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Modelling and optimisation of shared renewable energy microgrid for proposed UK residential community

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ABSTRACT

To end fossil fuel usage in new residential housing, new ways of powering future buildings need to be explored. This paper formulates an optimal solution using available technology for a case study of a proposed 1000-property housing estate in the UK, without the use of gas, maximising a shared renewable energy grid, and minimising grid electricity. Predicted energy demand for 2050 was modelled in 1-h periods over ten years for electricity usage, domestic hot water heating and electric vehicle charging. Heating degree day ambient temperature records over 10 years were used to calculate heating requirements. For the proposed location, 10 typical years of hourly wind and solar meteorological data were obtained and modelled to convert it into renewable energy potential for any proposed scenario. Additionally, the ability to add energy storage and different levels of housing thermal insulation standards was modelled. Numerous different systems and scenarios were explored, analysed, and tested for energy production vs demand, energy security, financial costs, and benefits. A practical optimal solution was concluded, depending on key performance indicators. Using real data, this research demonstrates that community-owned renewable energy smart grids for housing estates are not only possible but also offer considerable financial benefits for homeowners.

1. Introduction

One of the primary challenges the world is facing today arises from climate change caused by carbon dioxide and other greenhouse gas emissions [1]. Approximately 26 % of the UK's carbon dioxide emissions are produced by residential households [2]. To power future housing estates and local industries, there is a proposal to shift towards new localised and decentralised renewable energy systems as an alternative to the centralised fossil fuel-powered national grid system [3]. Decentralised local renewable energy-enabled microgrids offer many advantages [4], including reduced energy losses due to shorter transportation distances for electricity. This also alleviates stress on the often overloaded centralised national grid electrical system. In the future, with the electrification of heat and transport [5], this will become critical. In local decentralised microgrids, the variability of renewables such as solar and wind energy in both the short and long term requires careful analysis, along with energy storage and grid backup solutions to ensure energy security [6], and thus reduce carbon dioxide emissions. This approach to localised energy production underscores the importance of analysing microgrids to find predictable, pragmatic, and optimal solutions.

The United Kingdom is dedicated to achieving its carbon reduction targets [7] through the implementation of green energy strategies, with a special emphasis on nurturing low-carbon electricity generation and seamlessly integrating low-carbon technologies across critical applications such as heating and transportation [8]. This ambitious target aligns closely with the targeted timeline for achieving comprehensive decarbonisation by 2050 [7]. Amidst this coming energy paradigm shift, the anticipated surge in electricity demand is expected to grow, with projections spanning from a 50 % to a substantial 100 % increase, because of the electrification of transport and heating [9].

It is predicted that a notable growing proportion of the future overall electricity supply will come from variable wind and solar sources. These renewable alternatives encompass a spectrum of controllable low-carbon power generation mechanisms. As the energy landscape dynamically transitions towards a heightened reliance on these inherently variable energy sources, a central challenge surfaces: the management of an intricate equilibrium between electricity production and consumption. This equilibrium, frequently referred to as "flexibility", requires frequent adjustments to ensure seamless alignment and

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integration between electricity supply and demand, even when generation conditions encounter short-term abrupt fluctuations. The crux of this balance of equilibrium rests upon the short- and long-term accurate modelling of the electricity generation and consumption profiles [10].

Confronted with the impending surge in flexibility due to increased variable renewable energy sources within the future power grid, an innovative approach becomes key. This increase in flexibility demands, for its fulfilment, needs a proactive analysis of low carbon alternatives, effectively predicting and optimising the metrics of this coming paradigm shift [11–15].

The search for an optimal low-carbon energy solution for residential housing is part of this transition, although optimal solution methodologies can be used in many other fields such as business and industry [16]. The models in this research encompass diverse considerations spanning long-term hourly meteorological data, renewable energy production, financial dimensions, and building insulation standards. This comprehensive evaluation is underpinned by a meticulous application of quantitative modelling, which comprehends and describes the intricate interplay among these variables. This paper provides an analysis using a case study focusing on powering a proposed residential housing estate utilising a shared wind, solar, and energy storage grid, which is modelled from fundamental principles to dissect the intricacies of such systems and explore advantageous optimal solutions. As an example, an illustrative case study is used in the form of a housing estate comprising 1000 properties located in Yorkshire, UK. This building project is currently, at the time of writing, in the stages of planning and serves as an innovative example of the pursuit of energy provisioning optimisation for future projects. At the heart of this novel shared energy grid [17] is a community electricity supply drawn from a smart grid infrastructure, which is designed to harness the virtues of shared energy distribution optimisation using today's "off-the-shelf" technology.

Similar work has been carried out in other regions with comparable environmental and economic contexts. For example, Arevalo et al. [18] analysed hybrid PV–wind–hydrokinetic systems in Ecuador using a HOMER-based optimisation framework. The study demonstrated how system performance and economic feasibility are strongly influenced by local resource conditions and energy management approaches. The results obtained from this study correlate with the results presented in this work, where seasonal demand patterns and resource variability form the optimal balance of generation and storage within large housing estates. The Ecuadorian case study demonstrated the need to coordinate the technical design with socio-economic realities, and shows the importance of customising smart grid solutions to the specific climatic and policy environment.

In light of the growing demand for new housing estates and increasing pressure from government regulatory bodies to improve energy efficiency and reduce the carbon footprint, a comprehensive and efficient tool for the design, evaluation, and optimisation of community microgrids is required. This tool should be based on a microgrid modelling approach and provide effective instrumentation to enable house builders and community members to make informed decisions about the content, structure, and use of the smart microgrid integrated into a housing estate.

This paper outlines the development of detailed demand models for household domestic electricity. Additionally, the future demand for electrified heating, electric vehicle charging, and electric-powered domestic hot water is modelled. Hourly load profiles over 10 years are considered, and scenarios with varying levels of thermal insulation in houses are analysed. The model considers hourly time periods as well as longer-term seasonal variations in demand, as well as the variance in heating demand caused by ambient temperature fluctuations.

Wind and solar energy production are assessed using a combination of hourly capacity factor data and wind turbine power curve analysis. The paper highlights the importance of accurate wind and solar data and highlights the variability of energy production for different renewable energy scenarios. For each scenario, the research integrates the demand and supply models to create a comprehensive global housing estate model that evaluates the balance between renewable energy production, energy storage, and residential demand. A detailed financial analysis is conducted to assess the economic viability of each scenario and compare it with the self-sufficiency benefits of each scenario from the power grid. The analysis includes infrastructure costs, operation and maintenance expenses, energy purchases from the grid, and grid export income, and calculates simple payback times.

Through the insights gained from this quantitative modelling and historical metrological data, a holistic methodology unfolds. This multidimensional approach develops into a strategic blueprint that harmonises electrical supply and demand, energy storage, financial prudence, building heat loss metrics, and ecological sustainability into a coherent whole. This study contributes valuable insights into the integration of renewable energy and storage solutions within the residential sector, as well as any other electrical energy supply and demand environment such as business, industry, government buildings, housing associations, hotels etc. The results offer guidance for community energy schemes [19], policymakers, developers, and homeowners in making informed decisions about sustainable energy infrastructure.

Unlike previous assessments of renewable microgrids in island and coastal regions by Karagiannopoulos et al. [20] and Ghiasi et al. [21], this study focuses on large grid-connected inland housing estates, where pronounced seasonal load variations, notably different wind variations, climate-driven heating, and diverse residential behaviours significantly influence system performance. By integrating these factors with smart grid optimisation and national grid interactions, the work provides a novel, scalable framework for urban decarbonisation.

The proposed shared renewable energy microgrid is modelled as a grid-connected system that interfaces with the Distribution System Operator (DSO) network through a defined point of common coupling (PCC) to ensure technical coordination and regulatory compliance. While current UK legislation limits private or community-operated generation connections of this type to systems below 1 MW, it is acknowledged that this regulatory threshold is expected to evolve in response to national decarbonisation and distributed energy policy developments.

The contribution to the knowledge of this paper are as follows: (1) an hourly 10-year housing estate energy demand model is constructed with the addition of electric vehicle charging and electrical heating generated by hourly 10-year temperature records in the proposed location and varying degrees of thermal insulation; (2) an hourly renewable energy model is formulated consisting of 10 years of wind and solar data in the proposed case study location and the conversion of this resource into electrical energy production in varying sizes and combination scenarios of renewables and storage; (3) a novel graphical display of the results in which important insights can be gained. Overall, the summarised contribution of the paper is to prove, using real data, that community-owned renewable energy smart grids for housing estates are not only possible but have considerable financial benefits for homeowners, and it is advantageous for property developers to build such projects, which would prove popular with buyers.

2. Case study and methodology

The optimal solution to powering residential housing whilst minimising fossil fuel considers many different aspects of energy, finance, and house construction, and as such quantitative modelling is used throughout. A new 1000-property residential housing estate located in Yorkshire, UK which is in the planning stage is used as a case study. All houses will not be supplied with gas and will share the supply of electricity from an optimised smart grid, with the specification of each house being a UK average size and average UK energy usage. Because renewable energy production and demand are dominated by and dependent on weather conditions in any given location and its variability, long-term historic weather data (hourly over 10 years) are obtained and translated into theoretical renewable energy production as shown in Fig. 1.

The energy modelling of the housing estate is based on the principle of the energy balance between generation and consumption. Therefore, the energy balance for the housing estate over a certain period of time can be expressed as follows:

$$E_G + E_W + E_S = E_D + E_{HW} + E_{SH} + E_{EV} + E_{ST} \quad (1)$$

where E_G is the imported/exported national grid energy; E_W is the onsite wind energy produced; E_S is the onsite solar energy produced; E_D is the direct electricity demand; E_{HW} is the domestic hot water demand; E_{SH} is the domestic space heating demand; E_{EV} is the electric vehicle charging/discharging; E_{ST} is the energy storage charging/discharging. Note that E_G, E_{EV} and E_{ST} can have both positive and negative values in contrast to the conventional sources and loads.

The model is designed to stimulate the housing estate energy performance on a 1-h basis; therefore, all components in (1) can be represented as a series in the matrix form, where the value of each matrix element is corresponding to the model sampling time of 1 h. The grid energy, solar energy and wind energy hourly series in matrix form are

$$\mathbf{E}_G[i]; \quad \mathbf{E}_S[i]; \quad \mathbf{E}_W[i] \quad (2)$$

where i is the i-th hour of the energy hourly series over a model simulation period of time; $\mathbf{E}_G$[i] is the column matrix of the energy grid series; $\mathbf{E}_S$[i] is the column matrix of the onsite solar energy series; $\mathbf{E}_W$[i] is the column matrix of the onsite wind energy series.

The energy of the consumed components in (1) are represented by two-dimensional matrices. The column in the matrices is related to the series hours (i) whereas the row reflects the number of households in the estate. Hence,

$$\mathbf{E}_D[i,k]; \quad \mathbf{E}_{HW}[i,k]; \quad \mathbf{E}_{SH}[i,k]; \quad \mathbf{E}_{EV}[i,k]; \quad \mathbf{E}_{ST}[i,k] \quad (3)$$

where k is k-th household in the estate, $\mathbf{E}_D[i,k]$ is the direct electricity demand matrix; $\mathbf{E}_{HW}[i,k]$ is the domestic hot water demand matrix; $\mathbf{E}_{SH}[i,k]$ is the domestic space heating demand matrix; $\mathbf{E}_{EV}[i,k]$ is the electric vehicle charging/discharging matrix; $\mathbf{E}_{ST}[i,k]$ is the energy storage charging/discharging matrix.

Component sizing strategies selected for the modelling can be approached with several different key performance indicators, which could be used depending on a housing developer's or client's motivations, such as: (1) minimising dependence on the grid; (2) lowest upfront cost; (3) shortest payback time; (4) minimising carbon emissions.

As discussed above, the number of households h in the planning estate is 1000; this figure is selected for the simulation ($h = 1000$). The period of time used for the housing estate modelling covers 10 years, which constitutes 87600 h. Therefore, the total number of items in the energy time series is $n = 87600$.

Using hourly 10-year average meteorological conditions at the proposed location, the following values were calculated. The total renewable energy production over 10 years E_{RP} is:

$$E_{RP} = \sum_{i=1}^{n=87600} \left(E_{S(i)} + E_{W(i)}\right) \quad (4)$$

The total number of hours in the model period was considered for metrological data; however, when the wind and solar energies are not active (the wind is not blowing or the sun is not shining), the output of energy will be zero for these hours, and only energy positive when wind and solar production are possible.

The electricity used by one (k-th) household over 10 years $E_{H(k)}$ is defined as

$$E_{H(k)} = \sum_{i=1}^{n=87600} \left(E_{D(i,k)} + E_{HW(i,k)} + E_{SH(i,k)} + E_{EV(i,k)}\right) \quad (5)$$

Over or under energy production by the total housing estate for each (i-th) hour $E_{TOT(i)}$ is determined by the following expression:

$$E_{TOT(i)} = \left(E_{S(i)} + E_{W(i)}\right) - \sum_{k=1}^{h=1000} \left(E_{D(i,k)} + E_{HW(i,k)} + E_{SH(i,k)} + E_{EV(i,k)}\right) \quad (6)$$

The housing estate smart grid would, in effect, act as a community energy aggregator, where each property would have a shared ownership of the system under the control of a community energy shared benefits business."

If the hourly energy $E_{TOT(i)}$ is positive $E_{TOT(i)} > 0$, then the estate exports the energy at the i-th hour; if the energy $E_{TOT(i)}$ is negative $E_{TOT(i)} < 0$, then the energy from the grid is required to meet the energy balance for the estate during the i-th hour. The total energy estate over/under production over 10 years is calculated as

$$E_{TOT} = \sum_{i=1}^{n=87600} E_{TOT(i)} \quad (7)$$

where E_{TOT} is the total 10-year estate energy production; E_{TOT+} is positive in case of overproduction, or E_{TOT-} is negative in case of underproduction.

Energy losses in an uncongested smart grid typically remain within 6–10 %, but congestion can raise this higher under stressed conditions. While round-trip efficiency of storage has been considered in this research, future work will define and predict these losses and design methods to minimise them and reduce instability.

The variability of demand for energy will largely depend on conditions such as the size and occupancy of the house, future electric vehicle charging behaviour, and the use of hot water and electricity directly. Ten-year ambient temperature HDD (Heating Degree Days) data were obtained for the location, and heat losses were modelled with various building standard insulation levels. Cost values were sourced and modelled to consider the overall financial benefit analysis of different scenarios. Variables in the model were adjusted to reflect and test different scenarios and to produce optimum systems as shown in Fig. 2.

As for potential inaccuracies, only 10 years of meteorological data

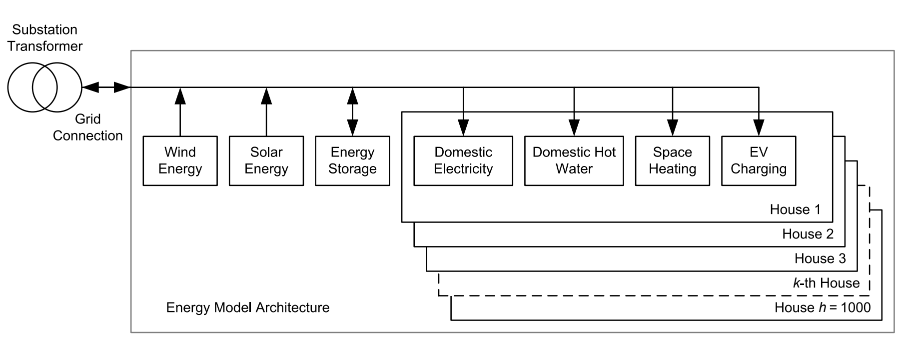


Fig. 1. Illustration of the energy model architecture.

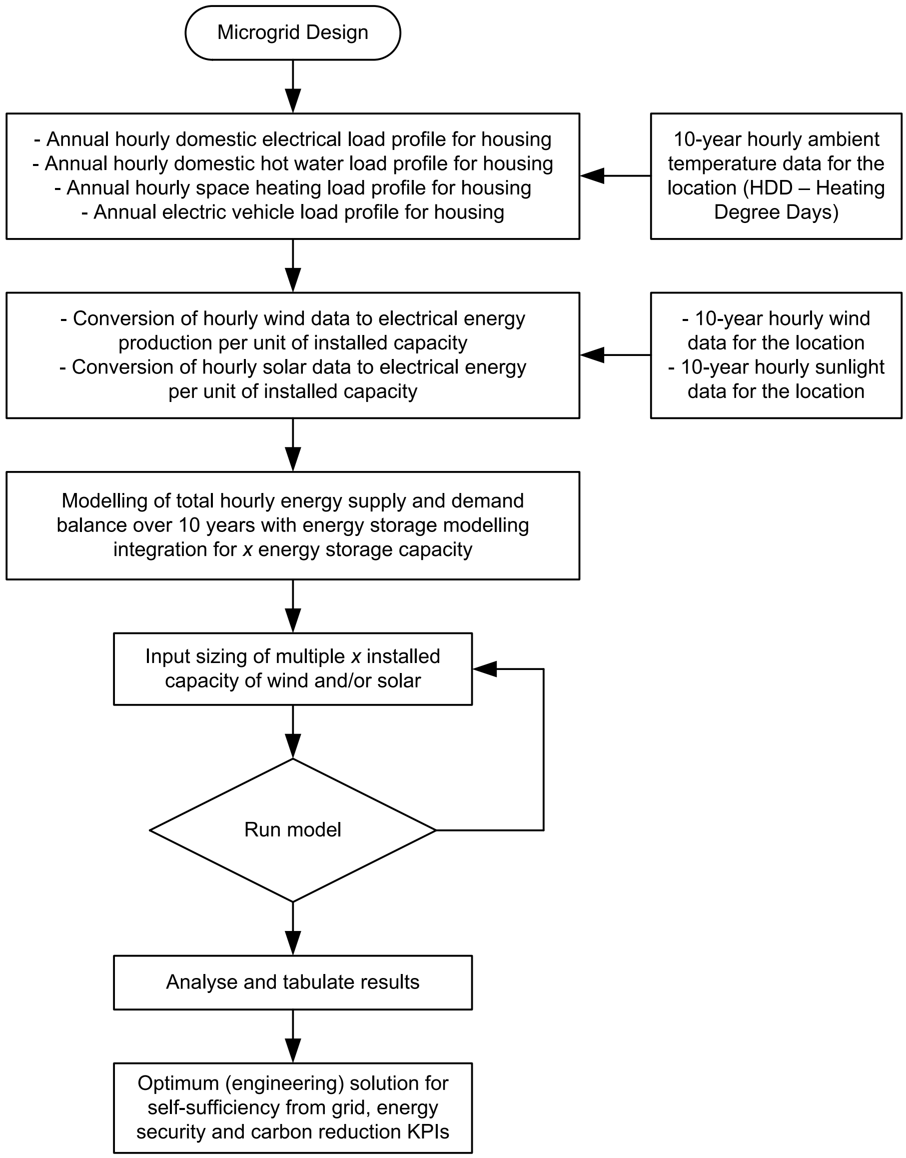


Fig. 2. Smart grid design methodology (x indicates the size of wind, and solar storage in each scenario).

were used in this analysis, which may not be sufficient to analyse extreme periods of unusual weather, such as a one in 500-year event. It is critical for accurate local onsite measured wind and solar data to be obtained prior to any commercial decisions being taken. With the onset of the effects of human caused climate change, this may be critical, as weather patterns are changing rapidly and are difficult to predict. Also, it was assumed that each house was an average size in this model; however, in reality, the size, shape and orientation of each house once set in stone could be considered for more accuracy. The method of calculating heat loss used an average size house and an overall U value to achieve a target fabric energy efficiency (TFEE). For more accuracy, individual components specified, design and U values could be calculated. It was assumed there were many houses (1000) in this model, where all the renewable smart grid infrastructure is shared with each house. This gives a good economy of scale which may not be present in smaller schemes.

3. Energy demand modelling

3.1. Household electricity

Household electricity is all the electricity used in a property except for space/hot water heating and EV (Electric Vehicle) charging. Elexon [22] residential domestic 10-year average profiling load data (domestic) for different seasons of the year are used, which accounts for hourly and sessional variations. It is important to take seasonal changes into consideration, as the difference between high summer and winter is significant, as shown in Fig. 3. Winter loads are considerably higher than summer loads, particularly during the evening period between 18:00 and 20:00.

Peak clipping, valley filling and load shifting have not been considered. A conservative estimate of electricity reduction due to more energy efficient appliances' rollout and occupiers throwing away their old inefficient appliances is 10 % saving across the profile; however, this can be easily changed in the model.

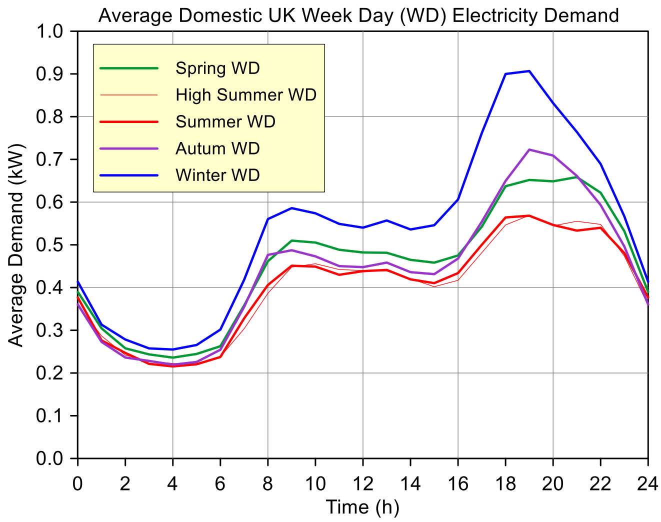


Fig. 3. UK domestic load profile variations. Visualised data from Ref. [22].

3.2. Heating

An average UK size property 105 m^2 [23] floor area is used to work out heating loads. The heating load is distributed across the year by using HDD [24] for a 15.5 °C baseline. The nearest meteorological (temperature measurement) weather station data to the proposed location over 10 years is used. A feel of the variation in temperatures from summer to winter and from year to year can be seen in Fig. 4(a).

A target value of 15 kWh/m^2/year max space heating load TFEE for Passive house criterion, or the option of 53 kWh/m^2/year for part L of the mandatory UK building regulations, was modelled, to analyse the effects of different insulation values. However, any value can be used if a developer wants to specify their own insulation levels. Using heating degree days, daily space heating loads for an average house were calculated for a year, as shown in example Fig. 4(b). The daily total space heating demand was then spread over 24 h using a typical daily profile as shown in Fig. 5(a) [25].

The cost of electric heating has traditionally been high because electricity from the grid is considerably more expensive per kWh than gas. However, in the case of having a plentiful supply of zero margin cost, renewable, low carbon electricity regularly on demand, which would otherwise be exported to the grid for a minimal sum, then electric heating running costs and carbon emissions would be advantageous. Analysis showed the added infrastructure costs of heat pumps, together with the 60–75 % reduction in electricity demand (assuming COP of 3 or 4) for heating, far outweighed the costs of direct electric heating in the case of having abundant zero margin cost electricity.

3.3. Domestic hot water (DHW)

Passive house standards predict an average of 3.5 kWh/day/property for hot water demand [26] however. A conservative 4.5 kWh/day property average is used for domestic hot water. This equates to 42.8 Wh/m^2/day/property for a 105 m^2 average size house [23]. The seasonal annual profile variation for DHW does not show as much of a pronounced seasonal variation towards the colder temperature months as space heating; however, it is still significant. The variation in energy for DHW with temperature varies by approximately 40 % from summer to winter and as such is modelled. Once the daily domestic hot water load has been calculated, this is spread over 24 h using the domestic hot water average domestic demand profile shown in Fig. 5(b).

3.4. Electric vehicle charging

Hourly Data from ‘Development of GB electric vehicle charging profiles’ [27] with a sample size 179,199 EVs, for 1 average vehicle for 1 year, was adjusted for the number of vehicles per household. The average number of cars per household in the UK (2018) is around 1.2 with rates dropping to around 0.8 in London [28], so it was assumed as a conservative estimate each house would have 1.2 EVs. The data was used to give hourly data for total EV load per hour over the model period, adjusting for both hourly, daily, and weekly variations as example shown in Fig. 6(a) and (b).

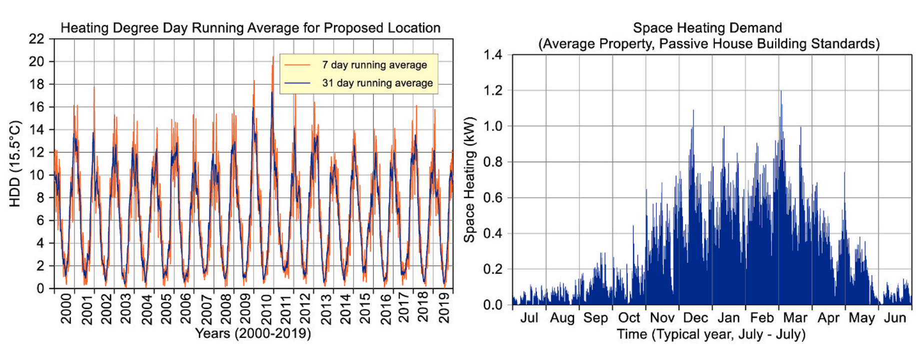
3.5. Total supply modelling

Bringing together demand for household electricity, electric vehicle charging, domestic hot water and space heating, a total demand profile was formulated for every hour over a 10-year period, which is used later to test against various renewable energy production scenarios. Fig. 7(a) and (b) are indicative examples demonstrating the contrast in summer (1–8 July 2002) and winter (7–13 January 2002) demands which need to be securely met.

4. Renewable energy supply modelling

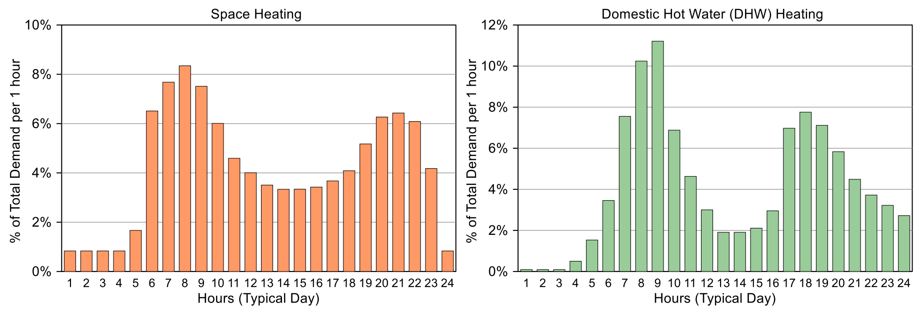
4.1. Wind energy production

Hourly onshore capacity factor (CF) wind data was obtained giving an average yearly CF [29] of 0.32 which is realistic. This was thought to be a good starting point, but in a real-life scenario, more accurate location specific wind data from anemometer measurements would need to be obtained. A data set of 800 commercially available wind turbine power curves [30] was obtained and analysed to find the optimum output for the wind speed profile of the site. A reasonable size wind turbine to supply this magnitude of wind energy was around 2–3 MW



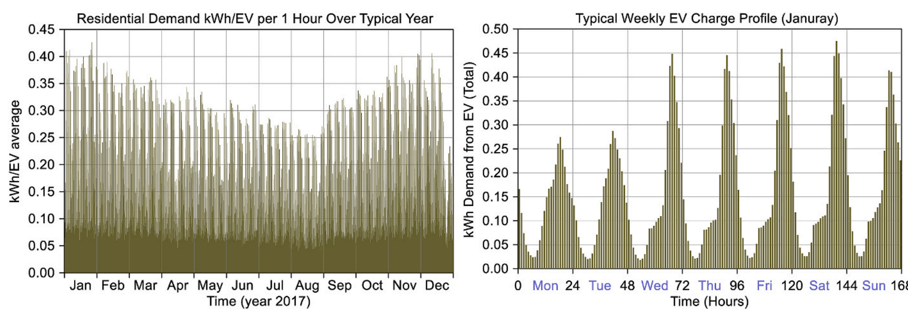
(a) (b)

Fig. 4. (a) Heating degree days running averages at the proposed location over 20 years. (b) Daily space heating demand example over a typical year. Visualised data from Ref. [24].



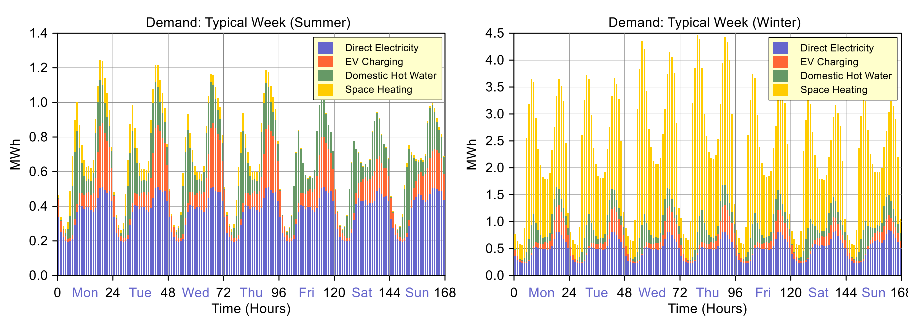
(a)   (b)

Fig. 5. Average domestic daily profile for (a) space heating and (b) hot water. Visualised data from Ref. [25].



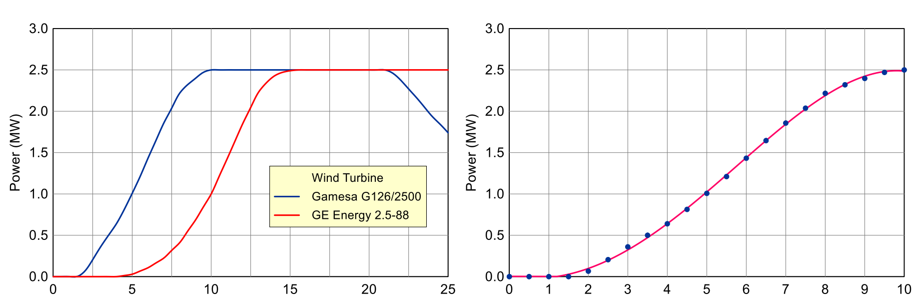
(a)   (b)

Fig. 6. Typical EV demand profile for 1 average EV over (a) 1-year (2017) and over (b) 2 nd week in January 2017. Visualised data from Ref. [27].



(a)   (b)

Fig. 7. Examples of total housing estate (1000 houses) hourly demand breakdown for household electricity, electric vehicle charging, domestic hot water, and space heating for typical (a) summer and (b) winter week.



(a)   (b)

Fig. 8. (a) A comparison of power curves of two wind turbines designed for high and low wind speeds. Visualised data from Ref. [30]. (b) Curve to derive an equation to convert wind speed into power for Gamesa G126/2500.

nameplate capacity. There was a surprising difference between the largest and smallest total energy production for 2.5 MW wind turbines which highlights the importance of careful turbine selection depending on wind resource. The power curves of the wind turbines are shown in Fig. 8(a).

As such, the Gamesa G126/2500 2.5 MW was chosen for this location as the wind speeds may be conservatively relatively low. To convert the wind speed data to energy, an equation was derived from the power curve of the selected wind turbine using a trendline with a 4th-order polynomial, giving an R^2 value of 0.999 as shown in Fig. 8(b).

This hourly wind and energy production data was then input into the model over the 10-year period, where the total installed capacity of wind turbines could be adjusted to test various scenarios. An analysis of the energy production variability for any hourly wind speed data and the number of wind turbines could be gained from this, as shown in Fig. 9 (a).

Interestingly, wind data was downloaded from the NASA Earth data [31] database for an approximately 40-year period (1980–2020) at 50m above ground level in the proposed location, but it was found that the wind energy potential differed significantly when ran through the model as shown in Fig. 9(b).

The NASA data gave a 40-year capacity factor (CF) of double what average commercial wind farms produce, and was not used to work out energy production. However, the CF average National Grid data [26] was thought to be more accurate and conservative, so this was used throughout. However, the 40-year NASA [31] data was useful concerning variations in long term wind speed. Extracting and analysing the hourly wind speed data from 1980 to 2019 and combining to give a simple average yearly wind speed for the location of the proposed development, it can be seen in Fig. 10(a) that the simple long-term average is remarkably stable, indicating the scheme will have a high confidence of long-term energy security.

However, to analyse short-term periods of low levels of wind (and hence energy security using wind power), minimum average wind speeds were found over the 40-year period. The minimum running averages of hourly wind speed were identified for different periods of time (3, 6, 12, 24, 48, 72, 168, 672, 1440 and 2160 h). Periods were then generated as displayed in Fig. 10(b).

4.2. Solar energy production

Ten-year hourly records of solar radiation data [32] from the UK Met Office were obtained from the nearest recording location to the proposed housing estate. One-hour average irradiance (kJ/m^2) was converted into power produced (W). The Watts of sunlight were converted into a solar capacity factor using an average solar panel with a zero production cut in for low levels of sunlight. The solar resource varies from summer to winter as expected, but is remarkably predictable year on year. Fig. 11 shows solar radiation data over 10 years.

However, we can not assume a perfect optimum orientation of every solar panel in the array (38 Degrees elevation (in this location) facing exactly due south). This, of course, would never be possible because most houses will have a different direction facing the roof, and it must be assumed that there may be some shading to some of the panels on the estate. To account for the above inefficiencies, an orientation and shading adjustment has been applied of a conservative 70 % of optimum; however, this is adjustable in the model. The solar radiation was converted into kWh power production. The conversion rate is based on the conventional PV model presented in Ref. [13]. Fig. 12(a) shows a typical yearly production if 4 kWh peak were placed on each roof of 1000 houses, and Fig. 12(b) shows a typical June week production as an illustration of variability.

4.3. Energy storage modelling

The energy storage charge/recharge algorithm model is shown in Fig. 13.

The type of battery selected can shape both costs and performance. Lithium-ion is the most practical choice at the time of writing due to its efficiency, affordability, and availability, though different chemistries vary in safety and cycle life. As Lithium-ion is readily available "off the shelf" and with plentiful service agents available familiar with the technology, this is a pragmatic choice for a first of a kind proof of concept grid. The economics must account for degradation. Most lithium-ion systems require replacement within 8–12 years, with end-of-life typically set at 80 % capacity.

5. Global model (combining supply, demand, and storage models)

All the models from the above were brought together in a global hourly model over 10 years, so the balance of any given scenario could be viewed. Many scenarios were generated, and the energy balance, grid back up and over production eligible for selling to the grid and energy storage charge/discharge patterns etc. were observed. As an example, 2 × 2.5 MW (5 MW) wind turbines, 4kWp solar PV on every house and 3 MWh battery storage were input into the model with the following energy balance results obtained in Fig. 14(a).

From the generated models, different aspects of the system could be examined, such as the utilisation of the battery. The battery usage is shown in Fig. 14(b).

5.1. Supply and demand analysis with/without energy storage

To assess the effect of energy storage capacities, histograms were generated of positive and negative energy balance hours of each system (years 2002–2012) with different magnitudes of storage capacity (size of battery), and then this was compared and contrasted to the same

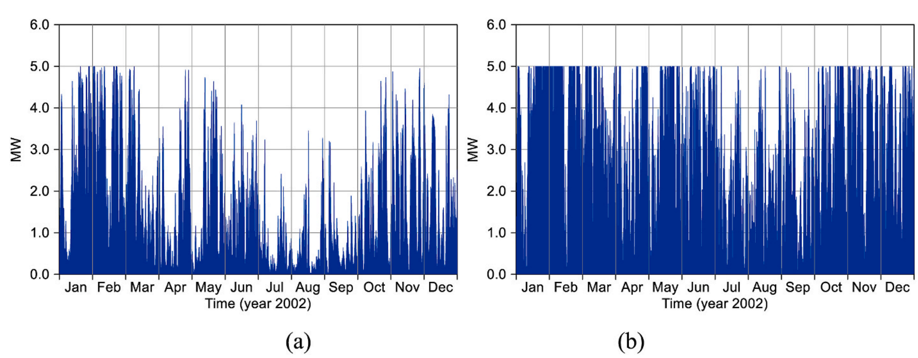
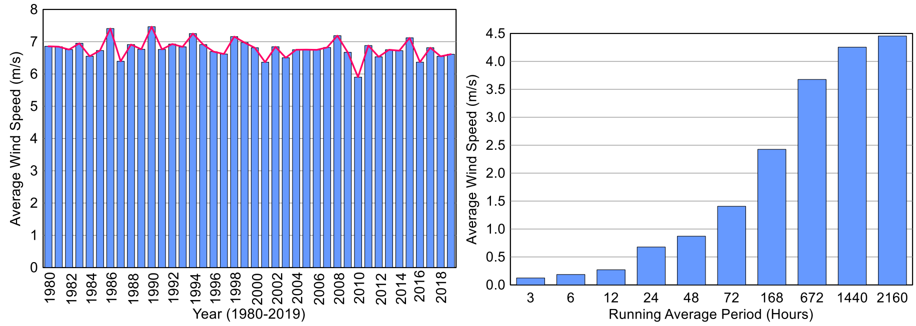


Fig. 9. Wind energy production for two Gamesa G126/2500 2.5 MW wind turbines (a) typical predicted average CF output, (b) using NASA data at 50m above ground level.



(a) (b)

Fig. 10. (a) Simple average wind speed at 50m above ground level 1980–2020 at the location of the project; (b) minimum average wind speed at 50m above ground level running averages for various time periods. Visualised data from Ref. [31].

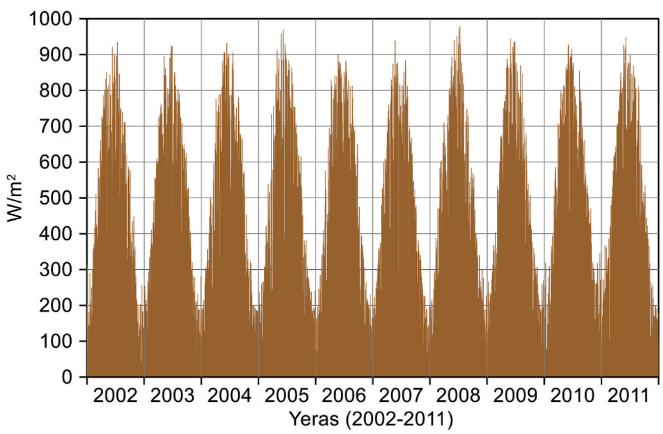


Fig. 11. Hourly radiation observations for 30 km north of the proposed project 2002–2012. Visualised data from Ref. [32].

histogram generated without any battery storage as shown in Fig. 15(a) and (b).

As expected, storage considerably reduces the grid back up needed in the system and increases self-sufficiency. The grid back up needed for different scenarios was generated over a typical year to understand the patterns and magnitudes required (example shown in Fig. 16). This is important as the maximum capacity of the wire connecting the grid needs to be specified, and the need may be reduced/increased using this analysis.

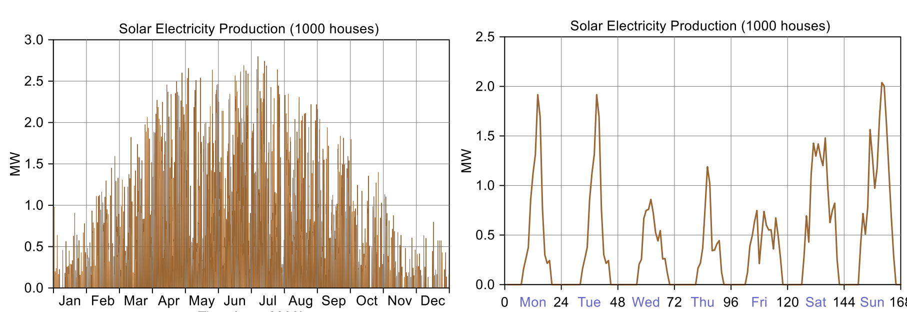
5.2. Effect of insulation levels of different building regulations

The heating loads required for housing of passive house construction and, as a comparison, the additional heating loads that would be required using UK legislative insulation levels were generated. Both insulation level heat demands were then fed into the global system to see what affect it would have on the overall energy balance for any given renewables scheme (over production or shortfall). The global energy balance using both passive house and Part L of the UK building regulations could then be compared. Fig. 17(a) and (b) show a 2.5 MW wind turbine, 4MWp of solar and 4 MWh of storage scenario and the energy balance using passive house compared with part L of the building regulations. This gives a demonstration of the effectiveness and relative advantages of the global model of insulation levels for any specified renewable energy system, and later on used to analyse the cost benefits of more insulation compared with adding more renewables or storage to the system for the same money.

Out of interest, a typical housing solar PV system in the UK is sized at 4MWp. Using this on each house with no other input was analysed in the model. This scenario does not offer many benefits to a decentralised grid or carbon reduction, the scenario falling well short of providing an effective total energy solution and still requiring substantial grid back up as shown in Fig. 18.

Multiple scenarios of combinations of wind, solar and storage capacities were run through the model. The optimum engineering solution with the KPI of reduced carbon emissions and high self-sufficiency was found to be houses built to passive house standards, 4 x Gamesa G126/2500 wind turbines (10 MW), 5 MWh storage, no solar and grid connected, giving an almost 90 % self-sufficiency from the grid. Solar was found not to be attractive in this situation as considering the embodied carbon of the panels, which does not make up for the electricity generated and particularly the lack of electricity generation in the winter months and at night, facilitating the need for bigger battery storage.

It was found that the infrastructure capacity needed goes up exponentially, the closer to 100 % self-sufficiency is required. This optimum



(a) (b)

Fig. 12. Solar PV (4kWp on every roof) power production for 1000 houses (a) over two years, (b) over one week in June 2002.

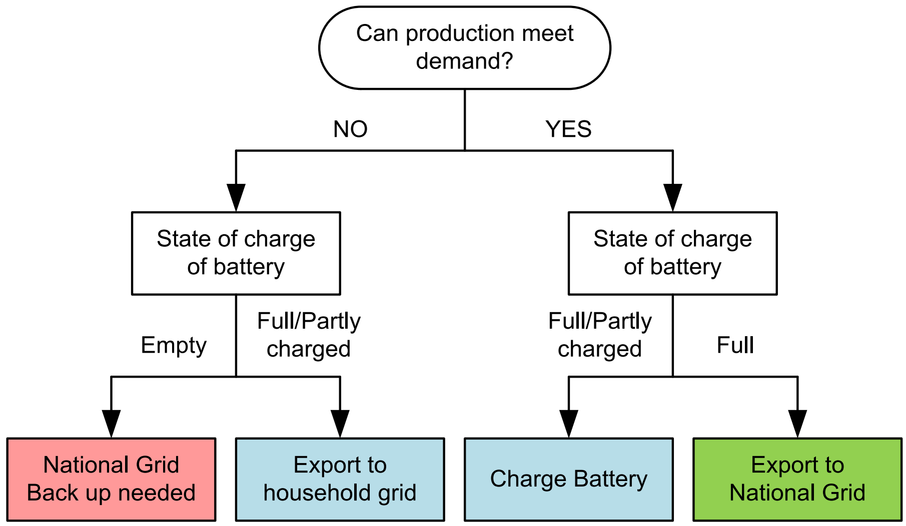
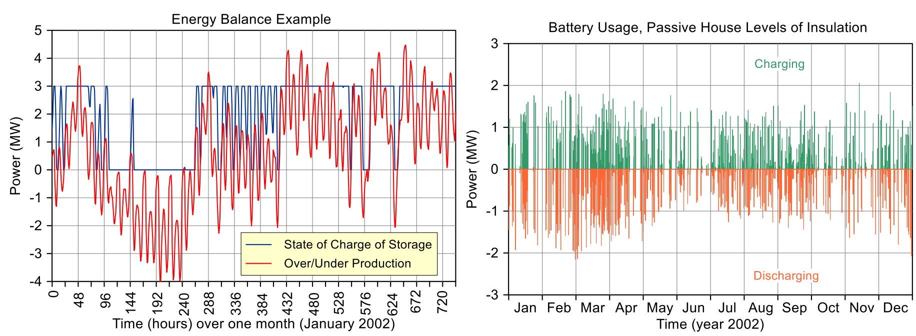
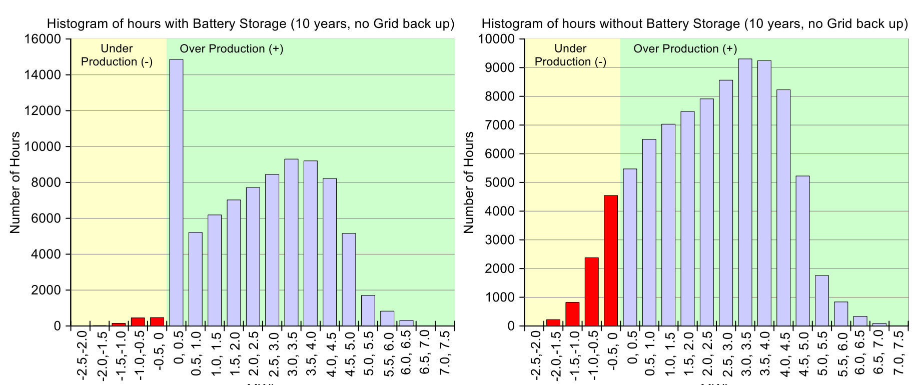


Fig. 13. Schematic of how electrical energy storage is implemented in the model.



(a) (b)

Fig. 14. Example for two wind turbines (total 5 MW), 4 kWh peak of solar (typical array) on each roof and 3 MWh battery storage: (a) energy balance over January 2002, (b) battery usage over 1st year of model (2002), passive house building standards.



(a) (b)

Fig. 15. Histogram profile of over/under production (10 years 2002–2012) for system having two wind turbines (total 5 MW), 4 kWh peak of solar (typical array) on each roof, passive house building standards: (a) with 10 MWh battery storage, (b) without battery storage.

carbon reduction system allows for the comfortable production of more than enough energy needed and gives energy self-sufficiency of around 90 % with the lowest amount of infrastructure. In addition, this system exports energy back into the grid at times of over production and has the safeguard of energy security with grid back up when there is no wind energy, and the storage is empty, which only accounts for 10 % of the time. Storage allows for the running of the estate (for a short period) with no loss of power, even in the unlikely event of there being no wind power and a national grid failure, creating greater security than the existing national grid alone.

Having 4 turbines and storage means that maintenance and breakdowns for short periods of one of them can be accommodated with

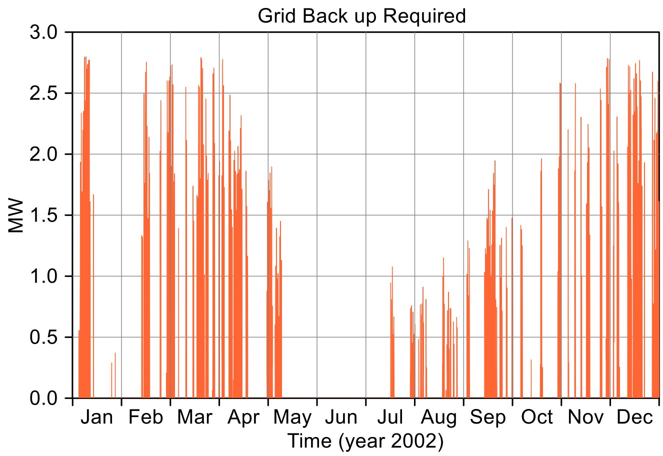


Fig. 16. Example of grid back up required for 1st year (2002) of the model for the system having two wind turbines (total 5 MW), 4 kWh peak of solar (typical array) on each roof and 10 MWh battery storage.

minimal disruption.

6. Financial modelling

A model was created and analysed quantitatively regarding the financial cost/benefit considerations of each scenario. The financial optimum solution will be a single use or a combination of wind, solar and battery with a certain specified insulation level of the property. Therefore, each combination of wind, solar and battery with their energy outputs in relation to demand will be calculated and compared with their total costs over and above the normal costs associated with a normal grid connected traditional housing development. A simple approach was taken i.e., a linear model cost £/MW was used for infrastructure and O + M costs when it was more likely to be a step change model because of economies of scale etc. Cost movements during the analysed periods, indicated (for instance, the RPI or CPI), were not considered. The procedure is shown in Fig. 19.

The cost of additional renewable energy infrastructure per household/year is determined as follows:

$$C_{IF} = \frac{W_{ic}C_{wic} + S_{ic}C_{sic} + B_{ic}C_{bic} + C_{PH}}{h} \tag{6.1}$$

where C_{IF} is the cost of additional infrastructure related to installation of renewable energy sources per house(£); W_{ic} is wind power installed capacity (MW); C_{wic} is the cost of the installed wind capacity per MW (£/MW); S_{ic} is the solar installed capacity (MW); C_{sic} is the cost of the solar installed capacity per MW (£/MW); B_{ic} is the installed capacity of batteries (MWh); C_{bic} is the cost of the installed capacity of batteries per MWh (£/MWh); C_{PH} is the additional cost of passive house standard (£); h is the number of houses ($h = 1000$).

From generating an hourly energy model over 10 years for each scenario, the grid backup was calculated for each year and the yearly average (over 10 years) grid back up multiplied with the electricity cost/unit (£$_{buy}$) to obtain the cost of purchased electricity to the homeowner (C_{buy}). The cost of purchased electricity to the homeowner/year (C_{buy}) is calculated using the following formula:

$$C_{buy} = \frac{£_{buy} \times E_{TOT-}}{h \times 10yeras} \tag{6.2}$$

were £$_{buy}$ is the unit cost of electricity purchased from the grid (£/kWh); E_{TOT-} is the total 10-year estate energy consumed (kWh); h is the number of houses ($h = 1000$).

Also, the yearly overproduction eligible for grid export value (electricity sold to the grid) was calculated over 10 years, and the simple 10-year is averaged. Then, it is multiplied by the specified unit export value of sold electricity (£$_{sell}$) (£/kWh) to derive the yearly grid export income C_{income} per year per house (10-year average) as follows.

$$C_{income} = \frac{£_{sell} \times E_{TOT+}}{h \times 10yeras} \tag{6.3}$$

where £$_{sell}$ is the unit export value of sold electricity to the grid (£/kWh); E_{TOT+} is the total energy the estate exports to the grid for 10 years (kWh).

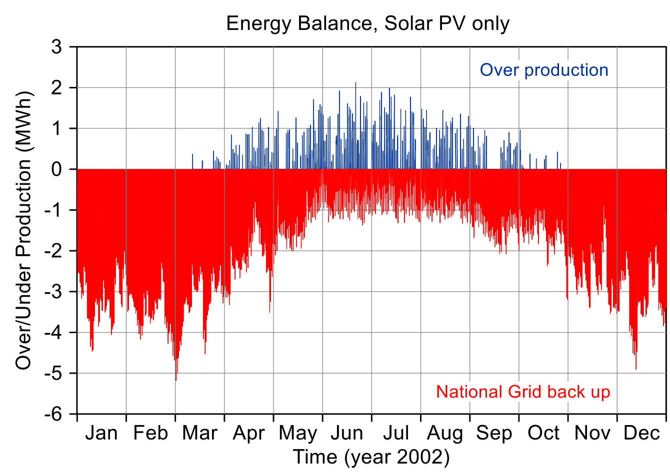


Fig. 18. Solar only: Year (2002) energy balance using a standard (4kWp) solar array on each house (no wind or storage and built to Part L building regulations).

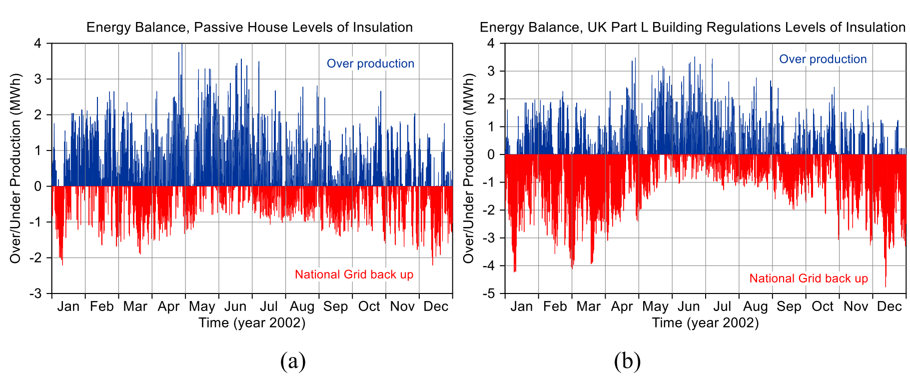


Fig. 17. Energy balance with 2.5 MW wind turbine, 4 MWp solar for 4 MWh energy storage, (a) passive house levels of insulation, (b) UK part L building regulations levels of insulation.

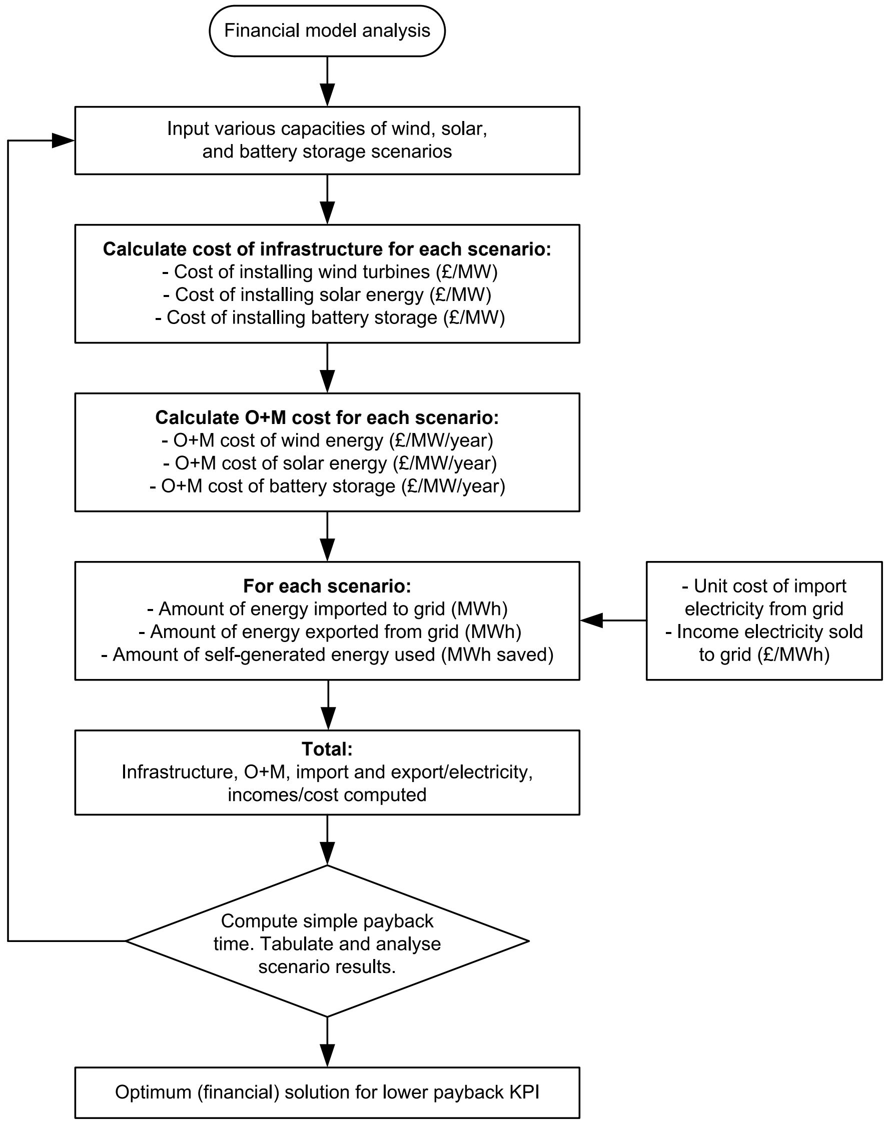


Fig. 19. Methodology of the financial model.

The (10-year) average yearly supply of electricity to an average homeowner if all the electricity was supplied by the grid is calculated as the energy demand and multiplied by the cost/unit of consumer electricity ($£_{buy}$) to give the cost of demand (C_{demand}).

$$C_{demand} = \frac{£_{buy}}{10years} \times \sum_{i=1}^{n=87600} \frac{\sum_{k=1}^{h=1000} \left(E_{D(i,k)} + E_{HW(i,k)} + E_{SH(i,k)} + E_{EV(i,k)}\right)}{h} \tag{6.4}$$

where $n = 87600$ is the number of hours in 10 years.

The additional cost of building to passive house standards (C_{PH}) (if required) was specified for an average size house as a % over and above the Part L of the building regulations and factored into infrastructure costs where specified (or not) and the reduction in heating costs (used energy) generated if applicable.

Yearly renewable energy operation and maintenance costs per house (C_{OM}) were next defined:

$$C_{OM} = \frac{W_{ic}C_{wom} + S_{ic}C_{som} + B_{ic}C_{bom}}{h} \tag{6.5}$$

where C_{wom} is the yearly operation and maintenance cost of wind energy (£/kWh) of installed capacity; C_{som} is the yearly operation and maintenance cost of solar energy (£/KWh) of installed capacity; C_{bom} is the yearly operation and maintenance cost of wind energy (£/kWh) of installed capacity.

An overall simple payback time calculation could be made for the extra infrastructure cost. Simple payback (SP) of the additional infrastructure of the scheme to a homeowner is calculated as

$$SP = \frac{C_{IF}}{C_{income} + C_{demand} - C_{buy} - C_{OM}} \tag{6.6}$$

where SP is the simple payback (years).

Using the above model, the payback time of combinations of multiple wind solar and battery power was generated and compared to the self-sufficiency of the system. Infrastructure costs, etc., could be added to the model to reflect changing economic times and do risk analysis and financial stress tests on any given scenario. To find the financial optimum solution, many scenarios were explored and analysed to assess various possibilities.

Building to passive house standards has a cost premium on traditional Part L of building regulation because of the increased level of insulation etc. required. Whereas the optimum engineering solution would be to build each house with the best insulation standards, creating the lowest energy demand (and energy requirement), the financial analysis is a trade-off between the upfront cost of additional building standards versus improved housing energy running costs. Research carried out by the Passive House Trust [26] demonstrates that the current best practice is at 9 % extra cost premium on traditional part L standard houses. However, Exeter City Council [26], with nearly 9 years' experience, are now building Passivhaus at a premium of just 8 % over baseline, and the steady-state projection of Passivhaus adoption at scale is around 4 %. For this analysis, a premium of 8 % on top of the mandatory Part L building standards was used. This equates to an additional building fabric cost of £18,783 for an average house (2020), with any renewables in addition to this.

In terms of energy production, no government subsidies or feed-in tariffs are used in this model. Because there is a readily available market in the house occupiers to buy the electricity produced, the market value for grid electricity was used. Any energy exported (unless a nearby buyer can be found) will be subject to the feed-in wholesale rate. The total upfront cost of each combination of system will be calculated, together with its operation and maintenance costs, and total energy output benefits, both in terms of expenditure saved by occupants not having to purchase energy and any income gained from feeding into the grid.

Example data imputed into the model to generate results is shown in Table 1; however, the model has been designed to be modified easily to analyse different scenarios and risk analysis in a changing energy environment.

7. Results

Using the above methodology, simple payback times on the cost of the additional infrastructure, of combinations of wind, solar and battery storage were generated and analysed together with the self-sufficiency from the grid as a percentage. Wind energy was analysed, and the simple payback times of different sizes of wind farm and battery size, with standard Part L of UK building regulations insulation levels, are displayed in Fig. 20(a).

Small 2.5 MW wind turbines and no battery give the quickest payback time, but quickly become uneconomic with increasing battery size. This is because there was not enough electricity in the first place being generated to use the full effect of the storage. Fig. 21(a) shows that the self-sufficiency from the grid possibilities from smaller systems is limited. Wind farm and battery infrastructure costs per house (if shared with 999 other houses) were analysed, and these costs were compared with self-sufficiency from the grid as shown in Fig. 21(b). Passive house insulation levels were next compared to Part L of UK building regulations insulation levels and analysed for their effect on simple payback times, as shown in Fig. 21(c) and additional infrastructure cost represented in Fig. 21(d).

Table 1
Example input parameters used for the analysis (based on autumn 2023).

Number of houses	1000
Size of wind turbines (Installed capacity MW)	5
Size of solar/Property installed capacity (kWp) per house	5
Total solar power (MW)	5
Storage capacity (MWh)	10
Electricity export value (£/MWh)	£100.00
Electricity cost (to householder) if purchased from grid (£/kWh)	£0.35
Solar PV cost (£/MW)	£1,000,000.00
Solar PV O + M cost (£/MW/year)	£10,500.00
Full total cost of wind turbines (£/MW)	£1,500,000.00
Wind O + M cost (£/MW/year)	£46,000.00
Energy storage cost (£/MWh) installed	£191,772.00
Energy storage O + M cost, warranty and augmentation (£/MW/year)	£16,719.00
Round trip efficiency of battery (%)	0.88
Passive house standard premium (%)	8
Average house price	£234,794.00

The simple payback times of different sizes of solar arrays and battery size, with standard part L of UK building regulations insulation levels, are displayed in Fig. 20(b). Small solar and no battery give the quickest payback time, but payback time is increased with higher battery storage. Generally, the results for solar were not as favourable as wind in terms of cost, payback time and self-sufficiency from the grid. Fig. 22(a) demonstrates that the self-sufficiency from the grid possibilities from smaller systems are limited, and Fig. 22(b) illustrates the cost of higher self-sufficiency with solar is excessive; however, the battery storage is used much more effectively than with wind energy, so long as there is enough electricity being produced for the battery to be utilised.

Next, combined systems of wind and solar scenarios were analysed with varying amounts of energy storage, as in Fig. 22(c). It was found that they offered little benefit over individual solar or wind systems. The extra infrastructure costs and complexities, not being worth the additional useable electricity produced. The battery storage sweet spot for this particular demand profile, considering cost and its benefit to the system, falls around the 10 MWh capacity. Further analysis was carried out using a fixed 10 MWh battery with various scenarios of wind and solar power, showing that there is little benefit to payback times of combined systems, offering little in the way of improved self-sufficiency for the additional costs, as illustrated in Fig. 22(d).

8. Conclusion

The paper shows that it is not just possible, but extremely beneficial to have a shared grid supported renewable energy smart grid. In addition to housing developments, this grid system would also be beneficial for business premises, government buildings, and housing associations, offering shorter payback times and additional opportunities to generate revenue by charging tenants for energy. The analysis shows that the closer to 100 % independence from the grid required, the infrastructure and costs increase exponentially, as the rare events of historically low wind or solar output periods must be catered for, and if longer periods of meteorological data were used i.e., 50 years, then costs may be higher still. An optimum system would be dependent on the clients' motivations and the importance of the clients' aims i.e., lowest payback time, highest independence from the grid or lowest up-front cost etc. However, it has been demonstrated that wind energy is a better cost-effective solution than solar overall. Battery size is important to specify depending on the type of renewable energy used, the demand profile and the size of the installed capacity. Solar energy benefits from energy storage more than wind energy, because the variability of solar being higher than wind. Extra-large battery storage in relation to the system is wasteful and underutilised, and will only be used in rare "extreme low wind or solar weather patterns. It was found that higher passive house insulation gave higher payback times without large gains in self-sufficiency from the grid, and standard insulation has cost advantages in situations where abundant low carbon, zero margin cost energy is available. Combined systems of wind and solar offered no advantages. To make a system run with complete energy security without any grid back up the off-grid scenario must store energy way beyond the hourly usage to cope with extreme periods of low renewable energy production. These "off-grid" scenarios were found to be vastly expensive and over engineered, and excess energy cannot feed energy back into the national grid for financial gain, but could possibly be used to produce green hydrogen. Heat pumps were found to be uneconomic where abundant zero margin cost energy was available, as the cost of installation and extra infrastructure never makes up for the reduced electricity demand saving, assuming a COP of 3–4.

The model proposed in this paper can be replicated for any location, provided that an electrical demand profile and relevant meteorological data are available. It can then be used to generate design recommendations for an optimal solution based on a client's key performance indicators. Both local and central government policies can further support such schemes by investing in national grid infrastructure, easing

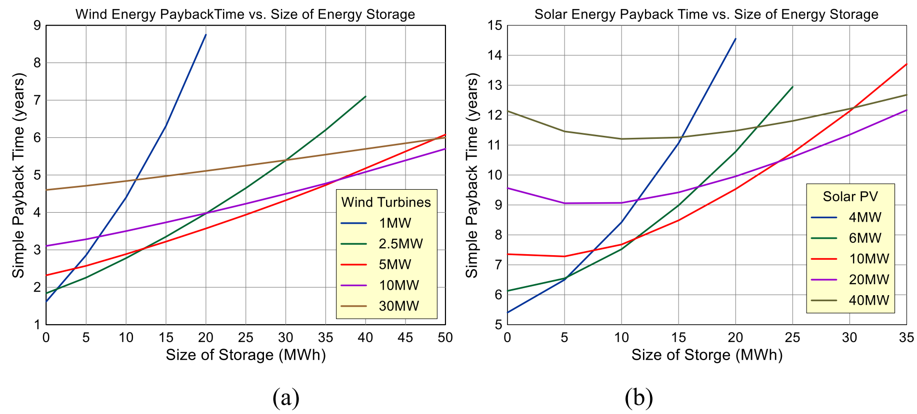


Fig. 20. Simple energy payback time vs. varying amounts of energy storage for (a) wind energy installations, (b) solar energy installations.

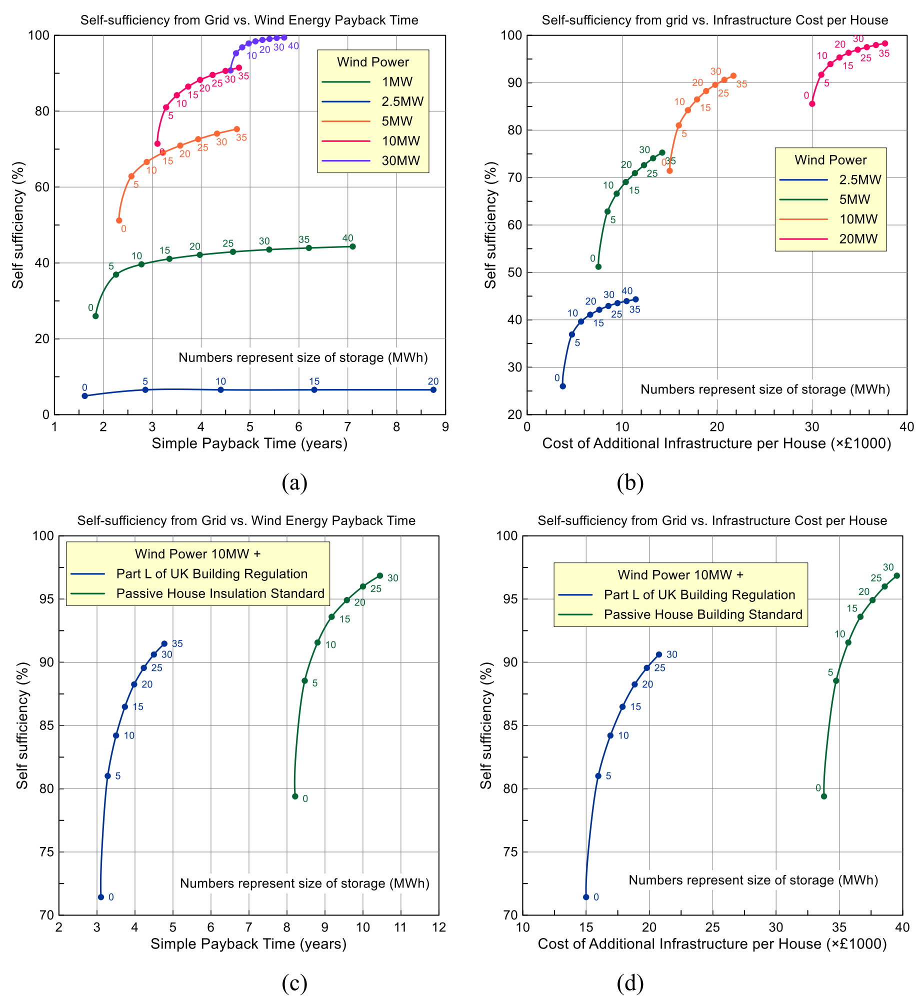


Fig. 21. System self-sufficiency from the national grid vs. (a) simple wind energy payback time at different level of energy storage and wind farm size, (b) additional infrastructure cost per house at different levels of storage and wind farm size, (c) simple payback time for 10 MW wind power scenario at different levels of storage and insulation standards, (d) additional infrastructure cost per house for 10 MW wind power scenario at different levels of storage and insulation standards.

planning restrictions, and offering grants to help mitigate developers' risks.

Future work on this model should focus on the analysis of a smaller number of houses, where the economies of scale will not be as beneficial as for a 1000-house estate. A local housing association in Wales is interested in this modelling for a new housing estate which, at the time of writing, is in the planning stage. Upon completion of the housing project, the comparisons will be made between predicted results and actual performance. The advantage of this model applied to smaller housing estate analysis is that it allows for testing the effect on metrics such as future falling renewable energy costs, wholesale energy price fluctuations or future fossil fuel cost shocks etc. It also provides ground to conduct an analysis of risk assessment, breakeven points and critical tipping points.

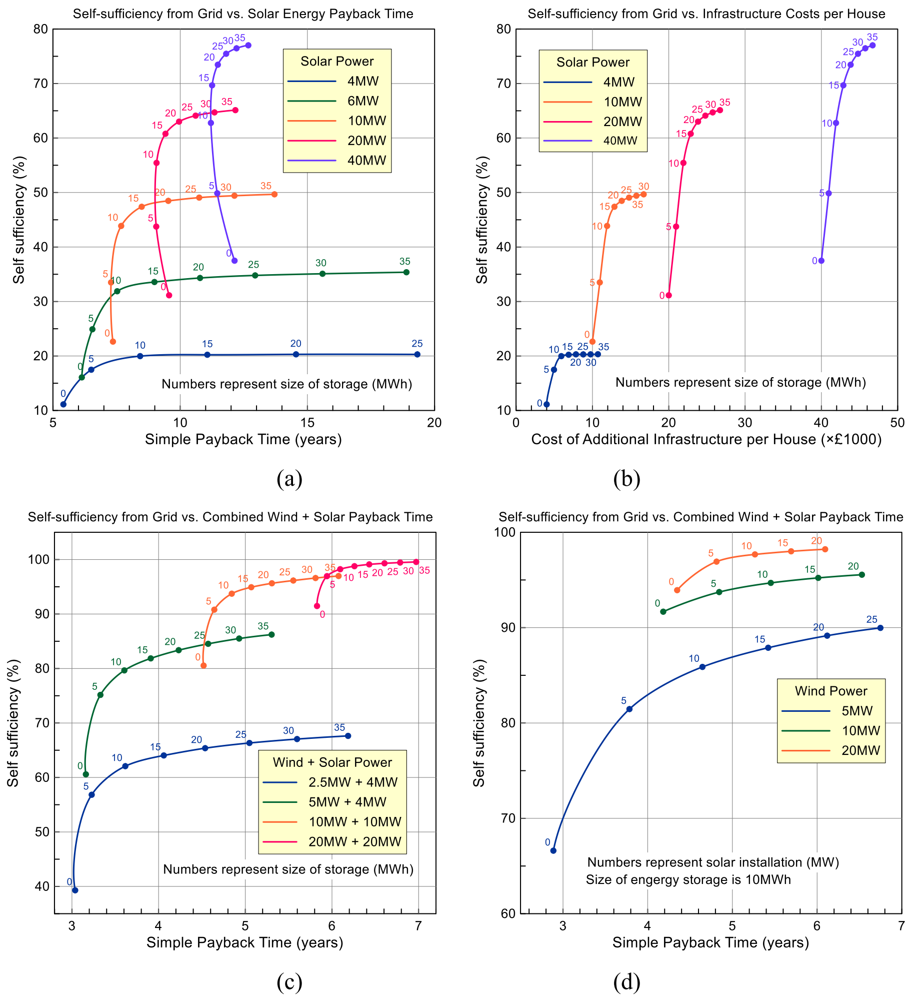


Fig. 22. System self-sufficiency from the grid vs. (a) simple solar energy payback time at different levels of energy storage and solar PV installation size, (b) additional infrastructure cost per house at different levels of storage and solar PV installation size, (c) simple combined wind and solar payback time at different levels of storage, (d) simple combined wind and solar payback time at a fixed size of storage battery of 10 MWh.

Additionally, a sensitivity analysis could be conducted to assess how variations in key external factors could affect system performance and economics. For example, solar and wind resources could be adjusted within a ±20 % range to account for interannual climate variability, and battery lifespan scenarios of 8, 10, and 12 years could be tested to simulate different usage patterns and degradation rates.

CRediT authorship contribution statement

David Sprake: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Shafiul Monir:** Writing – review & editing, Supervision, Project administration. **Yuriy Vagapov:** Writing – review & editing, Visualization, Supervision. **Robert Cameron Bolam:** Writing – review & editing, Resources, Investigation. **David Elcock:** Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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