that vehicles may vary significantly in communities, necessitating the inclusion of vehicle variety in vehicle charge load calculations. To address this, the ten most popular EVs in the UK and some of their technical features were examined. Table 3 lists these vehicles by popularity in the UK and shows their battery capacity and consumption rates adapted from [((Department for Transport (DfT) 2022; EV-Database, 2023))]. This information is then given as input for the MATLAB model, and the model randomly selects and assigns one of these cars for each vehicle in the community.

The total number of public EV chargers in the UK was just above 40,000 units at the end of April 2023. Although ultra-rapid chargers have the lowest share in the market, they are responsible for the charger group that provided the highest increase in the last four months (Department for Transport (DfT) 2023). Moreover, Zap-Map (Zap-Map, 2023) pointed out that the number of charging stations installed in homes and businesses is estimated to be more than 400,000, although the exact number is unknown. DfT (Department for Transport (DfT) 2018) also stated that these home chargers are mostly rated with 3 kW and 7 kW of power output. Therefore, this study assumes that the simulated community is equipped with both 3-kW and 7-kW chargers, with the model randomly selecting and assigning one of these chargers for each EV charging and discharging operation.

Table 3
Comparison of most popular EV models in the UK.

Popularity Rank	Vehicles	Type	Capacity [kWh]	Consumption Rate [kWh/mile]
1	TESLA MODEL 3	BEV	60	0.232
2	NISSAN LEAF	BEV	40	0.269
3	KIA NIRO	BEV	68	0.27
4	RENAULT ZOE	BEV	54.7	0.274
5	VOLKSWAGEN ID3	BEV	62	0.264
6	JAGUAR I-PACE	BEV	90	0.36
7	TESLA MODEL Y	BEV	60	0.267
8	AUDI E-TRON	BEV	93.4	0.34
9	BMW I3	BEV	42.2	0.261
10	HYUNDAI KONA	BEV	67.5	0.261

EV availability is another factor that affects the charging demand predictions of EVs. Modelling EVs' arrival and departure times is essential as this can impact the hourly charging loads imposed by EVs on the grid. Additionally, the hour-based charging needs of EVs are vital in efficiently planning and managing energy infrastructure. Unanticipated energy load on the grid can result in overloads and potential power outages. In this study, the analysis results of the UK 2000 time of use survey (TUS) by Wang and Infield (Wang & Infield, 2018) are used for EVs' arrival and departure times. TUS, conducted by the Office for National Statistics, is a survey that examines the travel behaviour of approximately 10,127 people (Burchardt, 2000). In this survey, travel-related data such as modes of transportation, travel times, and purposes are collected and then analysed. The survey aims to understand how participants allocate their time to activities like commuting, socialising, and education, focusing on the specific hours dedicated to these activities (Burchardt, 2000; Short, 2006). For this study, the vehicle percentages for arrival and departure time slots were obtained from (Wang & Infield, 2018) and normalised. The arrival and departure times were generated stochastically for the EVs in the community based on empirical distributions using the inverse transform sampling method. The two-sample Kolmogorov-Smirnov (K-S) test was conducted to assess the similarity between the generated and original samples statistically. The original distribution of the EV availability period on weekdays and weekends is shown in Fig. 6a and b, respectively.

This study analyses daily EV usage habits and mileage of vehicles to calculate the demand for EV charging. According to a travel report published by DfT (Department for Transport (DfT) 2022), vehicles in the UK travel 5200 miles per year; thus, the average daily travel is roughly 15 miles. However, to create a more realistic model for the mileage distribution, the annual travel ranges and percentages of vehicles taken from the DfT's National Travel Survey (NTS) (DfT, 2022) were used to create random samples. Two methods, Weighted Random Sampling (WRS) and Uniform Random Sampling (URS), were used to generate random samples. WRS was utilised as a first step to assign probability weights based on the raw data mileage ranges. Subsequently, URS was conducted to generate specific mileage values within these ranges. As an accuracy check step, a Chi-Square goodness-of-fit test was performed as a control step. This test determines how well the generated data matches the original distribution. It is worth mentioning that Plug-in Hybrid Electric Vehicles (PHEVs) are not considered in this study due to their reliance on traditional fuel sources for daily travel. The main reason for this decision is the complexities in modelling PHEVs, which use both electricity and traditional fuels. It is a challenge to accurately predict PHEVs' state of charges and electricity demand due to variable driving

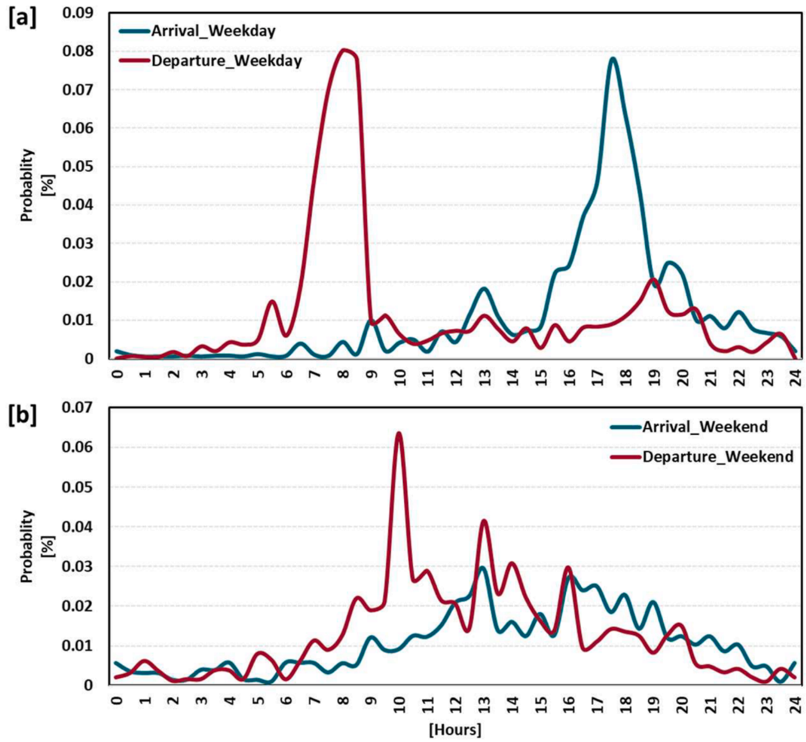

Fig. 6. Distribution of departure and arrival times of the vehicles, a) on weekdays and b) on weekends.

patterns and fuel usage.

MCS is a numerical technique used in probabilistic systems analysis by sampling random variables according to their probability distributions and calculating the resulting output variables. It utilises a computational model to perform experiments that provide statistical insights into the behaviour of complex engineering systems under uncertainty (Mahadevan, 1997). In the context of EV charging/discharging operations, MCS works by simulating thousands of scenarios for how EVs might be charged or discharged throughout a day or over longer periods. Each scenario can consider various uncertainties such as arrival times of vehicles, the duration of stay, the state of charge on arrival, and more. By aggregating the outcomes from these simulations, MCS can provide a probability distribution of potential demands on the charging/discharge infrastructure and the power network (Harris & Webber, 2014; Lopez et al., 2021; Wang & Infield, 2018).

In this research, the MCS stochastic model is used to simulate the variability in EV charging demand, taking into account a variety of parameters such as vehicle types, battery capacities, arrival times, stay durations, types of chargers and more, as detailed below. The proposed model utilises probabilistic distributions to capture the uncertainty inherent in these parameters, providing a detailed view of potential charging demand scenarios. A sensitivity analysis is also presented in the results section to illustrate the impact of parameter variability on system performance, offering a comparative assessment between systems with randomised variable EV parameters and those with fixed ones.

As can be seen in Fig. 7, in this research, MCS starts with the initialisation phase by defining key parameters such as the number of EVs (referred as 'n'), charging power rates, charging efficiency and the number of iterations (referred as 'i'). The required parameters for the ambient temperature effect on EV charging are introduced here. The approach utilised for this matter was developed by Hao et al. (Hao et al., 2020), who discovered that when the ambient temperature falls below 10 °C, the electricity consumption of EVs increases by 2.4 kWh per 100 km per each 5 °C decrease in temperature. Conversely, they found that when the temperature rises above 28 °C, the energy consumption of cars increases by 2.3 kWh per 100 km per each 5 °C rise in temperature.

A key element of the present methodology is using average daily temperature values to assess the impact of temperature on EVs' energy consumption during charging and discharging operations. This approach was necessitated by the limitations of the dataset, particularly the lack of detailed information on the exact usage times of the vehicles. As a result, while the research analysis provides a foundational understanding of temperature effects on EV energy consumption, it may not capture the full extent of intra-day temperature fluctuations. Despite this, this method can offer valuable insights into how ambient temperature variations broadly influence EV consumption and energy requirements.

The iterative process is the main part of MCS, where each iteration simulates a single instance of the charging demand scenario based on random input data sampling. In each iteration, MCS first generate random EV characteristics such as EV model, battery capacity, energy consumption rates, and arrival/departure times, which are sampled based on probability distributions of the given data. Following that, the simulation calculates the charging demand for each EV, and then the individual charging demands are aggregated to provide a system-level view of the energy required over the simulation period. It is also important to note that for the MCS model, the number of iterations and charging efficiency are set as 1000 and 90 %, respectively.

SOC is the ratio showing the total available capacity of the battery, and the depth of discharge (DoD) of a battery specifies the percentage of the battery's capacity that can be depleted. Factors such as driving models, travel distances, EV types, battery capacity, and consumption rates significantly affect the SoC of EVs. Consequently, there are inherent uncertainties in calculating the SoC for EVs.

Eqs. (1)–(3) can be used to determine the SoC and DoD of the batteries, as detailed in our previous study (Dik et al., 2023). In Eq. (1), $P_{battery}$ is the power capacity of the battery, and P_{supply} refers to the instantaneous power supply from the battery to the load at any given moment. Additionally, Q_D represents the amount of charge extracted from the battery at any given moment in Eq. (2).

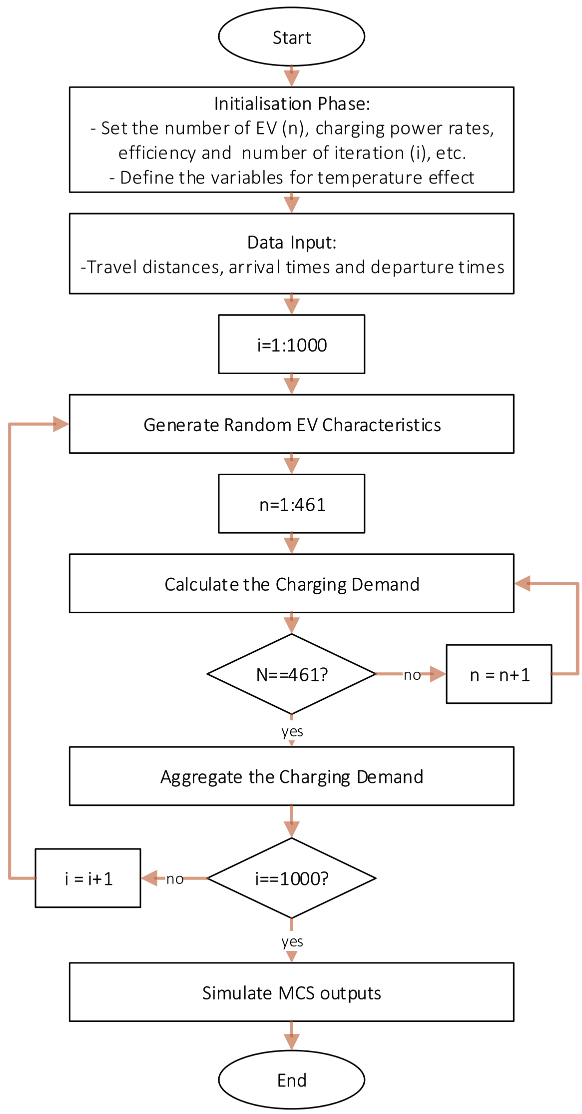

Fig. 7. Flow diagram of the MCS approach for EV demand forecasting.

$$SoC_t = SoC_{t-1} - \frac{1}{P_{battery}} \int_0^t P_{supply}(t)dt \tag{1}$$

$$DoD_t = \frac{Q_D}{P_{battery}} \times 100\% \tag{2}$$

$$DoD_t = 100\% - SOC_t \tag{3}$$

In the modelling conducted in this study, the SoC was calculated by including some important variables such as travel distance, car consumption rate, and battery capacity to account for uncertainties. Additionally, all the variables were randomly selected in each iteration, as previously explained. Eq. (4) demonstrates how the initial SoC was computed as part of this study's EV model by considering the travel distance of the vehicles. In Eq. (4), D_{mile} represents the daily travel distance driven by the car, measured in miles, before returning home, and μ_{EV} refers to the electricity consumption rate of the vehicle in kWh per mile.

$$SoC_{initial,n} = 80\% - \left(\frac{D_{mile,n} \times \mu_{EV,n}}{P_{battery}} \times 100\right) \tag{4}$$

The preferred charge/discharge SoC rate in vehicles is a controversial issue. The DfT (Department for transport (DfT) 2022) conducted a survey investigating the driving behaviours, EV charging behaviours, and attitudes to the public charging infrastructure of UK electric vehicle drivers. The survey asked vehicle owners about the level of their battery SOC before charging and after charging at home and in public places. 83 % of participants who charge at home typically charge their vehicles to a SOC of 70 % or higher, with 66 % of these participants charging their vehicles to a SOC of 80 % or higher. Although there were some outlier values in the survey results, the results showed that the median battery percentage level reported by EV owners before charging at home was 24 %, and it rose up to 94 % after charging. While current charging behaviours somewhat deviate from the 20–80 % SOC range, the benefits of maintaining this range—such as enhancing battery lifespan and ensuring cost savings—are well-documented in the literature (Bayram & Tajer, 2017; Koncar & Bayram, 2021; Kostopoulos et al., 2020; Ramadan et al., 2017). Additionally, Kostopoulos et al. (Kostopoulos et al., 2020) found that charging batteries above 80 % doubles the losses compared to charging between 20 % and 80 %. Considering the documented advantages of adoption to the 20–80 % SOC range, our study aims to model a scenario grounded in this optimal practice. Therefore, in the simulated community, it was assumed that vehicles were not charged beyond 80 % and not discharged below 20 %. The intention is not to disregard the current reality but to present a potential trajectory that maximises the benefits of EV usage. This approach can offer insights into potential grid support, energy savings, and battery health benefits that could be achieved if a shift towards this optimal charging behaviour were realised. This approach could also be a chance to visualise the outcomes of optimal charging practices for stakeholders and may show the tangible benefits of promoting such behaviours. This could also drive educational campaigns, technological innovations in smart charging, and even policy adjustments to encourage EV owners to adopt the 20–80 % SOC charging range to avoid increased waste from depleted batteries.

The amount of energy required for a full charge ($E_{80\%}$), the time required to meet this energy demand ($T_{80\%}$) and the hourly charging demand of the vehicle on the grid ($E_{EV\ load}$) can be calculated as shown in Eqs. (5)–(7), respectively. In Eq. (6), when the term $P_{charger}$ represents the power rating of the EV's charger, $\mu_{charger}$ denotes the efficiency charger, which is set at 90 % in this study.

$$E_{80\%,n} = P_{battery,n} \times (0.8 - SoC_n) \tag{5}$$

$$T_{80\%,n} = E_{80\%,n} \div \left(P_{charger,n} \times \mu_{charger}\right) \tag{6}$$

$$E_{EV\ load,t} = \min\left(\left(E_{80\%,n,t} \div \mu_{charger}\right),\ \left(P_{charger,n} \times 1\ hour\right)\right) \tag{7}$$

On the other hand, in this study, the Vehicle-to-Grid (V2G) technology and smart charging method (specifically the charging delay technique) have been utilised for the energy balance mechanism after showing the effect of the uncontrolled charging situation on the community grid. The methodological framework of the EV charging and discharging operations is shown in Fig. 8. This model is designed to optimise the community grid's balance by managing EV charging and discharging operations. The model considers the grid's demand profile, energy supplies, the vehicle owners' post-operation SOC preferences and the duration of EV parking.

As shown in Fig. 8, the model initially integrates the previously developed MCS logic to generate a random EV dataset with the aforementioned uncertainty and to manage charging and discharging activities. Energy data inputs, including electro-domestic and heat pump loads, renewable generation from solar PV and wind turbines, and conventional generation, are then imported into the model to calculate the grid's net electric demand. The simulation proceeds to loop through the fleet of EVs (n = 1 to 461 in scenarios 4&5) and iterates over multiple simulation runs (i = 1 to 1000) to ensure robustness and account for variability. In each iteration for each car, it is assessed whether there is

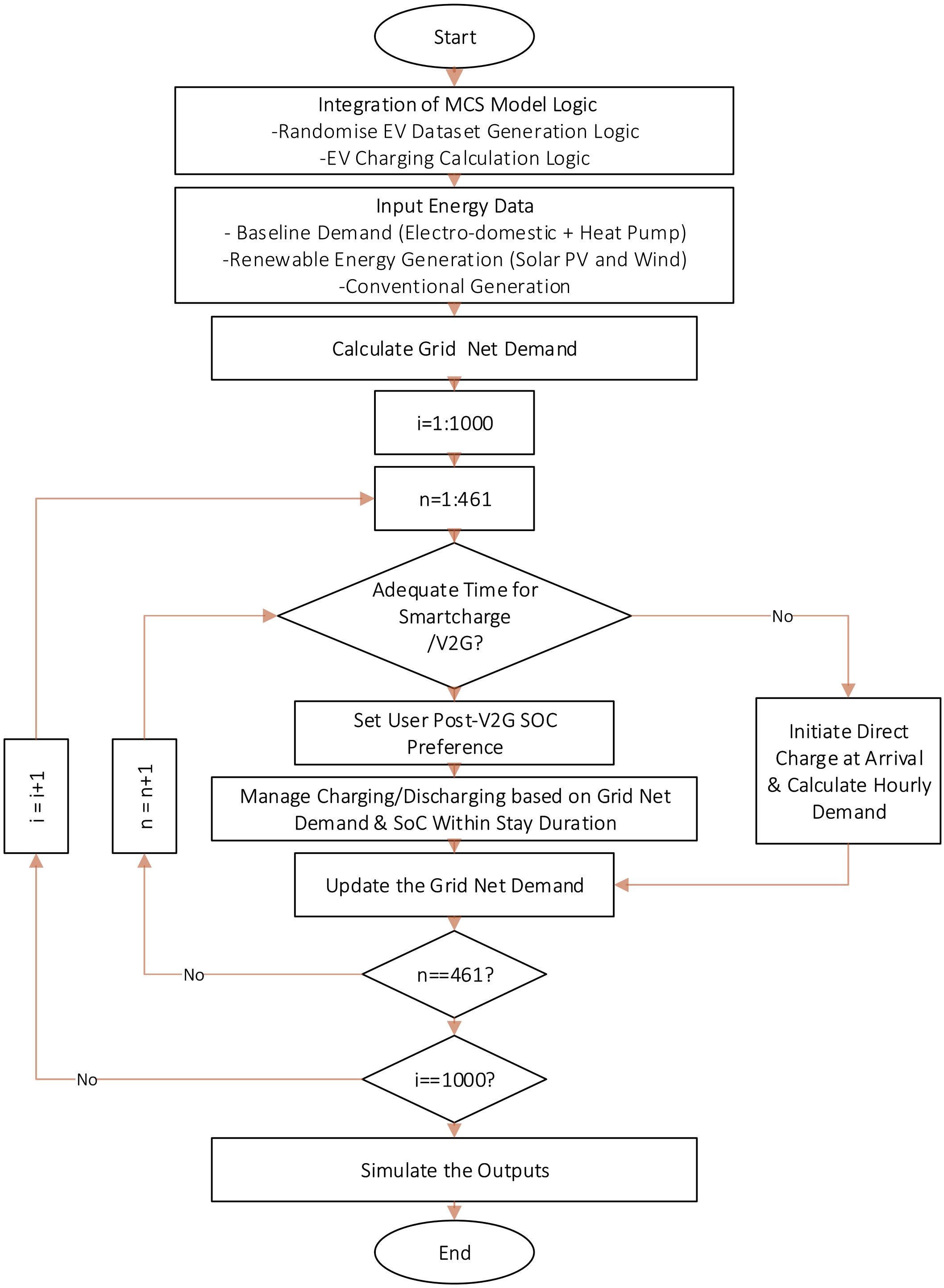

Fig. 8. Flow diagram of the model for EV charging and discharging under Smart Charging and V2G.

adequate time for charging delay or V2G strategies; if not, it defaults to initiating direct charging upon arrival and determines the hourly charging demand. A safety margin (SM) of 1.5 was used to identify unsuitable vehicles for smart charging or V2G as given in Eq. (8). That is, if the parking time of a vehicle is less than 1.5 times the time required for a full charge, then these vehicles are charged directly.

$$I_{unsuitable} = \left\{ n \mid \frac{T_{dep,n} - T_{arr,n}}{60} \leq T_{80\%} \times SM \right\} \tag{8}$$

Subsequently, the simulation organised the rest of the EVs according to their stay duration, ranging from short to long, and established SOC preferences for each EV participating in V2G discharge operations. These preferences were assumed using a uniform random distribution between 60 % and 80 %, drawing inspiration from the DfT survey (Department for transport (DfT) 2022).

To balance the grid and manage the charging and discharging activities, the hourly EV energy demand and supply can be calculated by updating Eq. (7), as expressed in Eqs. (9) and 10. Where $E_{grid\ surplus}$ refers to the energy available on the grid for EV charging after deducting the electro-domestic and HP demands, while $E_{grid\ deficit}$ represents the energy deficit exceeding the grid operational capacity limit.

$$E_{EV\ demand,t} = \min\left(\left(E_{80\%,n,t} \div \mu_{charger}\right), \left(P_{charger,n} \times 1\ hour\right), \left(E_{grid\ surplus,t}\right)\right) \tag{9}$$

$$E_{EV\ supply,t} = \min\left(\left(E_{available,n,t} \times \mu_{charger}\right), \left(P_{charger,n} \times \mu_{charger} \times 1\ hour\right), \left(E_{grid\ deficit,t}\right)\right) \tag{10}$$

The EV's SOCs and the grid net demand is continually and dynamically updated following each EV's energy transaction. The model also ensures that the grid's operational capacity remains below the threshold and that the discharged EVs reach their preferred SOC after the operation.

2.6. Approach for modelling thermal energy demand

This section details the steps performed to model the community thermal energy needs of the houses, which includes the space heating and hot water requirements of the houses in the simulated community. The location selected for the model was Nottingham, UK. IES VE software was used to model the houses and analyse the thermal energy demand.

IES VE is a dynamic thermal simulation tool designed for detailed evaluation and optimisation of building and system designs. It has been widely used in modelling heat transfer processes, including thermal insulation, building dynamics, and various environmental factors like climate and shading (Shahzad et al., 2020; Wei et al., 2022). The tool operates using real weather data and can simulate thermal conditions over periods ranging from a day to a year. It can provide a variety of outputs, from energy consumption to detailed performance measures like room temperatures and air exchanges. This makes it an invaluable tool for calculating the heating demand of the buildings. The techniques and equations employed in the tool are briefly outlined in Appendix 2.

Since the heating load of the building is related to the materials used in designing the house, the E.ON house was simulated in IES VE according to the actual fabrics used and the default user profiles such as occupancy schedule, lighting preference and thermostat settings. Hall et al. (Hall et al., 2013) analysed the E.ON Research House to evaluate energy efficiency and occupant comfort. They investigated various retrofit technologies and approaches in their study. The study conducted by Hall et al. was used as one of the key references for the thermal modelling of the present paper. Table 4 shows the main structural elements and the modelled U values of these structural elements. The data presented in Table 4 are taken from (Hall et al., 2013).

In the developed IES VE model, it is assumed that a family of four, comprising two parents and two children, lives in this house. Furthermore, temperature set points, lighting, and occupancy profiles for the home are illustrated in Appendix 3. These profiles are determined based on the hours of the day and differentiated for weekdays and weekends.

In the model, the user profile is introduced by taking into account the residents' night-time, morning-time, day-time, evening-time and late-night-time activities. The Chartered Institution of Building Services Engineers (CIBSE) environmental design guide (CIBSE, 2006) was used here to determine the heating profile of the house. Between 8:00 and 15:00 on weekdays, the occupancy percentage at home is 25 %, and the temperature is kept at 18 °C. Although the weekend occupancy rate varies depending on time, the temperature set value between 8am and 10pm is set as 21 °C to make an average temperature of kitchen, hall, bedrooms and living rooms due to possible day-long activities at home. During the sleep period, temperature values are set at 17 °C. Additionally, unlike the weekday profile, the temperature value for possible late-night activities is 19 °C between 22:00 and midnight on weekends. On the other hand, as shown in Appendix 3, the lighting profile varies depending on the occupancy profile and activities. While the lighting percentage is as low as 5 % during the night, this rate rises to 85 % when everyone comes home and in the evening.

The IES VE model used Nottingham's weather data. The total heating gain, maximum sensible gain, maximum latent gain and infiltration are set at 530 W, 90 W/person, 60 W/person, and 0.25 ach, respectively, as indicated in (Kutlu et al., 2022).

Following that, the domestic hot water requirement for the house is computed based on a 7-h demand, factoring in morning routines (2 h) and evening periods (5 h) on a typical day. The daily hot water requirement per individual and the hot water temperature is set at 30 L and 60 °C, respectively.

Table 4
Materials and their corresponding U-values.

Roof [W/m^{2}K]	Floor [W/m^{2}K]	External Wall [W/m^{2}K]	Window [W/m^{2}K]	Door [W/m^{2}K]
0.13	0.12	0.54	0.7	3

2.7. Approach for modelling heat pump systems

Heat pumps are systems that move the heat from a cold environment (source) to a warm environment (sink). This heat transfer requires external electrical energy, and the amount needed depends on various factors. The primary performance parameter of a heat pump is the temperature difference between the heat sink and the heat source. In this research, common types of heat pumps, including ASHP, SAHP, and GSHP were analysed. The performance effects and energy consumption of these HP types have been introduced and compared by modelling them within the study.

The most common type is the ASHP, whose performance directly depends on ambient temperature. This reliance can be a drawback in very cold temperatures. SAHP utilise solar energy, storing it in a buffer tank. Their performance is better than the ASHPs as long as the buffer tank's temperature remains higher than the ambient temperature. However, their effectiveness depends on the solar profile of the location. Lastly, GSHP offers the most stable performance amongst these options as the earth's temperature doesn't change considerably compared to ambient temperature.

HP modelling operates on certain assumptions, regardless of the type of HP used. Since the heating requirements are determined using IES VE, the HPs are designed to provide an amount of heating that precisely matches the building's heating demand profile. Therefore, the condensation temperature of the heat pumps is maintained at a constant 70 °C. This approach ensures that the hot water delivered to the building can reach approximately 65 °C, a temperature sufficient for hydraulic heating systems such as radiators.

Coefficient of performance (COP) of an HP is calculated by Eq. (11):

$$\mathrm{COP} = \frac{\dot{Q}_{cond}}{\dot{W}_{comp}} \tag{11}$$

Where $\dot{W}_{comp}$ and $\dot{Q}_{cond}$ are compressor consumption and condenser load, respectively.

For GSHP energy calculations, COP is taken constant. This is in line with the assumptions made in reference papers, which typically use a COP value of 3 (Doroudchi et al., 2018; Han et al., 2022). Therefore, the electricity consumption of the GSHP is calculated using the COP equation. However, the electricity consumption of ASHP and SAHP must be calculated using more detailed heat pump modelling. The evaporating temperature for the ASHP is determined by considering it to be 10 °C lower than the ambient air temperature (Kutlu et al., 2023), ensuring adequate heat transfer rate between the air and the refrigerant (Hundy, 2016).

It is important to note that ASHP systems require defrosting when the ambient temperature falls below 2.5 °C, and the relative humidity exceeds 70 %. An empirical equation, developed by Roccatello et al. (Roccatello et al., 2023), is employed to account for the defrosting phenomena during ASHP operation. They conducted experiments at ambient temperatures ranging from 2.5 °C to −4 °C, and relative humidities of 70–80 % and 90 %. The equation determines the required COP drop, which is then used to update the calculated electricity consumption when defrosting occurs.

$$COP\ drop = a + b \cdot RH + c \cdot T_{am} + d \cdot RH \cdot T_{am} + e \cdot T_{am}{}^{2} + f \cdot RH \cdot T_{am}{}^{2} + g \cdot T_{am}{}^{3} \tag{12}$$

Coefficients in the correlation are a = 15.05, b=−0.2543, c = 0.01351, d= −0.007022, e = 0.4319, f=−0.005945, g = 0.03681.

SAHP consists of evacuated solar collectors, a buffer tank and an HP unit. The solar collectors capture solar energy and store it in the buffer tank, which serves as the heat source for the heat pump. The temperature of the buffer tank varies based on the heat input from the collectors and the heat extracted by the heat pump. The details of the ASHP and SAHP modelling were the subject of previous publications (Erdinc et al., 2023) and (Dik et al., 2023), respectively. The present study considers a solar collector area of 30 m^2, considering the building's floor area, and an 800-litre buffer tank is used.

In winter conditions, solar irradiance can vary significantly from day to day. On days with low solar irradiance, the heat collected may be insufficient to meet the heat pump's evaporator load. Consequently, the temperature in the buffer tank drops, leading to reduced HP performance. As the area available for solar collectors on the roof limits the size of the solar collector array, the performance of SAHP systems may fall below that of ASHP systems when relying solely on the SAHP unit for heating. Therefore, during the cold winter months (December and January), the heating load of the SAHP is restricted to 30 % of the total heating requirement. This strategy allows the system to capitalise on the higher performance of the SAHP, while its contribution to the overall system performance remains limited to 30 %, with the remaining heat supplied by the ASHP. This contribution percentage was determined based on various simulations, for instance, when SAHP covered 100 % of the heating load, the COP was significantly lower than the sole ASHP COP. With a coverage ratio of 40 %, the overall COP was found to be 3.45 % higher than the sole ASHP COP. However, when the coverage ratio is 30 %, overall COP improvement reaches 5.65 % in January.

To calculate the overall COP for the SAHP system in January and December, Eq. (13) is used:

$$COP_{SAHP-J,D} = \frac{\dot{Q}_{demand}}{\dot{W}_{SAHP} + (1 - cover) * \dot{W}_{ASHP}} \tag{13}$$

Where *cover* represents the coverage ratio of SAHP heating in relation to the total demand. As the supplied heating is lesser, buffer tank temperature remains higher than the ambient temperature, leading to reduced compressor consumption. However, to determine the overall COP, the consumption of the ASHP must also be included as given in Eq. (13).

2.8. Modelling techniques for solar PV and wind energy generation

Solar PV and wind energy systems are amongst the most crucial energy solutions for the sustainable energy supply of communities. This section discusses the modelling technique used to predict the electrical outputs of on-grid solar PV and wind energy systems, which are expected to be integrated at varying scales from the short-term to the long-term, as detailed before. The renewable energy system model employed in this study is required to capture these resources' intermittent and fluctuating outputs accurately. This is essential to maximise the utilisation of energy derived from these sources through EVs, ensuring a safe and efficient transfer to the grid.

In each of the outlined scenarios, the generation capacities from both renewable and conventional energy sources have been determined to reflect realistic and strategic energy mixes (details in the scenario reasoning section). For instance, in Scenario 1, 25 % of the grid capacity is designated to come from renewable energy sources, specifically solar PV and wind energy, which contribute 60 % and 40 % of the renewable mix, respectively. The remaining 75 % of the energy is sourced from conventional generation methods. All summarised capacity values for PV and wind energy, corresponding to each scenario, are detailed in Table 5.

This study modelled the proposed on-grid wind and solar energy systems using the HOMER Pro-microgrid software (HOMER Energy by UL, 2023) to estimate the potential electricity generation from these sources. HOMER stands for Hybrid Optimisation of Multiple Energy Resources. HOMER Pro is a comprehensive and powerful software widely recognised in the literature for analysing the design of hybrid renewable energy systems and optimising their integration into the grid (Allouhi et al., 2022; Ekren et al., 2021; Rahmat et al., 2022). It simulates equipment by evaluating all possible combinations for optimisation in microgrid designs. This software stands out in grid integration analyses of conventional and RESs and is trusted by governments and energy experts (HOMER 2023).

HOMER Pro-also has advanced capabilities to simulate the impacts of weather variability on solar and wind energy outputs with precision in modelling renewable energy generation. Given the critical importance of accurate renewable energy supply forecasts, HOMER Pro's deterministic simulations are particularly suited for capturing the dynamic fluctuations of solar and wind power generation (Mehta & Basak, 2020; Rahmat et al., 2022). This approach is complemented by the stochastic modelling of EV charging behaviour, providing a balanced methodology that addresses the uncertainties in both energy supply and demand. The integration of HOMER Pro's deterministic tool within the broader stochastic framework enriches the research by thoroughly analysing the intermittent nature of renewable energy sources.

Modelling of the on-grid renewable system in HOMER Pro-was carried out in five steps, as shown in Fig. 9. The first two steps involved determining the location of the simulated system as Nottingham, UK, and defining the region's solar irradiation, ambient temperature, and wind speed values. The solar radiation, ambient temperature, and wind speed data were transferred from the IES model used in this study, which utilised the EnergyPlus weather data database (EnergyPlus, 2023), to ensure consistency in weather conditions across the overall model.

The PV system design is performed in the next step using HOMER Pro-software, which offers a library of various PV models for system modelling. For this study, the Sunpower E20–327 solar PV panel was selected. Detailed specifications of the chosen PV panel are presented in Table 6. All information regarding the PV panel was sourced from the HOMER Pro-software (HOMER Energy by UL, 2023).

HOMER Pro-estimate the potential electricity generation from the sources by operating with a set of fixed equations and algorithms, conducting analysis based solely on user-defined parameters and system configurations. The software calculates the power outputs of PV arrays using Eq. (14), which is defined as follows:

Table 5
The proposed capacity values for PV and wind energy by scenarios.

Scenarios	S1	S2	S3	S4	S5
Solar PV Capacity [kW]	60	100	100	120	180
Wind Turbine Capacity [kW]	40	100	100	180	120

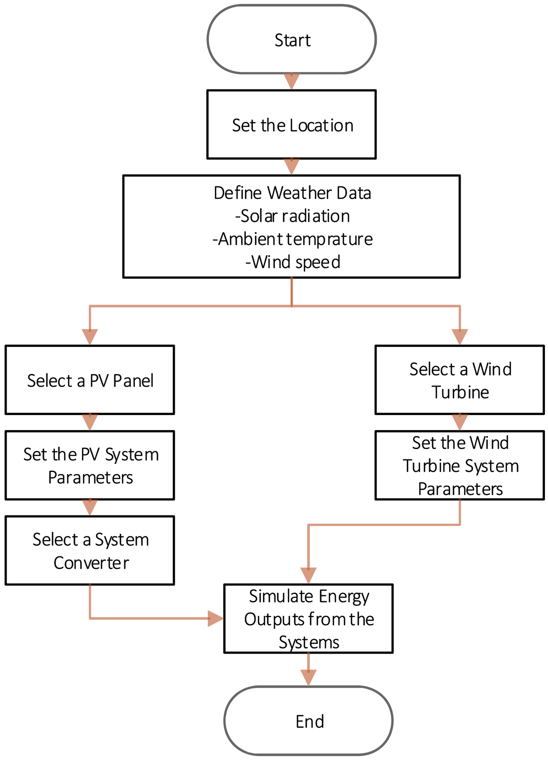

Fig. 9. The simplified modelling steps for on-grid solar PV and wind energy systems in HOMER Pro.

Table 6
The characterisation of the solar PV panel utilised in the model.

Specification	Details
Model	SunPower E20–327
Panel Type	Monocrystalline Flat Plate
Rated Capacity	0.327 kW
Panel Efficiency	20.4 %
Temperature Coefficient	−0.380 %/ °C
Nominal Operating Cell Temperature	45 °C

$$P_{PV} = Y_{PV} \times f_{PV} \times \left(\frac{G_T}{G_{T,STC}}\right) \times \left[1 + \alpha_p \times \left(T_c - T_{c,STC}\right)\right] \tag{14}$$

Where Y_{PV} is the rated capacity of the PV array and measured in kW. f_{PV} which is the PV derating factor is also considered in the equation as a percentage. This is a rate showing efficiency losses due to some real weather conditions such as ageing, dirty surface, and snow cover. The PV derating factor, in the analysis, was adjusted to 88%, following the default value given in the software. Solar radiation on the PV array during the current time step (G_T) in kW/m^2 and the standard test condition radiation ($G_{T,STC}$) of $1kW/m^2$ are the key parameters in Eq. (14) to calculate power output from the PV array. Temperature effects are also accounted for via the temperature coefficient (α_p) in%/ °C, and the PV cell temperatures both in the current time step (T_c) and under standard test conditions ($T_{c,STC}$), determined as 25 °C.

Table 7
The characterisation of the wind turbine utilised in the model.

Specification	Details
Model	Eocycle EO10
Nominal Capacity [kW]	10
Hub Height [m]	16
Cut-in Wind Speed [m/s]	2.75
Cut-off Wind Speed [m/s]	20

On the other hand, the Eocycle EO10 wind turbine, selected from the software's library, was used for the wind energy system design. Details about the turbine can be found in Table 7. All information regarding the PV panel was sourced from the HOMER Pro-software (HOMER Energy by UL, 2023).

The wind turbine energy system's output is realised in a few steps in the software (HOMER, 2023). Since the wind speed measurement height (U_{anem}) may differ from the turbine's hub height, the software initially calculates the wind speed at the turbine hub height (U_{hub}). This is caried out using a logarithmic law, as outlined in Eq. (15). Where, 'Z_{hub}' and 'Z_{anem}' represent the hub height of the selected wind turbine and the anemometer height, respectively, both also expressed in meters. The term 'Z_0' refers to the surface roughness length, a parameter indicating the terrain's roughness around the system's location. In the current analysis, this value was set to represent 'few trees' and was taken as 0.1. Following that, the software uses Eq. (16) to calculate the wind turbine output (P_{WTG}). Where $P_{WTG,STP}$ is the wind turbine output power based on the power curve of the turbine, 'ρ' refers to actual air density and 'ρ_0' represents air density at standard temperature and pressure.

$$U_{hub} = U_{anem} \times \frac{\ln(Z_{hub} \div Z_0)}{\ln(Z_{anem} \div Z_0)} \tag{15}$$

$$P_{WTG} = \left(\frac{\rho}{\rho_0}\right) \times P_{WTG,STP} \tag{16}$$

3. Results and discussion

3.1. Comparative performance analysis of heat pump systems

This section thoroughly examines HP systems, focusing on their operational efficiency across various seasons. It starts by analysing how seasonal heating demand fluctuations affect residential heating requirements, establishing the context for assessing HP systems' adaptability and efficiency. Following this, the section proceeds to a comparative analysis of different HP types, including ASHPs, GSHPs, and SAHPs, regarding their ability to meet heating demands and their electricity consumption. This evaluation aims to provide insights into selecting effective and efficient HP systems for sustainable residential communities.

While energy utilisation for heating generally decreases with warmer temperatures, reflecting a lower need for heating, this study specifically focuses on heating and domestic hot water requirements without considering the increase in energy demand for cooling in warmer months. The relationship between energy consumption and temperature is multifaceted, influenced by factors like regional climate and socio-economic status, which can result in varied electricity demand responses to temperature changes (De Cian et al., 2013).

In this context, the IES VE output captured in Fig. 10 presents a visualisation of the seasonal heating demand fluctuations and their consequential impact on residential heating and hot water needs. The graph details the heating demand in kW across a 48-hour timeframe for three different months, illustrating the diverse seasonal conditions and highlighting the necessity for HP systems that can respond to these demands. In December, heating demand can be significantly high and varies, with one observed day nearing 7 kWh. This variability indicates the potential for both higher and lower demands throughout the winter, posing a risk of substantial strain on the grid. Such fluctuations and high demands can necessitate robust heating solutions and efficient energy management to ensure grid stability. April's profile, marked by moderate peaks, suggests a transitional period where heating demands are present but less intense than in winter, reflecting the mild temperatures commonly experienced during spring. Despite July's overall minimal or non-existent heating demand, due to the warm weather significantly reducing or eliminating the need for space heating, there remains a consistent demand for domestic hot water heating.

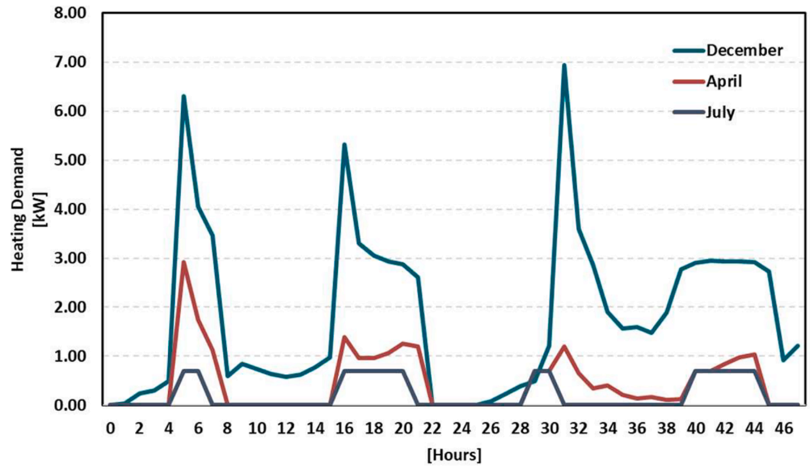

Fig. 10. Seasonal heating demand variation in a home in the simulated community.

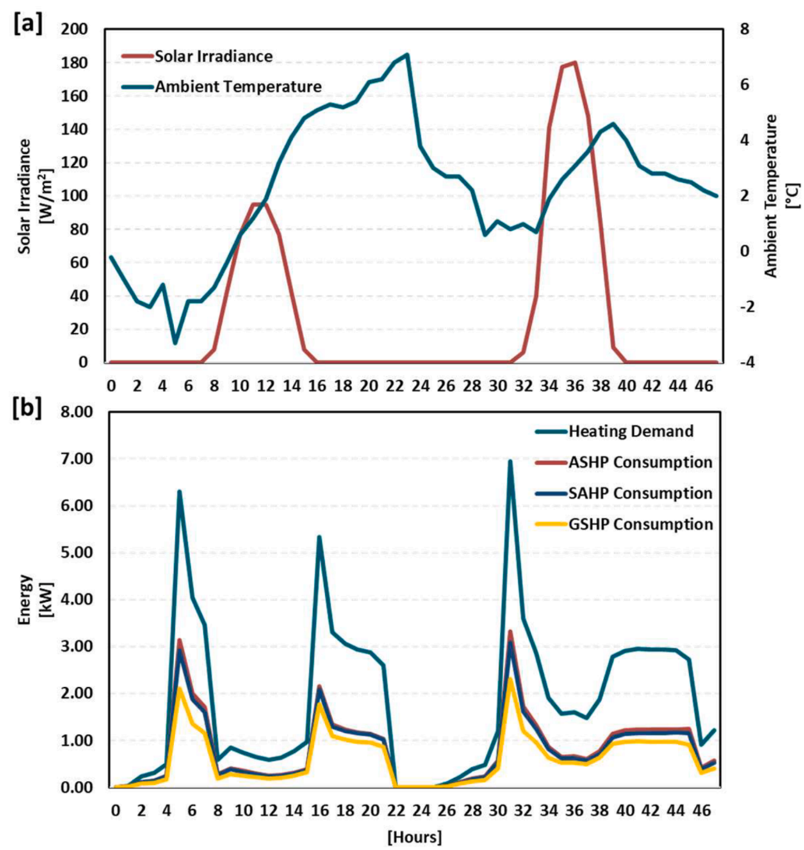

Fig. 11. a) Weather data of 48 h in December and b) Variation of electricity consumption profiles of HPs given heating demand.

Given the outlined seasonal variations in heating demand, with December experiencing significant high demands and July showcasing minimal to non-existent needs beyond hot water heating, the ensuing analysis turns to a closer examination of how different HP types—ASHPs, GSHPs, and SAHPs—perform under different conditions and proposed scenarios in the paper. This detailed comparison, initiated with an overview of solar irradiance and ambient temperature variations, aims to assess each HP type, focusing on their efficiency and electricity consumption patterns.

Fig. 11a shows a typical solar irradiance and ambient temperature variation in December for 48 h, including Friday and Saturday. As expected, the peak solar irradiance appears to be just under 200 W/m^2, on the first day, solar irradiance reaches a maximum of 100 W/m^2. At the same time, the ambient temperature varies between −3 °C and 7 °C. Fig. 11b shows the electricity consumption of three types of HPs to meet the calculated building heating demand. On weekdays, the building demand profile exhibits two peak periods: one in the morning and one in the evening. During the weekend, the morning peak is noticeable, while the evening peak is more subdued; however, the heating load is higher throughout the daytime. This profile is shaped by factors such as ambient temperature, solar irradiance, and, of course, the user profile and temperature settings within the building. The total heating demand for a given 48 h is 87 kWh.

The electricity consumption profiles of all heat pumps follow a pattern similar to the heating demand profile. amongst the heat pumps, the GSHP unit has the lowest total consumption, at 29 kWh. Its assumed constant COP of 3 makes it the best option for heating in December, as GSHP performance is not directly affected by severe weather conditions and high heating demand. In contrast, ASHP performance depends on ambient temperature and, most of the time in the given period, the ambient temperature is less than 4 °C, necessitating a performance reduction due to the need for defrosting. For this 48-hour period, the ASHP's electricity consumption is found to be 38.6 kWh, which corresponds to an average COP of 2.25.

SAHP performance is influenced by various conditions, such as solar irradiance, ambient temperature, and the demand profile. Since the heat source is limited, the buffer tank temperature fluctuates with heat charge and discharge cycles. As previously mentioned, SAHP performance can be lower than that of a conventional ASHP when the solar heat input is insufficient to cover the HP's evaporative heat load. For this reason, the SAHP's contribution to the heating demand is limited to 30%, allowing for 70% of the heating load to be provided by the ASHP. Consequently, electricity consumption is primarily dominated by ASHP performance. However, overall, the system still benefits from solar energy, as shown in Fig. 11b. The combined SAHP system's electricity consumption is 36.42 kWh, resulting in a COP of 2.38. This difference of 2.2 kWh in lesser consumption translates to a 5.6 % reduction in electricity use compared to the standalone ASHP unit.

Fig. 12 presents the same parameters but under April weather conditions. Fig. 12a shows solar irradiance peaking at 580 W/m^2. Notably, the longer solar hours are beneficial for SAHP performance as they allow for more heat collection and increase the buffer tank temperature. A higher buffer tank temperature reduces the pressure difference between the condenser and evaporator, leading to improved performance. The ambient temperature varies between 15 °C and 5 °C, resulting in fluctuating COP values for the ASHP.

Fig. 12b displays the heating demand profile and the electricity consumption of all heat pump units during 48 h of operation in April. On Friday, two distinct load profiles emerge as the temperature settings are adjusted to maintain comfortable conditions in the morning and evening. However, the building's heating demand is much lower compared to winter conditions due to higher ambient temperatures and the reduction in heating requirements afforded by solar heat input. In winter, the heating requirement exceeds 7 kW, but in April, it peaks at 3 kW, totalling 21.5 kWh over the two days under review.

The highest electricity consumption is observed in the ASHP unit, with a total of 8 kWh consumed over 48 h, resulting in a COP of 2.68. The COP for the GSHP is pre-set at 3, with a total consumption of 7.16 kWh. Yet, the advantage of having a GSHP is less pronounced due to the higher ambient temperatures. In contrast, the SAHP demonstrates promising performance with a COP of 9.4 on these selected days. The main reason is the high solar irradiance combined with the low heating demand, leading to an elevated buffer tank temperature and significantly improved SAHP performance.

Analysis of the weather conditions for two days in December and April demonstrates that the SAHP can perform up to 2.5 times better than the ASHP. However, it should be noted that the solar profile in April might not always be as favourable as on the days examined. These days represent the best-case scenario and offer insight into the potential performance in other months, such as May or June, when considering Domestic Hot Water (DHW) needs, which average around 5 kWh daily.

For this case, the COP calculations were extended to a monthly analysis to indicate the benefits of utilising an SAHP unit over an ASHP. The improvements in monthly COP were calculated at 5.65 %, 9.19 %, 55.23 %, and 156.13 % for January, February, March, and April, respectively.

3.2. Uncontrolled EV charging

The first set of analyses examined the availability of EVs in the community. The original distributions of arrival and departure times, as analysed by (Wang & Infield, 2018) from the UK 2000 TUS, were received in half-hour intervals and then used to generate 1000 random samples using the inverse transform sampling method. Fig. 13 presents

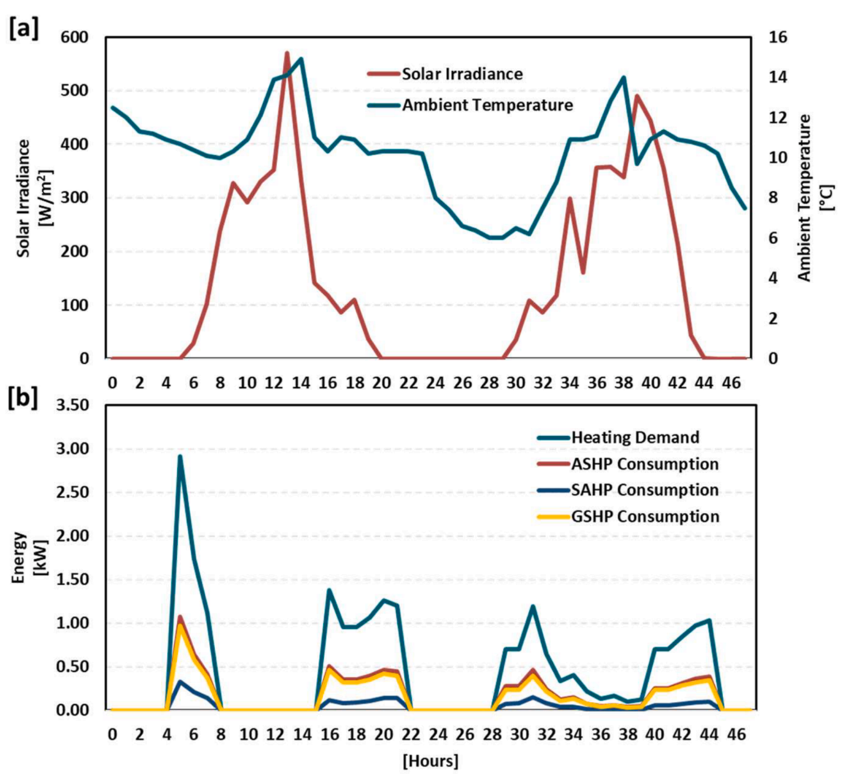

Fig. 12. Weather data of 48 h in April and b) Variation of electricity consumption profiles of HPs given heating demand.

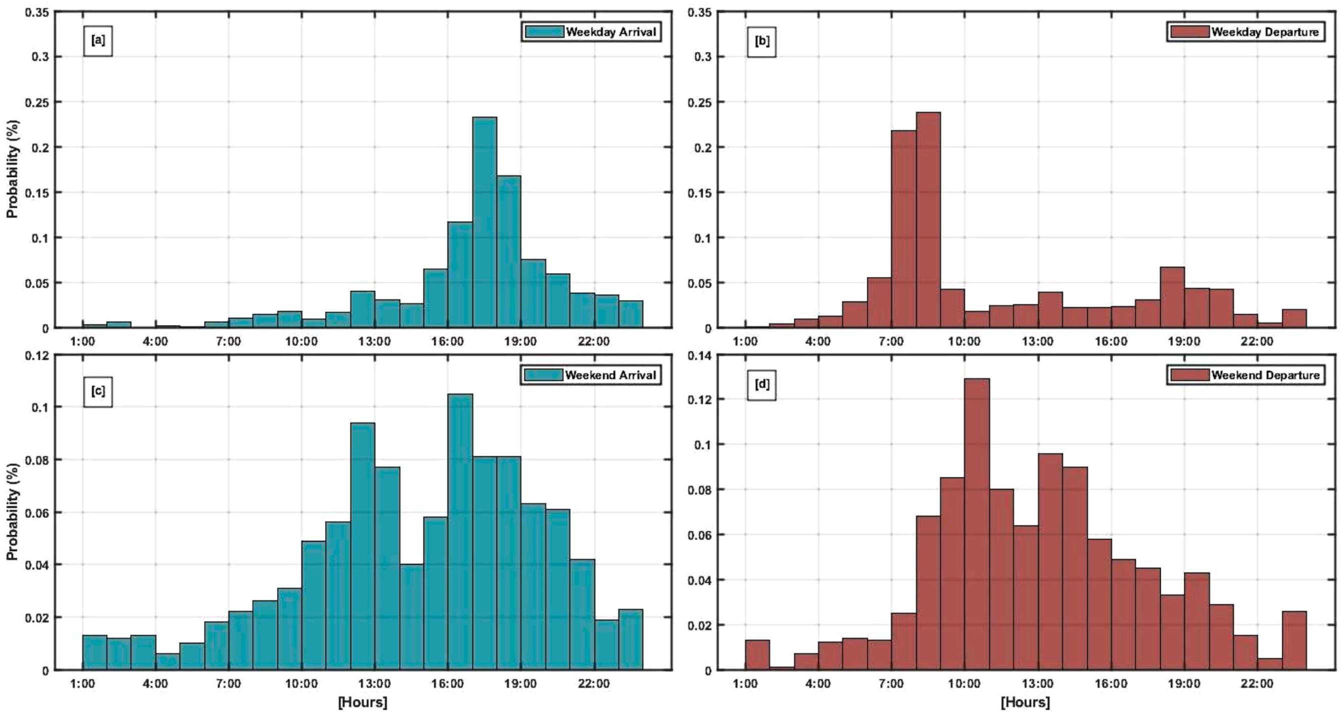

Fig. 13. The generated arrival and departure time distributions, a) arrival time on weekdays, b) departure time on weekdays, c) arrival time on weekends, and d) departure time on weekends.

the results obtained from the sampling method and gives a distinct pattern of the EV drivers' daily travel habits. It can be seen that the most significant population of EV owners leave the house in the early morning to commute and return around 5–6pm. However, the temporal distribution of vehicle travel during weekends exhibits a more homogenous pattern throughout the day.

A K-S test was applied to determine if the developed time series pattern followed the actual time series figure. The calculated p-values are 0.9716 and 0.8228 for the arrival and departure times, respectively, in weekday data. For weekend data, the p-values are 0.9916 for arrival times and 0.9771 for departure times. Using a significance level (α) of 0.05, this result shows that it failed to reject the null hypothesis that states two samples have the same distribution, for both departure and arrival times on weekdays and weekends.

The daily distance travelled by these EVs was considered to calculate the charging load of the vehicles in the community. The annual vehicle utilisation levels, on the mile-basis, provided by DfT were modelled for EVs in the community using WRS and URS methods, as detailed in the methodology section. The obtained distribution for 1000 random samples from the analysis is shown in Fig. 14. The findings indicate that vehicles are primarily driven between 10 and 20 miles per day in the community. This aligns very well with the average daily driving distance of 15 miles reported by DfT (Department for Transport (DfT) 2022) in 2023. The samples generated using WRS and URS were designed to follow the distribution that is already specified, but still, as a validation tool, the Chi-Square test was conducted in the model. The test result calculated the p-value as 0.4644. This means that it failed to reject the null hypothesis considering α of 0.05, that is, the differences between the original and empirical distributions were not considered statistically significant.

The initial phase of the research aims to analyse the simulated community grid to illustrate the impact of uncontrolled EV charging and grid status with total electricity demand, including electro-domestic load and HP consumption.

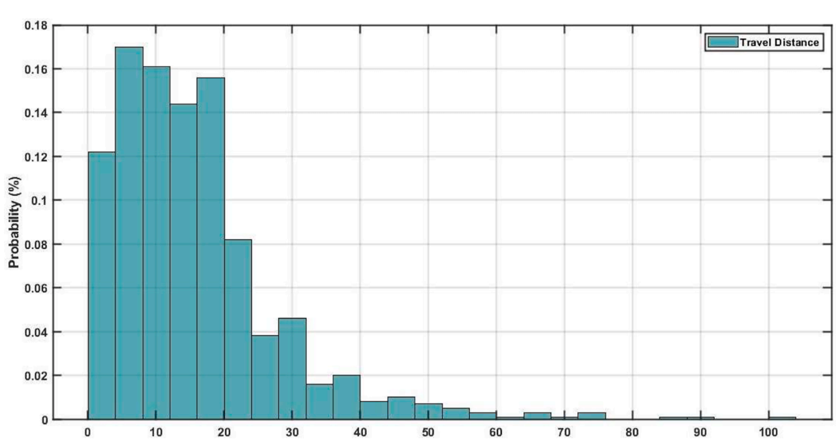

Fig. 14. Distribution of the daily travel mileage of the vehicles.

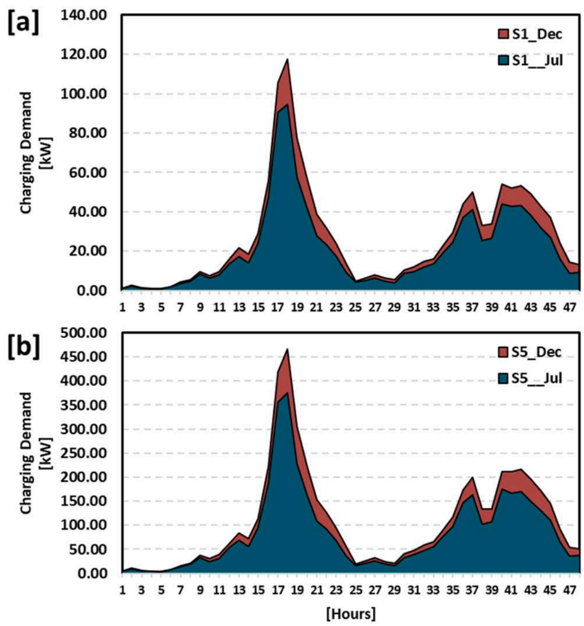

Fig. 15. EV charging demand on community grid with uncontrolled charging, a) Scenario 1, and b) Scenario 5.

MCS is performed to estimate the charging demand of EVs within the community under various scenarios, which include different penetration rates and seasonal variations. The MCS, designed to incorporate multiple uncertainties, was conducted for 116 EVs in Scenario 1, 231 EVs in Scenario 2, 346 EVs in Scenario 3, and 461 EVs in Scenarios 4 and 5, as determined in this research scenarios.

Scenario 1, and Scenario 5, were examined over a 48-hour period, capturing the dynamics of EV charging under uncontrolled conditions during both a typical winter day in December and a summer day in July. The MCS model outputs for the EVs' charging load in the community without a charge control strategy in Scenarios 1 and 5, is shown in Fig. 15. One of the coldest Friday (2 °C) and Saturday (2.52°) in December, as well as one of the warmest Friday (23.61 °C) and Saturday (21.01 °C) in July were selected to demonstrate the potential seasonal variations in EV charging demand. Fig. 15a presents the uncontrolled charging demand in Scenario 1 with 116 EVs on the selected Friday and Saturday, while Fig. 15b illustrates the demand in Scenario 5 with 461 EVs, for both the selected Fridays and Saturdays, respectively.

In the model, no charging management strategy is applied, and it is assumed that vehicles are directly plugged into the charger upon arrival. This approach provides insights into potential network challenges that could arise in future scenarios involving uncontrolled EV charging.

The analysis of EV charging demands in community grids reveals critical insights, particularly when considering the impact of temperature variations and EV penetration levels. In both scenarios under study, a significant increase in charging demand is observed during the colder month of December. This trend is more apparent in Scenario 5, where, on a colder Friday, the peak charging demand touches an alarming 466.32 kWh. This is nearly the grid's peak capacity of 500 kW. The reason for the rise in charging demand is the increased internal resistance of batteries in cold weather, which reduces discharge efficiency and necessitates additional power for heating, as highlighted in reference (Hao et al., 2020). In contrast, during the warmer month of July, although the demands are lower, they remain substantial. For instance, in Scenario 5, which represents 100 % EV penetration, the peak demand hits 374.96 kW, indicating a considerable load on the community grid.

The comparative analysis of these scenarios indicates the possible scalability challenges of community grids. The peak charging demand in December jumped from 117.6 kWh with 25 % EV adoption (Scenario 1) to 466.32 kWh with 100 % EV penetration (Scenario 5). This dramatic rise underscores the necessity for a more robust grid infrastructure to support the growing popularity of EVs. In this point, the adoption of renewable energy supported EV charging stations could be a promising solution. Integrating renewable energy sources in EV charging infrastructure could significantly reduce the stress on the grid caused by high EV penetration, as suggested in the reference (Dik et al., 2023).

Additionally, the analysis showed distinct charging patterns between the selected Fridays (as a typical weekday) and Saturdays (as a typical weekend). Fridays consistently show a higher demand in both scenarios and seasons, which could be reflective of behavioural travel changes like weekday commuting and weekend events.

As known, there is a direct correlation between the number of EVs and the charging load created. On Friday, specifically in Scenario 5 with 461 EV units, considerably higher peak charging demands were observed. For instance, on the Friday of December, a typical weekday, the peak demand due to EV charging alone reached 466.32 kW at 6pm, which exceeds the operational capacity of the community grid. In contrast, this peak was just around 117.6 kW in Scenario 1, with 116 EV units at the same time. The charging demand pattern on weekdays typically starts low between midnight and early morning, gradually increases throughout the morning, and increases sharply in the evening. This pattern seems linked with typical commuting times, suggesting that full EV penetration could bring about a considerable challenge to grid capacity, especially during evening peak times on weekdays. It might be worth noting that even with a 25% EV penetration, the grid's peak demand capacity at 6pm on a weekday is significantly impacted by EV charging, especially in colder seasons.

A noteworthy observation is that on weekdays, scenarios with 75 % or higher EV penetration, without any charge control strategy, result in an additional grid demand of over 200 kW. This load accounts for more than half of the grid's operational capacity, emphasising the stress on existing distribution networks. The upcoming sections of this study will further explore how, especially during winter months, the increased need for heating can compound these challenges, potentially leading to inevitable grid management issues. However, the given MCS outputs for the EVs' charging load under uncontrolled charge would be beneficial for a better understanding of the effect of EVs on the distribution grid and strategic planning in grid infrastructure.

In addressing the impact of uncertainties on system performance, the study introduced a refined MCS model with uniform parameters—a 3 kW charger and a Tesla Model 3, reflecting the UK's most popular EV configuration. Fig. 16 compares hourly EV charging demands between this updated model and the original for December under Scenario 5, showcasing the influence of EV and charger diversity on demand predictions over 24 h.

The peak demand in the updated model was 397.61 kW at 6PM, notably less than the original model's 466.32 kW peak. Moreover, the total demand observed was 2264.24 kW, around 12% lower than the original's 2581.49 kW. These results highlight the impact of uncertainties such as EV specifications and charging behaviours on demand forecasting and system design. The analysis emphasises the need to account for a range of uncertainties to develop resilient power grid planning and operation strategies that are representative of real-world variability.

The next phase of the research explores the dynamics of total electricity consumption within a community integrating EVs without a charge control mechanism and different types of HPs under various scenarios, focusing on the impact of these sustainable technologies on the existing power grid. Our analysis revealed significant variance in peak electricity demands across scenarios, particularly when comparing the colder month of December to the warmer month of July. The total electricity consumption, combining the community's electro-domestic load, uncontrolled EV charging, and different HPs' consumption under various scenarios in December and April, is presented in Fig. 17.

In December, when the total heating load of the community was

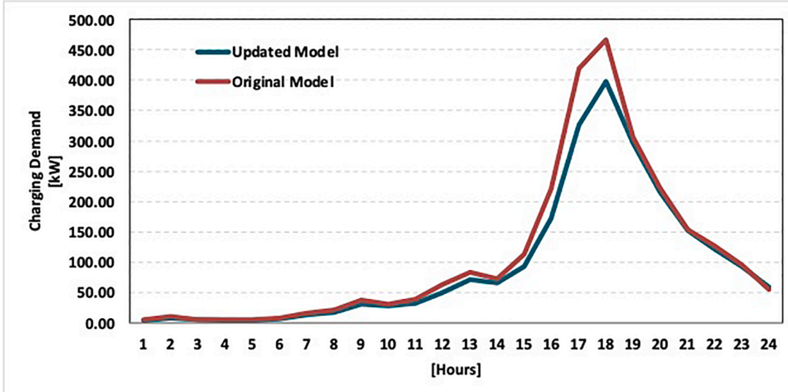

Fig. 16. Comparative analysis of hourly EV charging demand under uniform and variable parameter.

1016 kW, the peak demand with ASHP in Scenario 1, representing a 25 % penetration of EVs and HPs, was approximately 546.85 kWh at 5pm on a typical weekday. This demand considerably grew in scenarios with higher EV and HP penetrations, reaching about 1480.46 kWh at the same time in Scenarios 4 & 5, corresponding to 100 % penetration. During weekends in December, the grid load was higher. Considering Scenario 4&5 with ASHPs, the total daily electricity demand in the community on a selected Friday was 13,231 kWh, while on Saturday, this increased to 14,191 kWh due to the rising heating demand. Additionally, on an hourly basis, the peak load on the Saturday morning at 8am in Scenario 1 was 506.64 kWh with ASHP, which increased by approximately 200 % to 1508.02 kWh in Scenarios 4 & 5. As can be seen in Fig. 17a, even the 25 % penetration scenario in December exceeded the network's operational capacity of 400 kW and even the peak capacity of 500 kW. This is indicative of potential overloading problems in the UK's current distribution networks during the colder months in the near future, necessitating the rapid integration of energy management methods.

In April, when temperatures rose and the community's total heating halved to 521.9 kW compared to December, significant potential overloading situations were still observed on the grid. The peak demands were generally lower, because of the reduced heating requirements. In Scenarios 4 & 5 with ASHP, for instance, the peak demand was around 786.59 kWh. However, in scenarios with more than 50 % penetration of sustainable technologies, the network's operational and peak capacity values were exceeded. A key point, as seen in Fig. 17f, is that introducing SAHPs, benefitting from increased solar radiation in April, effectively reduces the peak network demand, unlike ASHP and GSHP, keeping the net demand below the 500-kW capacity. In July, when temperatures exceed 20 °C and the heating load due to domestic hot water needs is only 146.64 kW, the stress on the grid significantly decreases. However, the current network, considering weekday loads, can only accommodate up to 50 % technology penetration. It has been observed that technology integration exceeding 50 % during summer months, even with the use of GSHP, leads to overloading problems on the grid.

3.3. Community network evaluation

In the context of sustainable technology integration in power grids, the implementation of smart charging and V2G technologies presents a promising solution for managing grid load by increasing renewable energy usage and supporting network decarbonisation. Fig. 18 demonstrates the performance of these technologies in a 50 % EV and ASHP penetration scenario during the peak demand months of December. The figure was generated from the output of the 100th iteration of the model, which in total comprises 1000 iterations, serving as an illustrative example.

In Fig. 18, the smart charging and V2G model was applied to a simulated community for 48 h, covering a typical cold Friday and Saturday (around 2 °C) in December. The data reflects the relation between EV charging demand, EV discharging (V2G), baseline demand (comprising electro-domestic consumption and ASHP usage), and the regulated demand on the grid by the control mechanism, including smart charging and V2G.

This analysis revealed a significant moderation in the total electrical load when compared to the earlier uncontrolled system findings, where peak loads under Scenario 2 in December reached 857.81 kWh on weekdays and 841.04 kWh on weekends (as illustrated in Fig. 17b). The introduction of the smart charge and V2G model successfully regulated the demand, maintaining grid stability even during peak hours.

The V2G technology and smart charging played a crucial role in this moderation. The model in this study considers the departure times of vehicles and their SOC requirements to determine the most optimal charging and discharging times. During periods of low grid demand, vehicle charging is directed through smart charging protocols, efficiently utilising off-peak hours. Also, when the grid experiences demand exceeding its capacity, the V2G protocols take place to transfer energy back to the grid from the available vehicles. This dual approach not only ensures the efficient use of energy sources but also plays a critical role in stabilising the grid during high-demand periods.

The model manages vehicle charging processes while accommodating the preferences of vehicle owners for their post-operation SOC within the framework of smart charging and V2G participation. Key parameters in this process include the availability of the vehicle and the sufficiency of energy within the network. If sufficient energy is available on the grid, vehicles can be charged up to 80 %, but the process ensures that vehicles are at least charged to the minimum preferred SOC by the end of the operation. Fig. 19 illustrates the final SOC of vehicles as observed in the 100th iteration on a typical weekday (on Friday) in December and April under Scenario 2. As shown in Fig. 19a, despite some vehicles not achieving a full 80 % charge in the high-demand month of December, the decreased demand on the grid in April allows for vehicles to be fully charged. This variation underscores the impact of grid demand on charging outcomes and the adaptability of the model to different energy availability scenarios. Furthermore, in Fig. 19, it is observable that there are designated spaces for certain EVs. This indicates that these are the EVs that lack sufficient time to participate in V2G and Smart Charging and are, therefore directly charged upon arrival at home.

Fig. 20 presents a comparative analysis of charging demand, heat pump electricity consumption, and electro-domestic load in the community before and after the implementation of Smart Charge and V2G technologies in Scenario 3 (December) and Scenario 5 (April). The analyses across various scenarios demonstrate that this dual approach effectively utilises excess energy in the grid and manages to bring the excess demand below the network's capacity limits, even in cases of 100

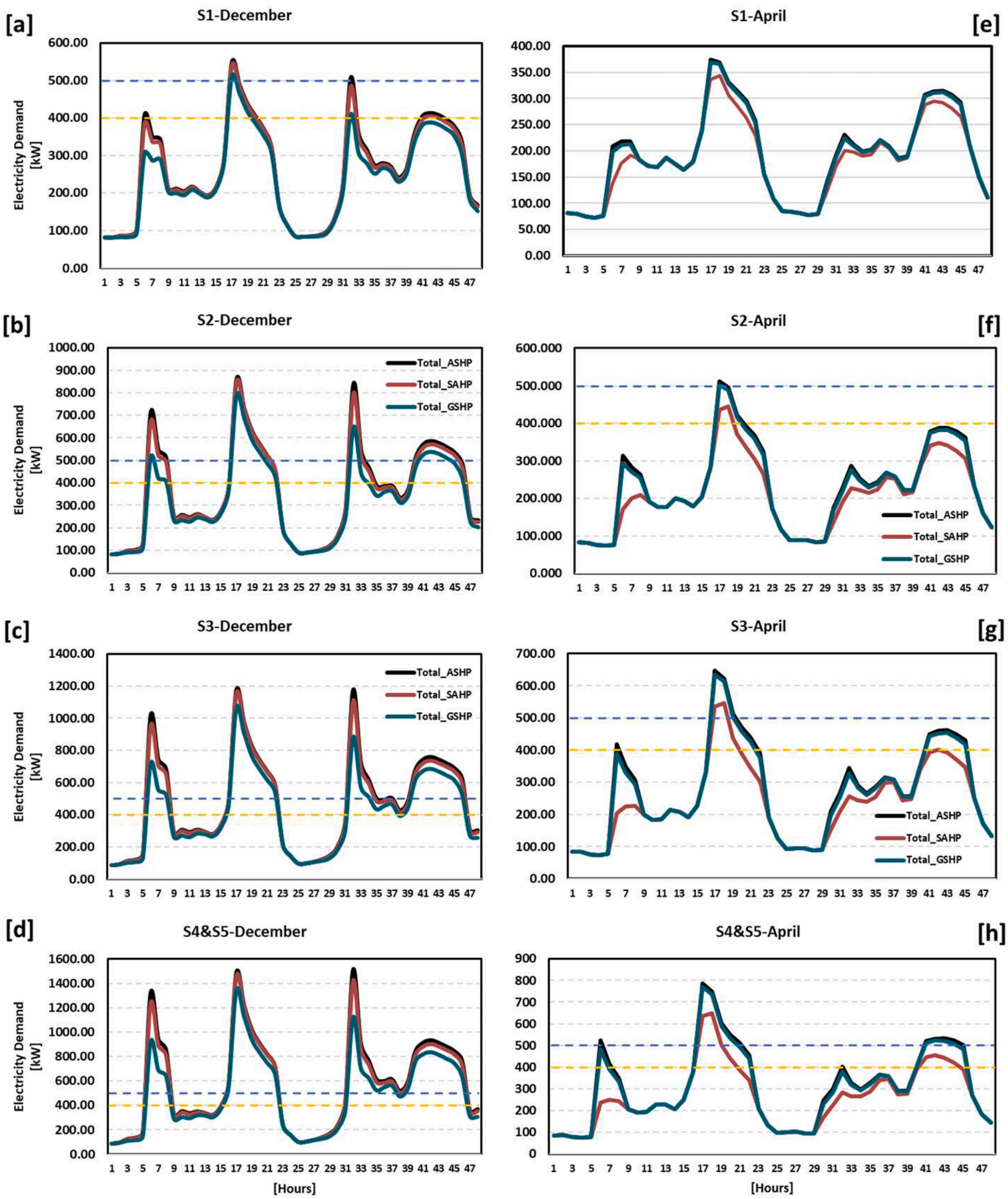

Fig. 17. Total electricity demand of the community on a weekday including grid operational (yellow dashed line) and peak (blue dashed line) capacity, a) Scenario 1 in December, b) Scenario 3 in December, c) Scenario 5 in December, d) Scenario 1 in April, e) Scenario 3 in April, and f) Scenario 5 in April.

% sustainable technology integration in months other than the winter season. As seen in Fig. 20d–f, in April, the balanced network capacity does not exceed the operational limits even during peak hours. However, in the colder months, such as December, where temperatures drop and the EV charging load increases due to colder weather, this dual approach operates efficiently, with up to 50 % penetration. Nevertheless, in the winter season, the reduced efficiency of ASHPs and SAHPs under low-temperature conditions leads to marginal insufficiency problems in the network capacity. This is evident in Fig. 20a and b, where, even in the 75 % penetration scenario during weekends, the grid exceeds the 500-kW peak capacity by small margins of 29.64 kWh and 4.92 kWh, respectively. However, as observed in Fig. 20c, the issue of capacity excess appears to be addressed by the utilisation of GSHPs because of the higher COP of GSHPs in winter compared to the other types.

These findings underscore the need for more enhanced energy management mechanisms or potential increases in network capacity to accommodate the 100 % integration of these technologies during winter months in the UK's current distribution grid infrastructure. Table 8 illustrates the necessary network capacity enhancements to support the grid system during winter months under a scenario with 100 % EV and HP penetration when integrating V2G and Smart Charge systems.

3.4. *Renewable energy contribution*

This section analyses the energy generation outputs from an array of solar photovoltaic (PV) and wind turbine installations across five

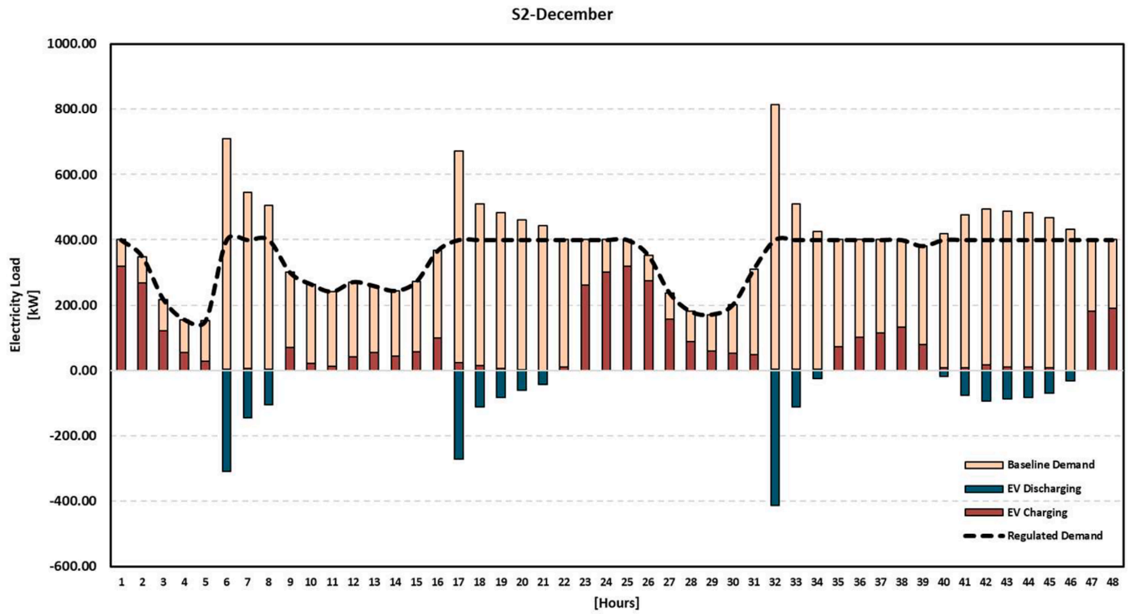

Fig. 18. Analysis of EV charging and discharging, baseline demand (ASHP consumption and domestic electricity usage), and regulated net demand in the 100th iteration on the selected Friday and Saturday of December under Scenario 2.

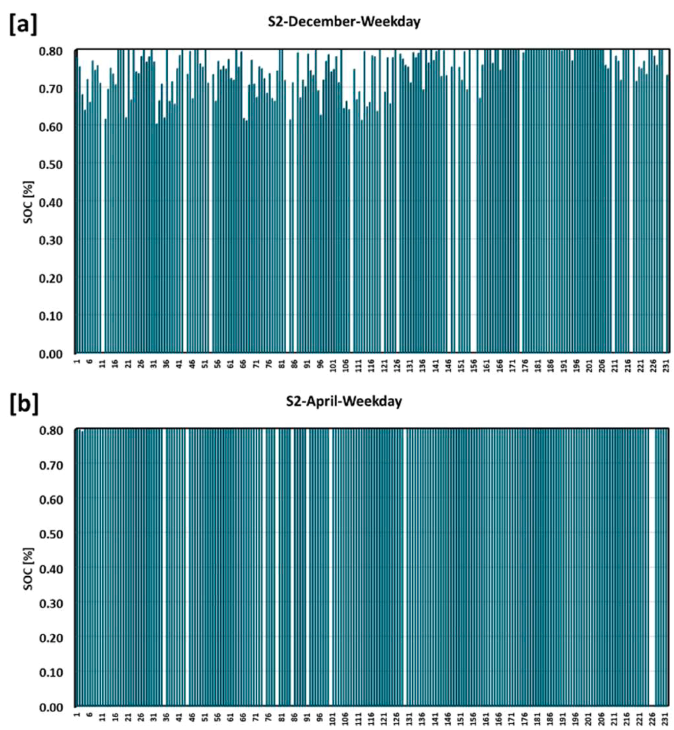

Fig. 19. Final SOC of vehicles as observed in the 100th iteration of a weekday under Scenario 2, a) in December and, b) in April.

scenarios within a simulated community. The scenarios are designed to represent a spectrum of renewable energy system sizes, ranging from smaller-scale installations in a short period to more sustainable power networks in a long-time horizon, as part of the community's distributed energy resources (DERs). As detailed in Table 5, Scenario 1 features a 60-kW solar PV paired with a 40-kW wind system, providing a baseline for comparison against the more extensive systems in the following scenarios. Scenarios 2 and 3 have equal capacities of 100 kW for both solar PV and wind systems to evaluate the impact of balanced renewable generation. Scenario 4 scales up to a 120-kW solar PV system alongside a more extensive 180-kW wind turbine setup, exploring the effects of a wind-dominant energy mix. Lastly, Scenario 5 inverses the dynamic with a 180-kW solar PV and a 120-kW wind system, assessing the potential of a solar-dominant approach.

Fig. 21 presents the monthly energy outputs from the installed solar PV and wind turbine systems across the five scenarios. The figure shows the performance of each renewable energy configuration, measured in MWh, offering a detailed view of the generation capabilities throughout the calendar year.

Examining the monthly energy outputs from the solar PV and wind turbine systems, it is apparent that there is a significant variation in generation, both within each scenario and across the different configurations. These fluctuations are primarily related to the inherent variability in solar irradiance and wind speeds throughout the year.

The analysis of monthly energy outputs reveals notable trends across the five scenarios, emphasising the impact of system size and seasonal variability on renewable generation. Scenario 1 shows pronounced seasonal variation with peak solar output in July (6.79 MWh) and wind in January (18.77 MWh). Scenarios 2 and 3, with equal capacities of 100 kW for solar and wind, yield a substantial combined output, exemplifying the benefits of system scaling. March's output of 40.65 MWh, for example, represents a significant increase (approximately% 130) from Scenario 1′s output, underscoring the enhanced energy generation through capacity scaling.

In Scenario 4, the 180-kW wind system dominates, peaking at 84.5 MWh in January, while Scenario 5, with a 180-kW solar PV system, peaks in solar generation at 20.39 MWh in July, nearly tripling S1′s annual solar output, and maintains a significant wind contribution with 56.33 MWh in January. These scenarios illustrate the strategic complementarity between wind and solar power to provide a reliable energy supply and contribute significant CO_2 emissions savings, particularly during the winter months.

This data underscores the importance of renewable energy systems that are designed by considering specific local conditions and the potential for substantial environmental benefits, providing a further understanding of the strategic advantage of combining solar and wind to meet energy demands sustainably.

After highlighting the variability in solar and wind energy generation across various scenarios, it is essential to address how this uncertainty

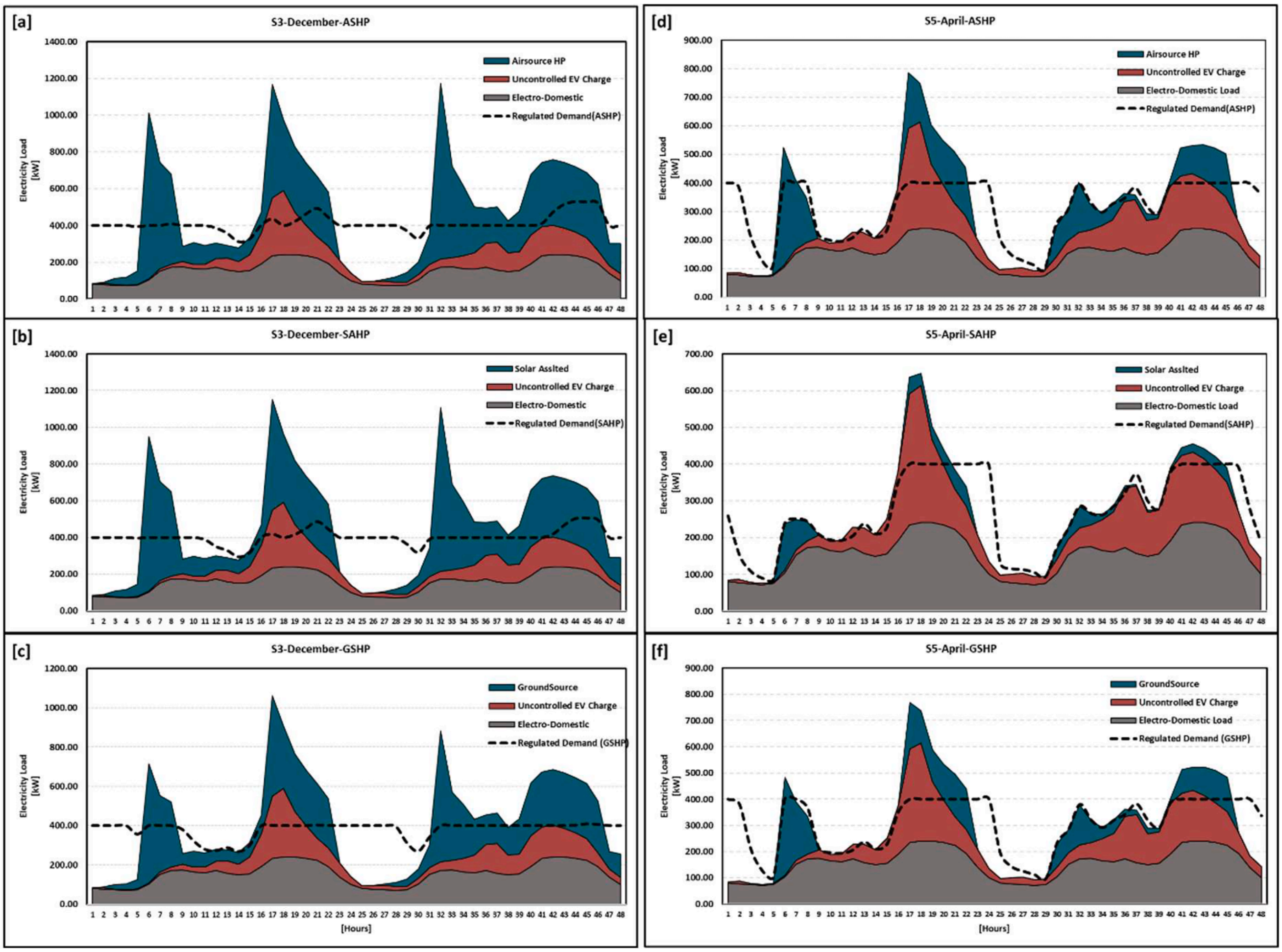

Fig. 20. Comparison of Charging Demand, Heat Pump Electricity Consumption, and Electro-Domestic Load Before and After the Application of Smart Charge and V2G, a) ASHP in December, Scenario 3, b) SAHP in December, Scenario 3, c) GSHP in December, Scenario 3, d) ASHP in April, Scenario 5, e) SAHP in April, Scenario 5, and f) GSHP in April, Scenario 5.

Table 8
Network capacity enhancements for 100 % EV and HP penetration with V2G and smart charge integration.

Penetration Scenarios	Operational Capacity [kW]	Peak Capacity [kW]
100 % EV and ASHP	525	625
100 % EV and SAHP	500	600
100 % EV and GSHP	425	525

affects the reliability and stability of the community energy network. The inherent uncertainties in RES, such as fluctuating solar irradiance and wind speeds, necessitate adaptive and resilient energy system designs. To mitigate these challenges, the paper suggests integrating energy storage solutions and hybrid renewable systems, which can buffer against variability and ensure a consistent energy supply. Additionally, adopting smart grid technologies underscores the importance of responsive and flexible grid management to accommodate the dynamic nature of renewable energy generation. Moreover, future research directions could also focus on enhancing forecasting models for RES to improve predictability and developing strategies to align community members' behaviour with renewable energy availability.

Hourly data for solar radiation and wind speed were collected for a representative Friday and Saturday in April and July, as depicted in Fig. 22. The figure provides insights into these environmental parameters' daily and seasonal variability.

In April, solar radiation and wind speed variability presented distinct patterns. The solar radiation exhibited a mean value of 0.135 with a standard deviation of 0.163 during these two days, indicating moderate daily variability. The wind speed in April had a mean of 5.36 m/s and a standard deviation of 1.23 m/s, showing a relatively steady wind flow with occasional fluctuations. This steadiness in wind speed is advantageous for wind energy generation, offering a reliable energy source with predictable outputs in the community's region.

In contrast, the data from July showed different variability patterns. The solar radiation had a higher mean of 0.279 and a standard deviation of 0.295 during these two days, reflecting more intense and variable solar exposure compared to April. This increased variability in solar radiation could lead to higher, yet less predictable, solar energy generation. The wind speed in July showed a slightly lower mean of 4.75 m/s but maintained a similar level of variability to April, with a standard deviation of 1.15 m/s. This better consistency in wind speed throughout the seasons benefits wind energy projects by providing a more reliable and stable wind energy source across different times of the year. Although the data from these two days indicate a relatively stable pattern in wind speed, the observations also included days with significant fluctuations, featuring either no wind or extreme wind speeds. Such variability can notably impact the output of wind energy generation systems.

Fig. 23 shows how strategic integration of renewable sources in community networks can significantly contribute to meeting community

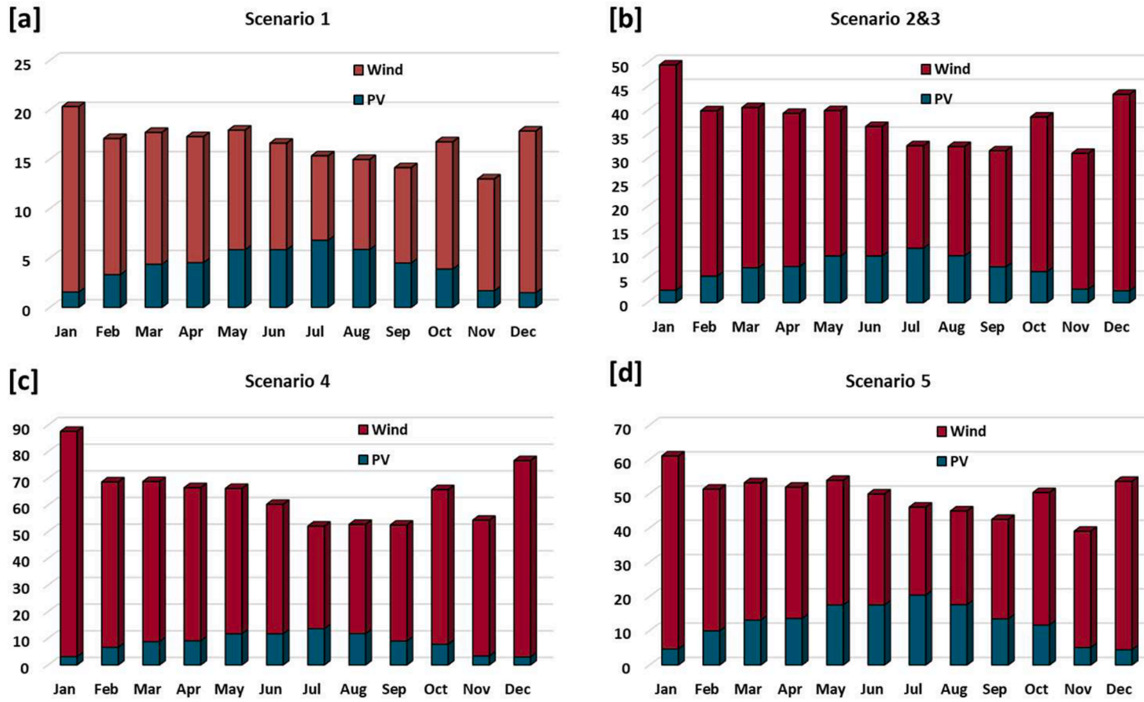

Fig. 21. Comparative monthly energy outputs from solar PV and wind turbine systems by scenarios a) in Scenario 1, b) in Scenario 2&3, c) in Scenario 4 and d) in Scenario 5.

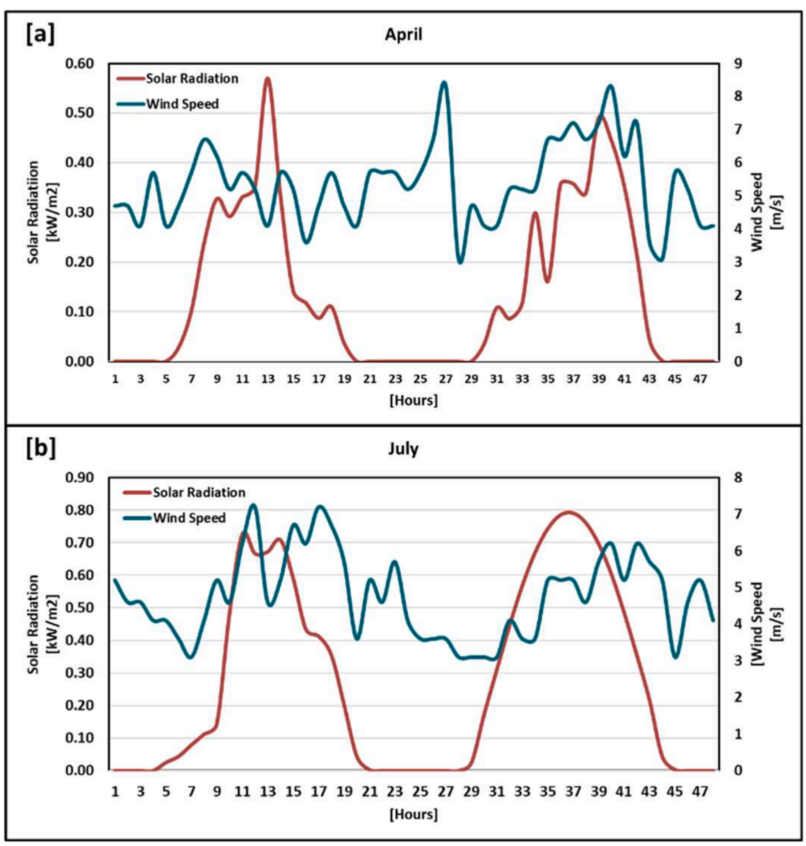

Fig. 22. Hourly solar radiation and wind speed on selected Fridays and Saturdays, a) in April, and b) in July.

energy demands in the regulated network. This system, equipped with technologies such as V2G and Smart Charging, not only supports the grid balance but also increases the potential usage of renewable energy sources.

In April's Scenario 4 (Fig. 23a), the data reveals an interesting interplay between renewable energy generation and regulated demand within a residential community. Before dawn, wind generation considerably sustains the energy supply, with an output of 113.44 kWh at 1am

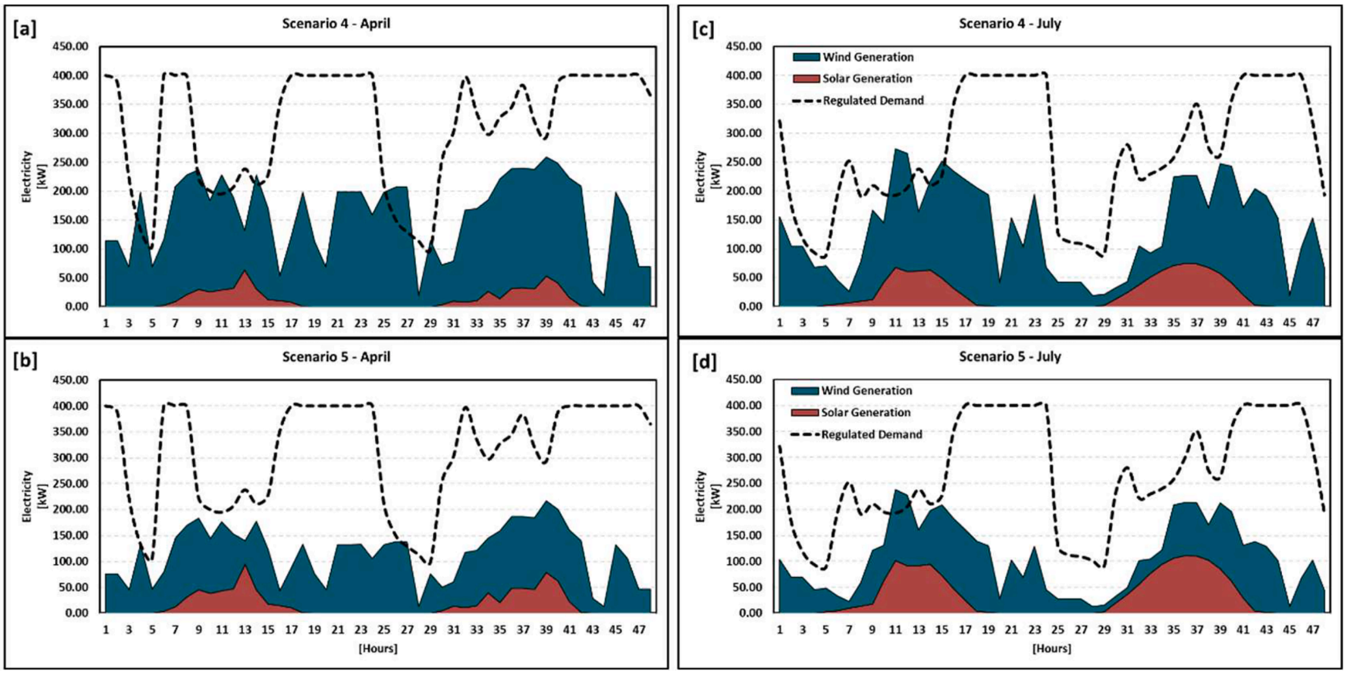

Fig. 23. Hourly analysis of solar and wind energy generation versus regulated net demand (including ASHPs) in the community network with V2G and Smart Charge integration, a) in Scenario 4 (April), b) in Scenario 5 (April), c) in Scenario 4 (July) and, d) in Scenario 5 (July).

against a demand of 400 kWh. As solar generation begins post-dawn, it peaks at 31.27 kWh at noon, demonstrating the potential of solar power during daytime hours. However, the peak solar hours do not align with the peak demand periods, as the community's demand is lower during the day when most residents and their vehicles are likely away from home. This mismatch causes a challenge for solar energy utilisation in EV charging, especially in such kinds of simulated communities that only consist of dwellings. This situation also highlights the critical importance of integrating storage solutions with PV systems to manage and utilise solar energy effectively during periods of peak demand. Conversely, the stable nature of wind energy, providing substantial generation consistently, becomes crucial, particularly at night. For instance, at 11pm, wind generation nearly meets the regulated demand, offering almost 200 kWh (half of the grid operational capacity) when there is no solar generation. This stability is a cornerstone for smart charging strategies, allowing for the deferral of EV charging to night time, thus enhancing the use of wind energy, and reducing reliance on non-renewable sources. The April data underscores the system's adaptability, ensuring the efficient use of renewable energy and demonstrating the significant potential of integrating wind generation with smart energy management technologies in residential communities.

July's data from Scenario 4 (Fig. 23c) further explains the impact of solar PV on the grid. On a clear sunny day, solar generation peaks, significantly contributing to the total energy mix and, at times, resulting in excess generation. For instance, at 12pm, there is a notable increase in solar generation, leading to surplus energy (approximately 180 kWh in the four hours) when combined with wind generation at 11am, 12pm, 2pm, and 3pm. This surplus should be transitioned into the national grid in on-grid systems to avoid possible balance problems.

During the days analysed in April under Scenario 4, the community's RESs (solar PVs and wind turbines) were key contributors to meeting a substantial portion of the electricity demand. The total community demand over these two days was approximately 15,007 kWh, with installed RESs covering around 7441.5 kWh, nearly 49.6 % of the total demand. Similarly, in April's Scenario 5, the demand was again 15,007 kWh, and RESs contributed 5539.17 kWh, accounting for approximately 36.9 % of the demand because of the decreased wind turbine and increased solar PV capacity.

Moving to July's data, Scenario 4 shows a total demand of 12,924.3 kWh, with RES providing 6318.75 kWh, fulfilling about 48.8 % of the community's needs. In Scenario 5 for the same month, RES supply to the community was 5115.73 kWh, equating to nearly 39.6 % of the total demand.

On the other hand, considering the combined total of selected Fridays and Saturdays, a 25 % renewable energy system integration (60 kW solar capacity and 40 kW wind capacity), as observed in Scenario 1, yielded renewable energy production of 1849.4 kWh in April (with 273.54 kWh from solar PV and 1575.84 kWh from wind) and 1728 kWh in July (with 513.98 kWh from solar PV and 1214 kWh from the wind turbine). It is noteworthy that even in a solar-dominant renewable energy system, the total renewable production in July, which has maximum solar irradiance, was less than that in April. This underscores the significant contribution of wind turbines to this kind of system in the UK. Despite the reduction in solar radiation in December, the strong output from wind energy supports the system. Additionally, in the 50 % renewable energy system integration scenario, the total renewable energy generated in the community on the selected Fridays and Saturdays was 4395 kWh in April (455.9 kWh from solar PV and 3939.6 kWh from wind) and production of 3891.8 kWh in July (856.64 kWh from solar PVs and 3035.19 kWh from wind turbines).

The percentage coverage by RES indicates a significant shift towards sustainable energy practices and highlights the possible potential of using RESs, especially wind energy, for delayed EV charging operations. This kind of technology combination might be a way to pave the way for more environmentally friendly and energy-secure communities.

The paper validates the modelled renewable energy systems based on Scenario 1. This validation process employs benchmarks from existing literature and reports to assess the accuracy and reliability of the model's performance predictions. In the solar PV system analysis, an annual energy output of 827 kWh per kWp was calculated based on Scenario 1. This figure emerges from the total annual energy production of a 60 kW solar PV system, totalling 49,620.13 kWh. The CIBSE Energy Performance Group (Chartered Institution of Building Services Engineers (CIBSE) Energy Performance Group 2024) suggests that, as a general rule, a well-designed PV installation in the UK is expected to generate between 780 and 850 kWh per year per kWp, depending on the available solar irradiation. Additionally, an analysis conducted by Koumpli (Koumpli, 2017) has reported a solar PV system performance value of 855 kWh/kWp in the UK. Furthermore, a report by the UK Government (Department of Energy, and Climate Change (DECC) 2011), utilising performance ratio derived from the Department of Energy&Climate Change (DECC) projections and analyses by consultants Cambridge Economics Policy Associates (CEPA) and Parsons Brinckerhoff (PB), alongside OFGEM, indicates a performance ratio for domestic PV systems at approximately 850 kWh/kWp. This data was received from a case study involving a 2.6 kW solar PV installation in the UK. The performance ratio of 827 kWh per kWp, identified in the present study, is slightly lower than some reported values yet falls within the expected range of performance for solar PV systems in the UK context. The model's performance closely matches established benchmarks, with small differences. These differences can result from varying factors, such as exact project location, system design, and installation year, which affect comparisons. Despite these, the model's results are within expected ranges, confirming its accuracy.

On the other hand, the calculated annual energy output for the wind energy system in Scenario 1, achieving approximately 3700 kWh per kW of installed capacity, serves as an indicator of its efficiency. (Ryberg et al., 2019) have documented that in optimal locations within the UK, onshore wind turbines typically achieve between 3400 and 4000 kWh/kW. The performance of the simulated wind system in this paper closely aligns with this range. However, it is crucial to recognise that the variability in turbine performance depends on several factors, including rotor diameter and tower height (Junginger et al., 2005). Wind energy generation is also subject to a wide range of influences, including geographic location, technological choices, and specific environmental conditions, all of which can significantly impact the kWh/kW metric.

3.5. Urban energy futures: scability and technological impacts

This section explores the scalability of proposed energy solutions, the impact of consumer behaviours, and advancements in EVs and HPs. It assesses how these technological advancements and consumer behaviours influence proposed systems' effectiveness while examining the broader implications of system changes.

In the context of integrating EVs, HPs, and RESs into sustainable communities, alongside proposing grid management tools like V2G and Smart Charging, understanding the concept of scalability is paramount. Scalability ensures that these innovative solutions can adapt to urban environments' growing and dynamic electricity demands without introducing excessive costs or complexities. Factors influencing scalability include technological maturity, infrastructure readiness, regulatory support, and social acceptance. Additionally, the ability of renewable energy installations, HP systems, and EV charging infrastructure to evolve within urban constraints, such as space limitations and existing grid capacities, is crucial. Urban spaces present unique challenges to the scalability of these technologies, including restricted areas for renewable installations and increased grid capacity needs due to elevated EV charging demands. The retrofitting requirements of HPs in existing buildings and potential battery degradation from V2G applications add complexity to scalability. Addressing these challenges may involve innovative urban planning, smart grid technologies, and policy frameworks designed to support the seamless expansion of these technologies, transforming the vision of sustainable urban communities into a practical reality.

Understanding consumer behaviour in energy consumption is essential for optimising grid efficiency and achieving sustainable energy solutions. Behavioural patterns, like peak-hour electricity demand and EV charging habits, significantly influence grid load (as EV-based changes illustrated in Fig. 16). The adoption rates and usage patterns of EVs and HPs are critical in modulating peak demand. This underscores the value of this paper's time horizon scenario methodology. Moreover, as discussed before, the integration of solar PV and wind turbines can impact grid effectiveness due to variable outputs, suggesting the inclusion of a smart RES prediction model in future enhancements. Factors such as socio-economic status, environmental awareness, access to technology, and incentives shape consumer behaviours, affecting household energy use and demand management. To shift towards sustainable communities with approaches like the proposed model, strategies to boost consumer engagement with EVs, HPs, smart charging, V2G systems, and renewables are essential, including educational programs, incentives, and policy measures. For example, consumer preferences in HP selection, notably the shift from ASHPs to more efficient SAHPs, significantly affect energy demand, highlighting the importance of guiding consumer choices towards sustainable technologies. Therefore, tailoring these strategies to consumer behaviour can significantly enhance the viability of energy solutions, promoting a more stable and sustainable power network.

The introduction of this paper discusses the current and projected states of EVs, HPs, and RESs, underscoring their critical role in decarbonising energy systems. Forecasts from leading energy agencies and companies and the UK's ambitious progress in renewable energy integration and EV adoption set a solid foundation for discussing upcoming technological advancements and their implications on future grid management strategies.Significant advancements in battery technology are anticipated to enhance EV range and charging efficiency notably, which is critical for transitioning to an electric-dominant transportation sector. With their larger battery capacities than PHEVs, BEVs are also expected to lead the EV market (Dik et al., 2022). This development towards larger battery capacities can bolster energy storage capabilities, potentially increasing the efficiency of V2G applications, a key component in this paper's proposed energy system model. Additionally, expansions in the operational range of HPs are projected (Harris & Walker, 2023). This development can enhance HP's viability in diverse climates and support broader adoption for heating needs. In the UK, significant improvements in home thermal efficiency are underscored by the rise in average energy efficiency ratings from 51.4 in 2008 to 66.3 in 2021 (Bolton, 2024). Enhanced energy efficiency can notably reduce heating demand and energy bills (Bolton, 2024). Therefore, if this upward trend continues, it is likely that future HP's energy consumption will decrease accordingly. These technological advancements are directly relevant to the study's energy management model, which explores the optimal integration of EVs to support community grids and enhance RES integration, including solar PVs and wind turbines. As such, they might expected to significantly bolster the capabilities of EVs for grid stabilisation and RES integration. On the other hand, the seamless integration of these advanced technologies into the energy grid may highly dependant on adaptive policy frameworks. Encouraging the widespread adoption of EVs, HPs, and RESs requires policies that support infrastructure development, incentivise technological adoption, and update regulatory standards.

3.6. Preliminary economic insights into sustainable technologies

The economic implications associated with proposed technologies are crucial for their widespread adoption and effectiveness. This subsection provides a preliminary examination of the economic considerations related to solar and wind energy systems and various HPs, focusing on their installation costs. While a comprehensive economic analysis extends beyond the scope of this paper and is designated for future investigation, the following overview serves to underline the significance of economic factors in the context of sustainable technology adoption.

Recent trends in solar PV installation costs in the UK, according to a GOV UK report (Department for Energy Security and Net Zero (DESNZ) 2023), reveal notable fluctuations. In 2022, the average cost for small-scale solar PV installations (0–4 kW) started at £1836 per kW and experienced a significant increase, reaching a peak of £2627 per kW by

January 2023. Notably, larger installations (4–10 kW and 10–50 kW) also saw substantial cost increases over the past year. The average cost per kW for installations sized 4–10 kW was £2220, whereas for those of higher capacities, the cost was more economical at £1392 per kW. In the UK, for PV systems with a capacity higher than 3.68 kW, installation requires prior approval from DNOs. This process may involve grid capacity evaluations or necessary network upgrades, with potential costs to the system owner (Dik et al., 2023). According to BEIS (Department for Business, Energy & Industrial Strategy (BEIS), 2020), for onshore wind systems, the capital costs encompass pre-licensing technical and design expenses, estimated at £64 per kW, alongside regulatory and licensing costs of £45.9 per kW. Additionally, the medium cost of infrastructure is expected to be around £3.3 million. Operational expenses are considered constant, amounting to £22,000 per MW. Furthermore, the connection and Use of System (UoS) charges for an onshore wind farm are reported to be steady at £3109 per MW per year. Additionally, the Smart Export Guarantee (SEG) enables producers of surplus electricity to sell back to the grid, with tariffs for approved installations up to 5MW ranging from £0.02 to £0.15 per kWh (Dik et al., 2023).

According to the Energy Saving Trust (Energy Saving Trust, 2024), the installation cost for an ASHP typically stands at around £14,000, with running costs influenced by system design, operational methods, and factors such as radiator sizing, electricity tariff, and control mechanisms. Conversely, GSHP installation costs can significantly vary, typically around £28,000 for systems where the ground loop is buried in trenches, with higher expenses if boreholes are required. Costs are influenced by access to the ground, the chosen heat pump's brand, model, and size, property size, heating needs, and whether it involves new installations or upgrades. Residents in England and Wales may benefit from a £7500 grant for ASHP and GSHP installations under the Boiler Upgrade Scheme, offering financial relief and encouraging the adoption of these sustainable heating solutions. More details can be found in (Energy Saving Trust, 2024). For the cost of SAHPs, the installation costs include both the ASHP installation expenses and the additional costs of solar collectors.

4. Conclusions

This study investigates the dynamic interplay between EVs, HPs, and community-scale distribution networks, adopting RES integration and innovative EV charging strategies to navigate system uncertainties. Employing a sophisticated stochastic model, it explores the transformative potential of smart charging and V2G technology in enhancing renewable energy utilisation and securing distribution systems against the unpredictable nature of energy demand and RES generation in sustainable communities. Based on the analysis, and considering the set conditions and assumptions, the conclusions are drawn as follows.

- ASHPs emerged as the highest electricity consumers, particularly affected by temperatures below 4 °C. In contrast, SAHPs, dependant on solar irradiance, outperformed ASHPs by up to 2.5 times under ideal simulated April conditions. Moreover, SAHPs exhibited significant performance gains over ASHP and GSHP units from January to April, with percentage increases in performance ranging from 5.65 % to an impressive 156.13 %, underscoring SAHPs' potential for superior performance under varying environmental conditions.
- Under uncontrolled charging conditions and full EV adaptation, EV charging demand significantly increases during colder months, exceeds the grid's operational capacity, and is nearing its peak capacity (466.32 kWh in December). In warmer months, EVs also present a substantial charging demand, reaching 374.96 kW in July, which places a considerable load on the community grid, especially at high EV penetration levels. Considering even only the charging demands of the community, it seems that the existing distribution networks in the UK are not ready for 100 % EV penetration.
- When considering the total electricity consumption, including the community's electro-domestic load, uncontrolled EV charging, and HP consumption, the grid capacity during winter months is insufficient even for scenarios with 25 % EV and HP penetration. In warmer months, such as April, the reduced heating demand provides some relief to the grid; however, it remains inadequate for handling more than 50 % of technology penetration. During summer months, if SAHP is excluded, the grid can operate effectively with up to 50 % penetration.
- Implementing smart charge and V2G models has effectively moderated peak electrical loads in 100 % penetration scenarios, with notable exceptions during the coldest months, such as December, where the approach still supports sustainable technology penetration up to 50 %. While V2G and Smart Charging have bolstered grid balance and the utilisation of renewable energy, notably for delayed wind power charging, the peak generation times for solar energy do not align well with the community's highest demand periods, challenging its use for EV charging in residential-only communities. Achieving full integration in the coldest winter months requires either enhanced energy management or an increase in network capacity by up to an additional 100 kW.

4.1. Limitations and future work

In reflecting on the findings of this research, it is recognised that specific areas require further exploration to advance the field of sustainable community energy systems comprehensively. While the present study has made marked steps in understanding the integration of EVs, HPs, and RESs into community grids, it is imperative to acknowledge the limitations inherent in the current approach and propose directions for future research.

A limitation of the study is related to the ambient temperature effect on EV energy consumption, where average daily temperature values were utilised due to the absence of detailed data on the exact usage times of the vehicles throughout the day. This methodological choice, while pragmatic under current data constraints, potentially overlooks the full nuanced impact of intra-day temperature fluctuations on EV energy consumption. Future studies should also aim to integrate exact vehicle usage times instead of only arrival and departure times to evaluate the ambient temperature's impact more precisely.

A vital area for future investigation involves conducting in-depth economic and policy analyses. Such efforts should encompass comprehensive economic assessments, including detailed cost-benefit analyses and evaluations of long-term economic impacts, alongside exploring the policy frameworks necessary for supporting a transition to sustainable energy systems. This direction is expected to offer nuanced insights into the financial viability and policy complexity of implementing sustainable energy solutions, guiding informed decision-making and policy development.

Moreover, while robust, the methodology employed in our study is constrained by its specific modelling approaches and assumptions regarding demand profiles and grid models. These limitations highlight the necessity of engaging in real-world pilot studies, and exploring advanced grid management strategies such as hybrid energy storage, DSM etc. in future research endeavours.

While comprehensive, the dataset utilised in our analysis may not adequately represent the variability across different geographic and socio-economic contexts. The scope of our study, primarily addressing current technology and policy states, necessitates an expansion to include prospective technological advancements and policy shifts. Investigating the potential impacts of emerging technologies on grid management and sustainability initiatives will be crucial.

Lastly, investigating the resilience of energy systems to extreme weather events and climate change impacts is crucial to ensure robust and adaptable energy solutions for the future. These diverse research areas collectively pave the way for further advancement and practical implementation of sustainable energy solutions in community grids.

CRediT authorship contribution statement

Abdullah Dik: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Cagri Kutlu:** Writing – review & editing, Writing – original draft, Visualization, Methodology. **Hao Sun:** Writing – review & editing, Visualization, Investigation. **John Kaiser Calautit:** Writing – review & editing, Supervision, Software. **Rabah Boukhanouf:** Writing – review & editing, Supervision. **Siddig Omer:** Project administration, Supervision, Writing – review & editing.

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.

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APPENDIX 1. The EO.N Research House at the University of Nottingham

Fig. A1

Fig. A1. The EO.N research house.

APPENDIX 2. Mathematical Framework of IES Virtual Environment Software

The given equations described here are sourced from the software manual detailing the modelling processes (IES, 2024).

In this design tool, Eqs. A.1 and A.2 are essential for simulating the principles of heat conduction and heat storage in building materials, respectively.

$$\underline{W} = -\lambda \times \nabla T \tag{A.1}$$

$$\nabla.\underline{W} = -\rho \times c \times \frac{\partial T}{\partial t} \tag{A.2}$$

In Eq. A.1, 'λ' refers to the material's thermal conductivity (W/m^2K), the term '∇T' represents the temperature gradient within the material (K) and '$\underline{W}$' is the heat flux vector indicating the rate and direction of heat transfer (W/m^2). In Eq. A.2, 'ρ' refers to the material's density (kg/m^3), 'c' is the specific heat capacity (J/kgK) and dT/dt represents the rate of temperature change, reflecting heat storage.

Tool uses Eq. A.3 to calculate the net heat storage in the building's air masses over time. In Eq. A.3, 'c_p' is the specific heat capacity of air at constant pressure (J/kWK), 'ρ_a' refers to air density (kg/m^3) and 'V' represents the volume of air in the unit of m^3.

$$Q = c_p \times \rho_a \times V \times \frac{dT_a}{dt} \tag{A.3}$$

Eq. A.4 is utilised to model convective heat transfer from air to the surfaces within a building. Where 'W' is the heat flux (W/m^2), 'T_a' is the air temperature, 'T_s' is the surface temperature, and 'K' and 'n' are coefficients that describe the convective heat transfer properties.

$$W = K \times (T_a - T_s)^n \tag{A.4}$$

In the software, Eq. A.5 is used to compute the rate of heat transfer from incoming air into a space. In the equation, 'Q' signifies the heat transfer rate (W), 'm' is the mass flow rate of air (kg/s), 'c_p' represents the specific heat capacity of air at constant pressure (J/kgK), T_i is the supply air temperature (K), and 'T_a' is the mean air temperature within the room (K).

$$Q = m \times c_p \times (T_i - T_a) \tag{A.5}$$

Eq. A.6 is also employed to calculate the net radiative heat loss from a surface. 'W' refers to the net radiative loss from the surface (W/m^2), 'h_r' is the surface heat transfer coefficient for radiative exchange (W/m^{2}K), 'T_s' is the surface temperature (K), and 'T_{MRT}' is the mean radiant temperature of the enclosure (K).

$$W = h_r \times (T_s - T_{MRT}) \tag{A.6}$$

In the software, Eq. A.7 is implemented to calculate the net long-wave radiation gain for an external building surface. In the equation, '$L^*(\beta)$' represents the net long-wave radiation gain (W/m^2), 'ε_e' is the emissivity of the external surface, '$L_{sky}(\beta)$' and '$L_g(\beta)$' are the long-wave radiation received from the sky and ground respectively (W/m^2), 'σ' is the Stefan-Boltzmann constant (W/m^{2}K^4), and 'Θ_e' is the absolute temperature of the external surface (K).

$$L^*(\beta) = \varepsilon_e \times \left[L_{sky}(\beta) + L_g(\beta) - \sigma \times \Theta_e^4\right] \tag{A.7}$$

APPENDIX 3. Set Temperature, Lighting and Occupancy Profiles for Weekdays and Weekends in IES VE Software

Fig. A3

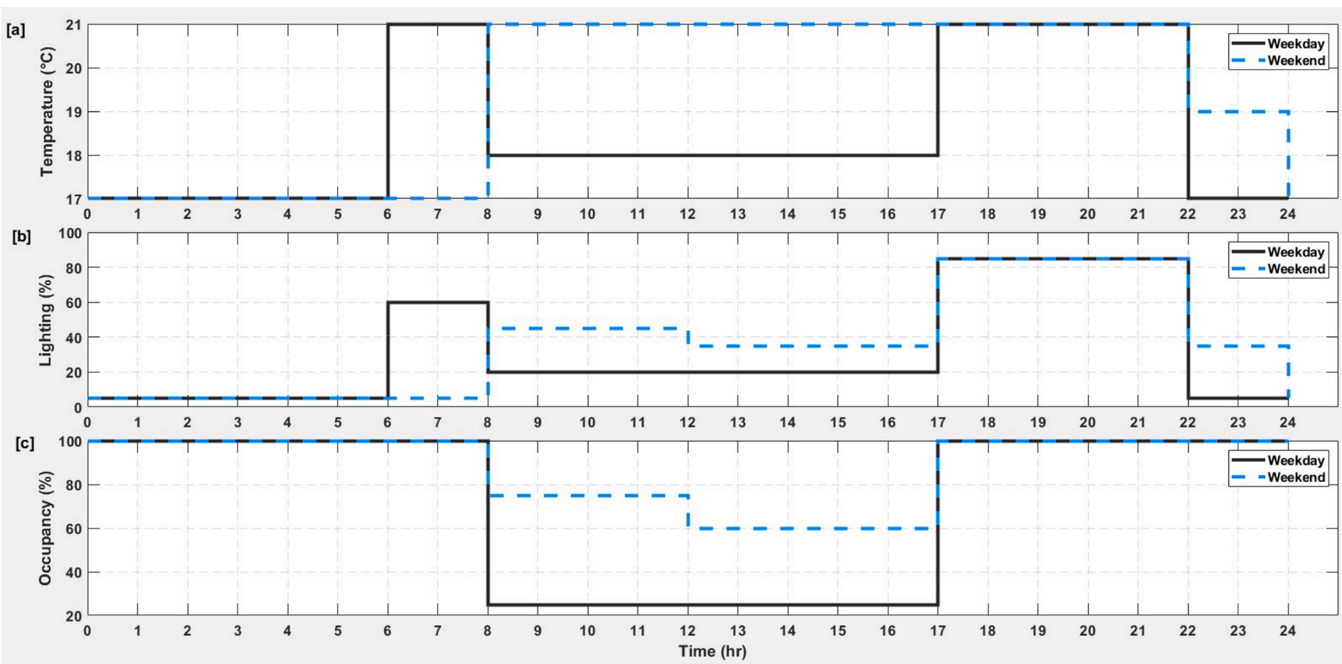

Fig. A3. Set temperature, lighting, and occupancy profiles for IES VE Model.

References

Abbasi, A., et al. (2023). Optimal demand response using battery storage systems and electric vehicles in community home energy management system-based microgrids. *Energies, 16*(13), 5024.

Allouhi, H., et al. (2022). Hybrid renewable energy system for sustainable residential buildings based on solar dish stirling and wind turbine with hydrogen production. *Energy Conversion and Management, 270*, Article 116261.

Arowolo, W., & Perez, Y. (2023). Rapid decarbonisation of Paris, Lyon and Marseille's power, transport and building sectors by coupling rooftop solar PV and electric vehicles. *Energy for Sustainable Development, 74*, 196–214.

Bayram, I. S., & Tajer, A. (2017). *Plug-in electric vehicle grid integration*. Artech House.

Bollen, M. H., & Rönnberg, S. K. (2017). Hosting capacity of the power grid for renewable electricity production and new large consumption equipment. *Energies, 10* (9), 1325.

Bolton, P. (2024). *Energy efficiency of UK homes*. House of Commons Library.

Bouckaert, S. et al., (2021). *Net zero by 2050: A roadmap for the global energy sector*.

Burchardt, T. (2000). UK Time use survey 2000–imputed net income and childcare expenditure variables. *London School of Economics*, 6.

Chartered Institution of Building Services Engineers (CIBSE) Energy Performance Group. *Carbon bites*. [Accessed 24.02.(2024).]; Available from: Www.cibse.org/media/c5mgedo5/cb5.pdf.

CIBSE. (2006). Environmental design: CIBSE guide A. *Chartered Institute of Building Services Engineers (CIBSE)*.

Daina, N., Sivakumar, A., & Polak, J. W. (2017). Modelling electric vehicles use: A survey on the methods. *Renewable and Sustainable Energy Reviews, 68*, 447–460.

De Cian, E., Lanzi, E., & Roson, R. (2013). Seasonal temperature variations and energy demand: A panel cointegration analysis for climate change impact assessment. *Climatic Change, 116*, 805–825.

Department for Business, Energy & Industrial Strategy (BEIS). *Onshore wind and solar pv costs review*. (2020). [Accessed 28.02.2024]; Available from: Https://assets.publishing.service.gov.uk/media/643820ad8b86bb000cf1b1ea/onshore-wind-and-solar-pv-costs-review.pdf.

Department for Energy Security and Net Zero (DESNZ) and Department for Business, Energy & Industrial Strategy (BEIS). *Energy consumption in the UK (ECUK)*. (2022).

[Accessed 17.07.2023]; Available from: Https://www.gov.uk/government/statistics/energy-consumption-in-the-uk-2022.
Department for Energy Security and Net Zero (DESNZ), *Provisional UK greenhouse gas emissions national statistics 2022*. (2023).
Department for Energy Security and Net Zero (DESNZ). *Solar photovoltaic (PV) cost data*. (2023). [Accessed 28.02.2024]; Available from: Https://www.gov.uk/government/statistics/solar-pv-cost-data.
Department for Energy Security and Net Zero (DESNZ) and Department for Business, Energy & Industrial Strategy (BEIS). (2021). *Heat and buildings strategy*. HM Government.
Department for Transport (DfT). (2018). *Electric chargepoint analysis 2017: Domestics*. Department for Transport (DfT).
Department for Transport (DfT), *Transitioning to zero emission cars and vans: 2035 delivery plan*. (2021).
Department for transport (DfT), *Electric vehicle drivers: Attitudes and behaviours*. (2022).
Department for Transport (DfT). (2022). *National travel survey 2021: Household car availability and trends in car trips*.
Department for Transport (DfT). *Licensed ultra low emission vehicles by body type and propulsion or fuel type*. (2022). [Accessed 14.07.2022]; Available from: Https://www.gov.uk/government/statistical-data-sets/vehicle-licensing-statistics-data-tables.
Department for Transport (DfT). *NTS0901: Annual mileage of cars by ownership and trip purpose: England, since 2002*. (2022). [Accessed 07.07.2023]; Available from: Https://www.gov.uk/government/statistical-data-sets/nts09-vehicle-mileage-and-occupancy.
Department for Transport (DfT). (2023). *Electric vehicle charging device statistics: April 2023*. Office for National Statistics.
Department of Energy & Climate Change (DECC). (2011). *Explanation of rate of return calculation for domestic PV*. [Accessed 24.02.2024]; Available from Https://assets.publishing.service.gov.uk/media/5a74abdeed915d7ab83b599d/3742-explanation-rate-return-calc-domestic-pv.pdf.
DfT. (2022). *Annual mileage band of cars, England: 2002 onwards (NTS0904)*. Department for Transport (DfT).
Dik, A., et al. (2023). An approach for energy management of renewable energy sources using electric vehicles and heat pumps in an integrated electricity grid system. *Energy and Buildings*, Article 113261.
Dik, A., Omer, S., & Boukhanouf, R. (2022). Electric vehicles: V2G for rapid, safe, and green EV penetration. *Energies, 15*(3), 803.
Dik, A., Omer, S., & Boukhanouf, R. (2023). Investigation of cost-effective electric vehicle charging station assisted by photovoltaic solar energy system. *Transportation Research Procedia, 70*, 423–432.
Dorotić, H., et al. (2019). Integration of transport and energy sectors in island communities with 100% intermittent renewable energy sources. *Renewable and Sustainable Energy Reviews, 99*, 109–124.
Doroudchi, E., et al. (2018). Approaching net zero energy housing through integrated EV. *Sustainable Cities and Society, 38*, 534–542.
Ekren, O., Canbaz, C. H., & Güvel, Ç. B. (2021). Sizing of a solar-wind hybrid electric vehicle charging station by using HOMER software. *Journal of Cleaner Production, 279*, Article 123615.
Energy Saving Trust. *Retrofitting the UK's housing stock to reach net zero*. (2021). [Accessed 05.12.2023]; Available from: Https://energysavingtrust.org.uk/retrofitting-the-uks-housing-stock-to-reach-net-zero/.
Energy Saving Trust. *Air source heat pumps* vs *ground source heat pumps*. (2024). [Accessed 28.02.2024]; Available from: Https://energysavingtrust.org.uk/air-source-heat-pumps-vs-ground-source-heat-pumps/.
EnergyPlus. *Weather data sources*. [Accessed 17.11.(2023).]; Available from: Https://energyplus.net/weather/sources.
Erdinc, M. T., et al. (2023). Performance improvement potential of a PV/T integrated dual-source heat pump unit with a pressure booster ejector. *Thermal Science and Engineering Progress, 37*, Article 101534.
EV-Database. *Current and upcoming electric vehicles*. [10.02.(2023).]; Available from: Https://ev-database.org/.
Fachrizal, R. (2020). *Synergy between residential electric vehicle charging and photovoltaic power generation through smart charging schemes: Models for self-consumption and hosting capacity assessments*. Department of Civil and Industrial Engineering.
Gholami, K., Karimi, S., & Anvari-Moghaddam, A. (2022). Multi-objective stochastic planning of electric vehicle charging stations in unbalanced distribution networks supported by smart photovoltaic inverters. *Sustainable cities and society, 84*, Article 104029.
Hall, M. R., et al. (2013). Analysis of UK domestic building retrofit scenarios based on the E. ON Retrofit Research House using energetic hygrothermics simulation–Energy efficiency, indoor air quality, occupant comfort, and mould growth potential. *Building and Environment, 70*, 48–59.
Han, M.-E., Alston, M., & Gillott, M. (2022). A multi-vector community energy system integrating a heating network, electricity grid and PV production to manage an electrified community. *Energy and Buildings, 266*, Article 112105.
Hao, X., et al. (2020). Seasonal effects on electric vehicle energy consumption and driving range: A case study on personal, taxi, and ridesharing vehicles. *Journal of Cleaner Production, 249*, Article 119403.
Harris, B., & Walker, A. (2023). *Heat pumps*. UK Parliament.
Harris, C. B., & Webber, M. E. (2014). An empirically-validated methodology to simulate electricity demand for electric vehicle charging. *Applied Energy, 126*, 172–181.
Heat Pumps London. *The latest heat pump statistics*. (2023). [Accessed 04.12.2023]; Available from: Https://www.heatpumps.london/blog/everything-you-need-to-know-about-heat-pumps.
Held, L., et al. (2019). The influence of electric vehicle charging on low voltage grids with characteristics typical for germany. *World Electric Vehicle Journal, 10*(4), 88.
HM Government. (2022). *Taking charge: The electric vehicle infrastructure strategy*. UK Government.
Hoehne, C. G., & Chester, M. V. (2016). Optimizing plug-in electric vehicle and vehicle-to-grid charge scheduling to minimize carbon emissions. *Energy, 115*, 646–657.
HOMER Energy by UL. [Accessed 17.11.(2023).]; Available from: Https://www.homerenergy.com/products/pro/index.html.
HOMER. *About HOMER energy*. [Accessed 17.11.(2023).]; Available from: Https://microgridnews.com/about/.
HOMER. *How HOMER calculates wind turbine power output*. [Accessed 08.12.(2023).]; Available from: Https://www.homerenergy.com/products/pro/docs/3.11/how_homer_calculates_wind_turbine_power_output.html.
Hundy, G. (2016). *Refrigeration, air conditioning and heat pumps*. Butterworth-Heinemann.
IES. (2024). *ApacheSim calculation methods: Virtual environment 6.3*. Integrated Environmental Solutions Limited. [Accessed: 05.12.(]; Available from Https://www.iesve.com/downloads/help/Thermal/Reference/ApacheSimCalculationMethods.pdf.
Ingram, S., Probert, S., & Jackson, K. (2003). *The impact of small scale embedded generation on the operating parameters of distribution networks*. PB Power, Department of Trade and Industry (DTI).
International Energy Agency (IEA). (2023). *Tracking clean energy progress 2023*. Paris: IEA.
International Energy Agency (IEA). (2023). *Renewable energy market update: Outlook for 2023 and 2024*. IEA Publications.
International Energy Agency (IEA). (2023). *Global ev outlook 2023*. Paris: IEA. Https://www.iea.org/reports/global-ev-outlook-2023.
Junginger, M., Faaij, A., & Turkenburg, W. C. (2005). Global experience curves for wind farms. *Energy Policy, 33*(2), 133–150.
Kavousi-Fard, A., & Khodaei, A. (2016). Efficient integration of plug-in electric vehicles via reconfigurable microgrids. *Energy, 111*, 653–663.
Kim, S., & Hur, J. (2020). A probabilistic modeling based on Monte Carlo simulation of wind powered EV charging stations for steady-states security analysis. *Energies, 13*(20), 5260.
Koncar, I., & Bayram, I. S. (2021). A probabilistic methodology to quantify the impacts of cold weather on electric vehicle demand: A case study in the UK. *IEEE Access, 9*, 88205–88216.
Kostopoulos, E. D., Spyropoulos, G. C., & Kaldellis, J. K. (2020). Real-world study for the optimal charging of electric vehicles. *Energy Reports, 6*, 418–426.
Koumpli, E. (2017). *Impact of data quality on photovoltaic (PV) performance assessment*. Loughborough University.
Kutlu, C., et al. (2022). Incorporation of controllable supercooled phase change material heat storage with a solar assisted heat pump: Testing of crystallization triggering and heating demand-based modelling study. *Journal of Energy Storage, 55*, Article 105744.
Kutlu, C., et al. (2023). Direct-expansion solar-assisted heat pump coupled with crystallisation-controlled supercooled PCM for shifting building electricity demand. *Energy and Buildings, 301*, Article 113660.
Liu, Z., et al. (2022). Co-optimization of a novel distributed energy system integrated with hybrid energy storage in different nearly zero energy community scenarios. *Energy, 247*, Article 123553.
Lo, K.-Y., Yeoh, J. H., & Hsieh, I.-Y. L. (2023). Towards nearly zero-energy buildings: Smart energy management of vehicle-to-building (v2b) strategy and renewable energy sources. *Sustainable Cities and Society, 99*, Article 104941.
Lopez, N. S., Allana, A., & Biona, J. B. M. (2021). Modeling electric vehicle charging demand with the effect of increasing EVSEs: A discrete event simulation-based model. *Energies, 14*(13), 3734.
Mahadevan, S. (1997). *Monte carlo simulation* (pp. 123–146). Mechanical Engineering-New York and Basel-Marcel Dekker.
Mehta, S., & Basak, P. (2020). A case study on pv assisted microgrid using homer pro for variation of solar irradiance affecting cost of energy. In *2020 IEEE 9th power india international conference (PIICON)*. IEEE.
MetOffice. *Weather and climate change*. (2023). [Accessed 14.07.2023]; Available from: Https://www.metoffice.gov.uk/.
Mohammadi, F., et al. (2022). The effect of multi-uncertainties on battery energy storage system sizing in smart homes. *Journal of Energy Storage, 52*, Article 104765.
National Grid ESO, *Future energy scenarios*. (2023).
National Grid. *How much of the UK's energy is renewable?* (2023). [Accessed 04.12.2023]; Available from: Https://www.nationalgrid.com/stories/energy-explained/how-much-uks-energy-renewable.
Owen, P., & Foreman, R. (2012). Powering the nation: Household electricity using habits revealed. *Energy Saving Trust/DECC/DEFRA, London*.
Rahmat, M. A. A., et al. (2022). An analysis of renewable energy technology integration investments in Malaysia using HOMER Pro. *Sustainability, 14*(20), 13684.
Ramadan, H. S., Becherif, M., & Claude, F. (2017). Energy management improvement of hybrid electric vehicles via combined GPS/rule-based methodology. *IEEE Transactions on Automation Science and Engineering, 14*(2), 586–597.
Research and Markets. *Solar-assisted heat pump market: Global industry analysis, trends, size, share and forecasts to 2030*. (2023). [Accessed 04.12.2023]; Available from: Https://www.researchandmarkets.com/report/solar-assisted-heat-pump.
Roccatello, E., et al. (2023). Impact of startup and defrosting on the modeling of hybrid systems in building energy simulations. *Journal of Building Engineering, 65*, Article 105767.
Ryberg, D. S., et al. (2019). The future of European onshore wind energy potential: detailed distribution and simulation of advanced turbine designs. *Energy, 182*, 1222–1238.
SERENE. *Sustainable and integrated energy systems in local communities*. [Accessed 23.02.(2024).]; Available from: Https://h2020serene.eu/.

Shahzad, S., et al. (2020). Analysis of the thermal comfort and energy performance of a thermal chair for open plan office. *Journal of Sustainable Development of Energy, Water and Environment Systems, 8*(2), 373–395.

Short, S. (2006). *Review of the uk 2000 time use survey*. London: Office for National Statistics.

Sinsel, S. R., Riemke, R. L., & Hoffmann, V. H. (2020). Challenges and solution technologies for the integration of variable renewable energy sources—A review. *Renewable Energy, 145*, 2271–2285.

SOLARGIS. *GlobalSs*. (2023). [Accessed 14.07.2023]; Available from: Https://globalsolaratlas.info/map.

The University of Nottingham. *Creative energy homes*. [05.12.(2023).]; Available from: Www.nottingham.ac.uk/creative-energy-homes/documents/ceh-brochure.pdf.

Tostado-Véliz, M., et al. (2022). Optimal energy management of cooperative energy communities considering flexible demand, storage and vehicle-to-grid under uncertainties. *Sustainable Cities and Society, 84*, Article 104019.

UKEVSE, *A guide on electric vehicle charging and DNO engagement for local authorities*. UK electric vehicle supply equipment association (UKEVSE) and western power distribution. n.d.

Wales Government. *Swansea community energy and enterprise scheme*. [Accessed 26.12.(2023).]; Available from: Https://www.gov.wales/sites/default/files/inline-documents/2019-09/swansea-community-energy-and-enterprise-scheme.pdf.

Wales Government. *Awel Co-op: Mynydd y Gwrhyd wind farm*. [Accessed 26.12.(2023).]; Available from: Https://www.gov.wales/sites/default/files/inline-documents/2019-09/awel-co-op-mynydd-y-gwrhyd-wind-farm.pdf.

Wang, Y., & Infield, D. (2018). Markov chain monte carlo simulation of electric vehicle use for network integration studies. *International Journal of Electrical Power & Energy Systems, 99*, 85–94.

Wei, S., et al. (2022). Deep learning and computer vision based occupancy CO2 level prediction for demand-controlled ventilation (DCV). *Journal of Building Engineering, 56*, Article 104715.

Western Power Distribution (WPD). (2020). *Connecting community energy: A guide to getting a network connection*. Western Power Distribution (WPD) and REGEN.

Zap-Map. *EV Market Statistics 2023: Tracking the growth in EV sales in the UK overtime*. (2023). [Accessed 25.09.2023]; Available from: Https://www.zap-map.com/ev-stats/ev-market.

Zap-Map. *EV Charging Statistics* (2023). [Accessed 20.07.2023]; Available from: Https://www.zap-map.com/ev-stats/how-many-charging-points/.

Zhu, G., Gao, Y., & Sun, H. (2023). Optimization scheduling of a wind–photovoltaic–gas–electric vehicles community-integrated energy system considering uncertainty and carbon emissions reduction. *Sustainable Energy, Grids and Networks, 33*, Article 100973.