

Modelling the impact of the electrification of heating and transport on the mix of wind, solar, and storage.

by

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Abstract

The mix of technologies in a future energy system is an important area of research. As the proportions of wind power and solar power generation capacities in the power system increase, energy storage becomes necessary to complement their variability due to weather. The subject of this thesis is how the wind/solar/storage mix will be impacted due to changes in electricity demand caused by the electrification of heat and transport using the UK as a case study.

To account for long-term weather effects, whilst keeping socioeconomic and technological factors constant, a novel method has been developed for incorporating heating electricity into the historic electricity demand. This enables the impact of heat pumps alone to be studied. The research reveals that for predicted 2050 heat pump penetration levels the monthly demand for electricity doubles in winter. This leads to an increase of approximately 30 TWh for each winter month and a 37% increase in year-to-year variability of electricity demand due to weather. Temperature dependent electric vehicle time series incorporated into the electricity demand show a seasonal variation far lower than for heat pumps, with annual demand varying over a range 14 TWh between years with EVs compared to only 10 TWh without.

These electricity demand time series were used in a novel high-level energy model to calculate the minimum energy storage required for a generation mix including wind, solar, base load and dispatchable power sources. To provide sufficient granularity and variation in conditions, hourly demand and generation time series based on 40 years of historic weather were used. The optimum wind/solar energy mix from perspectives of storage, excess energy and cost were investigated. It was found that heating electrification increases the proportion of wind energy required by between 3% and 5%. In contrast, a change to providing most transport by electric vehicles does not significantly change the optimum proportion of wind energy required. Providing all heating with boilers fuelled by hydrogen generated via electrolysis would require 7 times as much renewable energy compared to all heating provided by electric heat pumps. Energy lost due to curtailment exceeds energy lost to storage efficiency by an order of magnitude.

A sensitivity analysis on alternative model inputs showed that different wind generation time series have the most impact on predicted energy storage capacity. Simulated offshore and onshore wind and actual national grid generation all have different patterns. This can have a significant impact on storage requirements, a result that has not been noted before. Although previous research has shown the impact that wind turbine locations have on the amount of energy they generate, when they generate this energy has had little attention.

A novel comparison of four heat demand methods found that the method used by the when2heat dataset most accurately predicted the measured data which is an important result considering it has already been used by several other studies. The methods were validated against national gas time series, and measured data not previously used for this purpose. It was also found that peak electricity demand is very sensitive to the method of generating heat demand and hourly heat pump operating profiles, suggesting inaccuracies of 25% in previous estimates of future peak demand.

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Publications

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Abbreviations

ASHP	Air Source Heat Pump
BDEW	Bundersverbend der Engie und Wasserwirtschaftk – used for the name of a heat demand method based on the German gas company’s equation for estimating consumers gas usage
BECC	Bio Energy and Carbon Capture
CAES	Compressed Air Energy Storage
CAT	Centre for Alternative Technology
CCS	Carbon Capture and Storage
CDD	Cooling Degree Days
CDH	Cooling Degree Hours
CHP	Combined Heat and Power
COP	Coefficient of Performance (ratio of heat pump heat output to electricity use)
CO ₂	Carbon Dioxide
CP	Cooling Power of the wind
DAC	Direct Air Capture – extracting CO ₂ from the atmosphere.
DESSTINEE	Demand of Energy Services, Supply and Transmission in Europe. A model of the European energy sector to 2050
ECMWF	European Centre for Medium range Weather Forecasting
EI	Effective Illumination
ERA5	European Reanalysis
ESC	Energy Systems Catapult – body fostering links been energy industry and academia
ESME	An energy model
ESTIMO	An energy model
EV	Electric Vehicle
FES	Future Energy Scenarios. UK National Grid projections of possible future energy systems
GHG	Greenhouse gas
GHI	Global Horizontal Irradiance – solar radiation reaching the earth’s surface
GSHP	Ground Source Heat Pump
HDD	Heating Degree Days
HDH	Heating Degree Hours
LCOE	Levelized Cost of Electricity
LOESS	(Locally Estimated Scatter plot Smoothing). A generalization of polynomial regression and moving average.
LPG	Liquified Petroleum Gas – hydrocarbon gas used as a fuel.
MAPE	Mean Absolute Percentage Error
MERRA	Modern Era Retrospective Reanalysis for research and Applications – weather reanalysis data source from NASA
MERRA2	Updated version MERRA
MIDAS	Met office Integrated Data Archive System – UK Met Office source of weather station measurements.
NDM	Non-Daily Metered – classification of natural gas consumers
nRMSE	Normalised Root Mean Square Error
PV	Photo Voltaic. Solar panels that generated

R	Pearson's Correlation Coefficient
R^2	Coefficient of determination
RF	Random Forrest. A machine learning algorithm
RHPP	Renewable Heat Premium Payment – trial of heat pumps
SOC	State Of Charge
TIMES	An energy model
V2G	Vehicle to Grid. Using EV batteries as additional grid scale battery storage
ZCB	Zero Carbon Britain – future energy system plan from CAT

Nomenclature

$A_{a,g}$	Annual demand for heat use a (either a=space or a=water) at grid point g	TWh
$A_{a,y}$	Annual demand for heat use a (either a=space or a=water) for year y	TWh
α	Cost of storage capacity	£/kWh
B_h	Hourly baseline electricity demand time series	TWh
β	Cost of storage charging equipment	£/kW
C_b	Capacity of base load	days *
C_i	Initial amount of energy stored in the energy store	days *
C_m	Capacity of the energy store	days *
C_p	Capacity of Solar Photo Voltaic Generation	days *
C_v	Capacity of dispatchable generation	days *
C_w	Capacity of Wind Generation	days *
CP_t	Cooling Power	°C (m/s) ^{0.5}
D_t	the electricity demand at time t. D_d is daily electricity demand	TWh
δ_s	Threshold for considering to storage capacities as the same	days *
$\Delta T_{h,g}^{amb}$	Difference between the ambient air temperature and sink temperature for ASHP for hour h and weather grid point g	°C
$\Delta T_{h,g}^{soil}$	Difference between the soil temperature and sink temperature for GSHP for hour h and weather grid point g	°C
E_d	Total Electricity Demand over the period	TWh
E_{excess}	Excess (curtailed) energy	TWh
E_h	Hourly electricity demand time series	TWh
$\hat{E}_y$	Predicted electricity time series for year y	TWh
E_p	Energy generated from solar PV	TWh
E_w	Energy generated from wind	TWh
E_{sl}	Energy lost due to efficiency of the energy store	TWh
η	Storage round trip efficiency = $\eta_c \eta_d$	
η_c	Storage charge efficiency	
η_d	Storage discharge efficiency	
$f_{d,g,\alpha(a)}$	Demand factor for the proportion of the annual demand allocated to grid point g for day d and heat use $\alpha(a)$	
F_h	Historic hourly electricity demand time series	TWh
g	Weather grid point	
G_d	Daily historic gas demand time series	TWh
γ	Cost of storage discharge capacity	£/kW
$H_{a,d,g}$	Daily heat demand time series for heat use a and grid point g	TWh
H_d	Daily heat demand time series	TWh
H_{2018}	Heat demand for 2018	TWh
HDD_y	Heating Degree Days for year y	°C
i	Hour of the day	TWh
I_d	Additional daily EV electricity due to extremes of temperature	TWh
J_i	Hourly heat profile – proportion of the daily heat allocated to hour i	
K_b	Cost of baseload generation	£
K_e	Cost of energy storage	£
K_p	Cost of solar PV generation	£
K_v	Cost of dispatchable generation	£

K_w	Cost of wind generation	£
K_s	Proportion of heating from configuration s	
L_g	LCOE for gas generation	£/kWh
L_l	LCOE for onshore wind generation	£/kWh
L_n	LCOE for nuclear generation	£/kWh
L_p	LCOE for Solar PV generation	£/kWh
L_s	LCOE for offshore wind	£/kWh
M_h	Hourly hybrid heat pump electricity demand	TWh
ND	Number of days in the year	
NG	Number of weather grid points	
N_t	net electricity demand at time t	TWh
P_c	Maximum storage charge rate	GW
P_d	Maximum storage discharge rate	GW
P_E	Proportion of heating from ordinary heat pumps	
P_l	Proportion of onshore wind	
P_s	Proportion of offshore wind	
P_M	Proportion of heating from hybrid heat pumps	
P_g	Population at grid point g	
P_t	PV Energy generated at time t	days *
P_t^{cf}	Time series of solar PV generation capacity factors	
R_d	Daily gas time series from linear regression	TWh
R_h	Hourly electricity time series for existing heating technology	TWh
s	Heating configuration. A combination of use (space heating or water heating), source (eg ASHP or resistance heating) and sink (eg radiators or underfloor)	
SL	Storage lower bound	Days
SU	Storage upper bound	days
S_h	Hourly electricity demand time series with heating provided by heat pumps	TWh
S_t	Amount of energy stored at time t	days *
S_0	Initial state of charge of the energy store	days
$T_{d,g}^{amb}$	Mean daily ambient external temperature for day d and grid point g	°C
$T_{d,g}^{Ref}$	Reference temperature for day d and grid point g	°C
T	Temperature (Ok population weighted)	°C
T_c	Total Cost of electricity generation	£/kWh
T_d	Mean daily temperature for day	°C
T_{base}	HDD base temperature	°C
T_f	Threshold temperature below which a hybrid heat pump switches to a gas or hydrogen boiler	°C
U_h	Hourly electric vehicle time series	TWh
V_t	Dispatchable energy generated at time t	days *
W_t	Wind energy generation at time t (in days *)	TWh
W_t^{cf}	Time series of wind generation capacity factors	
W_f	Wind energy fraction	
X_t	Base load energy generation at time t (in days *) = C_b	
Z_t	Hydrogen demand time series	TWh
*	One day of energy is the mean daily energy of the 2018 historic electricity time series 818.8 GWh	

1 Introduction

The power system has always had to respond to an electricity demand that varies on an hourly, daily, and seasonal basis. But as the proportions of wind power generation and solar power generation increase, the supply side is also becoming more variable due to its weather dependence. One solution to supply side variability is to store energy during periods of high generation for use when the demand is high, but the generation is low. An important area of research considers what mix of generation and storage technologies are needed to balance supply and demand. This thesis is primarily concerned with how the mix of wind and solar generation will be impacted by changes in the electricity demand due to the electrification of heating and transport.

The rest of this chapter is structured as follows. Section 1.1 discusses the importance of the subject, the motivation for the research and the main research questions. Section 1.2 contains background to the field of energy modelling. Section 1.3 contains a brief literature review to establish the novelty of the research questions. Section 1.4 describes the structure of the rest of the thesis and summarises the main contributions.

1.1 Motivation and Research Questions

In 1952 when my uncle Douglas participated in the British North Greenland Expedition [1] which assessed glacial melting, it was known that global temperatures were rising, but not why. By 2018 the International Panel on Climate Change [2] reported that manmade emissions of greenhouse gases (GHG) are leading to dangerous changes to the world's climate. In response, in 2019, the UK government committed to net zero greenhouse gas emissions by 2050 [3]. A net zero energy system [4] that does not add any GHG to the atmosphere is an important step towards this goal. Emissions from energy supply come predominantly from the burning of fossil fuels. To achieve a net zero energy system, these need to be replaced by low carbon power sources such as wind and solar. The intraday variability of wind and solar can be mitigated to a limited extent by demand side management, but to cope with the seasonal variability, they need to be complemented by energy storage. Therefore, it is important to study the capacities of wind generation, solar generation and energy storage that might be needed in a future power system. The technology mix and feasibility of the transition have been identified as important research areas [5].

This change to renewable power sources such as wind and solar will result in a migration away from burning fossil fuels for kinetic energy and heat energy to delivery of energy in the form of electricity. The two most significant impacts on future electricity demand in cooler countries will be the electrification of heating and transport [6, 7]. Heating is the cause of 30% of primary energy demand in Europe [5] and 36% in the UK [8]. The migration from heating provided from fossil fuels such as natural gas to electricity is termed the electrification of heat. Similarly, transport, the largest emitting sector of GHG emissions, producing 24% of the UK's total emissions [9], is likely to migrate from oil based to electric vehicles (EVs).

These changes mean that in the future, both power generation and electricity demand will become more weather dependent. Wind power generation depends on windspeed, and solar power generation depends primarily on solar irradiance. Heating demand

depends on temperature so that a move to electric heating increases the sensitivity of the power system to weather variation [7]. EVs also use more energy with extremes of weather [10]. Therefore, it is also important to consider the effect of weather. However, research has found that using only a single year is not enough to capture the variation in renewable power generation caused by weather to fully test an energy model [11]. For this reason, it is important to consider at least 10 years of weather. The more variation in weather conditions, the more likely that periods where high demand and low generation occur at the same time are captured. For example, a model developed using a warmer year with lower heating demand, or a windy year with high power generation might not cope with a cold, calm year. In this study 40 years of historic weather data are used, on the assumption that the weather patterns of the past give a guide to those of the future. Other research [12] has found that the multi-decadal variability of wind generation based on historic weather to be greater than climate change impacts predicted by modelling, and [13] that the impacts of climate change on PV generation in Europe will be lower than that of wind.

This work brings together these aspects of changes to electricity demand, generation, and storage with sensitivity to weather. The research question in this thesis is how the future decarbonization of heat and transport will impact the optimal mix of solar, wind and storage in a power system with a high penetration of these technologies. To answer this question a model of the electricity system will be required, which will need to include wind power generation, solar power generation, electricity demand and energy storage. It will have to do this accounting for long-term weather variation. Factors other than weather must be kept constant, so that the impact of the changes to heating and transport can be assessed alone. If heating technology were changing over the analysis period, as it would be if historic electricity demand were used, then it would not be possible to tell which changes were due to weather and which to technology. Although the methodology developed here is used to study the impact of current heat pump technology it could equally well be used to keep technology constant at future levels, for example if heat pump COP and housing insulation improves.

Four subsidiary questions need to be asked:

- How should electricity demand time series incorporating heating electrification under long-term weather variation be generated which allows heating alone to be studied?
- How should an electricity demand time series incorporating electric vehicles under long-term weather variation be generated which allows the impact of EV's alone to be studied?
- How should the required energy storage be found from the proportions of wind and solar generation?
- How can the results be assessed?

This project will address these questions using the Great Britain energy system as a case study.

1.2 Background

This section starts by discussing the technologies to be used to achieve the required changes to the energy system. Background information on how the technologies will be modelled is then presented.

1.2.1 Power Generation

Historically the majority of UK electricity has been generated by thermal power plants [14]. Thermal power plants use heat energy to drive a turbine that powers an electricity generator. The heat is provided by combustion of fossil fuels such as gas, coal or oil, or from nuclear energy. However, because burning fossil fuels emits GHG, to achieve a net zero emissions energy system, either a switch to technologies which do not generate GHG is required, or these gasses must be removed from the air. Broadly, there is a combination of three options: remove the emissions, do not create the emissions in the first place, reduce (or smooth out) the energy demand.

Options for removing the gasses [15] include:

- Carbon Capture and Storage (CCS) – CO₂ is captured from the burning of fossil fuels in a thermal power station and stored. The storage could, possibly be under the sea, in old gas or oil wells. Chemical reactions could be used to convert the CO₂ into other compounds that could be stored more easily.
- Direct Air Capture (DAC) - CO₂ is captured directly from the air and stored in a similar way to CCS.
- Bio energy - biomass that when burned only generates the same CO₂ that would have been emitted from it rotting, can be considered carbon neutral.
- Bio energy and carbon capture (BECC) – this combines bio energy and carbon capture, so theoretically could generate negative emissions.
- Other interventions outside the scope of the energy system such as planting trees.

Common options for generating electricity without producing GHGs are shown in table (1-1)

Table 1-1 Low carbon electricity generation technologies

Technology	Pros	Cons
Solar PV / thermal	Cheap, large resource	Variable, takes space
Wind	Cheap, large resource	Variable, takes space
Wave	Large potential	Expensive
Tidal (barrage / stream)	Constant predictable cycle	Expensive
Hydro	Predictable	Small UK resource
Bio energy	Use when needed	Limited Resource
Nuclear	Constant	Expensive, cannot switch off, waste disposal problems
Geothermal	Constant	Limited UK Resource

Options for reducing electricity use include efficiency improvements and measures to reduce demand such as home insulation. Options for reducing peak demand, include demand response/shifting where consumers are incentivised to use energy at a different time such as overnight EV charging.

1.2.2 Energy Storage

The characteristics of different storage technologies determine their role within the power system. Short term storage for balancing the grid to maintain voltage and frequency requires storage with a high energy throughput, but low capacity. Whereas long-term storage to balance seasonal and interannual mismatches requires high capacity but does not need such a high throughput. Some of the storage technologies expected to play a role in the future are:

- Batteries: A chemical reaction generates electricity. The reaction is reversible so that the battery can be charged with electrical input, storing energy [16].
- Pumped Hydro: water flowing from a lake driving a turbine to produce electricity. Electricity used to run a pump to refill the lake, to store energy [16].
- Compressed Air Energy Storage (CAES): compressed air stored in a salt cavern used to generate electricity via a gas turbine. To store energy, electricity drives a compressor to compress air [16].
- Hydrogen Storage: Hydrogen stored in salt caverns, cylinders or tanks used to generate electricity via a fuel cell. Energy stored using electricity to create hydrogen via electrolysis of water [17].

A study on the economics of electrical storage [18] states that batteries are suitable for a period of a few hours, CAES and pumped storage are suitable for 6-10 hours. Power to gas such as Hydrogen are suitable for longer periods. All storage technologies can be characterised using the same measures. For example:

- Capacity: how much energy can be stored.
- State of charge: how full the energy store is.
- Charge rate: how quickly the energy can be stored.
- Discharge rate: how quickly the energy can be used (related to power rating)
- Efficiency: how much energy is lost in the process.
- Lifetime: often measured in charge – discharge cycles.

Table (1-2) compares some of these characteristics for various storage technologies. With pumped storage the rate at which energy can be stored is determined by the capacity of the pump which pumps water from one lake into another higher up. The amount of energy that can be stored is determined by the capacity of the lake and the rate of discharge is determined by hydro-electric generation capacity. With hydrogen, the charge rate is determined by the capacity of electrolyzers which use electricity to split water into hydrogen and oxygen. The amount of hydrogen that can be stored is determined by the size of the salt caverns in which it is stored, and the discharge rate is determined by the capacity of hydrogen electricity generation.

Table 1-2 – Characteristics of energy storage technologies.

Storage Technology	Capacity Determined by	Charge Rate Determined by	Discharge Rate Determined by
Battery	Stored Charge (Coulombs)	Current (Amps)	Current (Amps)
Pumped Storage	Size of the lake	Pump capacity	Hydro generation capacity
Hydrogen	Size of salt caverns or gas storage	Electrolyser capacity	Hydrogen turbine generator capacity
CAES	Size of salt caverns or gas storage	Compressor capacity	Generator capacity

The seven future plans for the UK power system reviewed in [19] all anticipate that more long-term storage will be needed. The plans discussed use batteries, pumped hydro, and Compressed Air Energy Storage (CAES) for short term storage. For long-term storage 6 of these plans use hydrogen and 1 uses methane made from hydrogen and biomass. The wind energy fraction, short term and long-term storage from these plans are summarised in table (1-3). The capacity of long-term storage ranges from 600 GWh to 80 TWh whilst that of short-term storage is much less, ranging from 29 GWh to 200 GWh. These plans were produced by:

- ESC – The Energy Systems Catapult – a body fostering links between the energy industry and academia.
- FES – Future Energy Scenarios by National Grid.
- CAT – Centre For alternative Technology, ZCB Zero Carbon Britain.
- CCC – Climate Change Committee.

Table 1-3 Seven Future UK Energy System Plans

Plan [19]	Wind Energy Fraction	Short term / batteries	Long Term Storage
ESC – C	80% – 99%	35 GWh	660 GWh Hydrogen
ECS – P	71% – 98%	29 GWh	600 GWh Hydrogen
FES – LTW	86%	203 GWh	16 TWh Hydrogen
FES – ST	80%	146 GWh	18 TWh Hydrogen
FES – CT	86%	194 GWh	18 TWh Hydrogen
CAT – ZCB	90%	200 GWh	80 TWh Hydrogen
CCC – B	83%	200 GWh	80 TWh methane from hydrogen and biomass

Vehicle to grid (V2G) systems where private electric vehicles loan out part of their battery capacity could make a significant contribution to the short-term storage. For example, 20 million cars (which is the low estimate of future car ownership) and a typical 40 kWh car battery create a total of 800 GWh.

1.2.3 Heating Technology

In 2018, 71% of Great Britain's heating was provided by natural gas [8]. The gas is burnt to heat water supplied directly as hot water or pumped through radiators to heat buildings. Such fossil fuel heating systems which can also be fuelled by oil or biomass emit carbon dioxide and therefore must be replaced. Possible alternative heating technologies include:

- Traditional electric “resistive heating” and storage heaters
- Combined Heat and Power (CHP)
- District Heating
- Electric Heat Pumps
- Using hydrogen as a fuel for boilers instead of natural gas

Resistive heating, such as a traditional electric bar fire, creates heat by passing an electric current through a resistor which converts the electrical energy to heat. This heat can be passed through bricks using overnight low-cost electricity in storage heaters to store the heat energy thermally.

Combined Heat and Power (CHP) is a process that combines localised power generation and heating. The waste heat from electricity generation is used to provide heating. Although the electricity has been traditionally generated using fossil fuels, some countries, for example Denmark [20] are planning a migration to using biomass or waste as a fuel.

With district heating, hot water is delivered in pipes to buildings, instead of having a heater in the building. The water can be heated via waste heat from power stations, industrial processes or via other forms of heating such as heat pumps. District heating is a promising technology for high housing densities [20], but its economic viability in the UK is uncertain due to higher cost at lower housing densities and lack of experience.

A review of domestic heat pumps [21] explains that rather than converting electric energy to heat energy directly heat pumps use electricity to pump heat from a colder location to a warmer one in a similar way to a domestic fridge. A fluid called the refrigerant is forced through an expansion valve, lowering its temperature so that it can absorb heat from the surroundings. The fluid then passes through a compressor raising its temperature, and then through a heat exchanger to heat water in the home. The ratio of the electrical energy used to the heat energy obtained is called the Coefficient of Performance (COP). This review concludes that in the future, most of the heat demand will probably be provided by electric heat pumps being the most efficient way of providing electric heating.

One alternative to fuel domestic boilers instead of natural gas is to use hydrogen. The hydrogen could be generated using excess electricity from wind and solar to split water into hydrogen and oxygen using electrolysis. This hydrogen would be piped through the existing gas network. This domestic use of hydrogen in the UK was only in a trial phase in 2019 [22].

A study analysing the impacts of future heating technologies [23] concludes that gas boilers are one of the worst technologies considering GHG emissions, only exceeded

by oil and LPG. They conclude that of the low carbon alternatives, the most economical is electric heat pumps.

1.2.4 Transport

It is anticipated that transport will mostly move towards Electric Vehicles (EVs) [24] apart from a small percentage fuelled by hydrogen. This is primarily due to the costs of the vehicles themselves and the cost of hydrogen fuel and associated infrastructure. However, the charging of the batteries for these vehicles will have a large impact on the electricity grid.

1.2.5 National Energy System Modelling

Changes to a country's energy demand, generation and storage can be investigated by computer models [25] to find the required mix of technologies for a net zero power system. For a country or region, questions such as how much wind generation, solar generation and storage are needed can be answered. These models consider the balance of energy supply, demand, and storage at hourly time steps to assess the generation mix in terms of energy, cost, or emissions. The challenge is to ensure a balance of supply and demand despite generation and demand all varying differently over time in different geographical locations. One significant cause of this variation is the weather where changes in wind speed, solar irradiance and temperature affect wind generation, solar generation, and energy demand. Mixing different energy sources such as wind and solar is known to reduce the variability of production [26] and improves the production / demand match. However, research has found that a single year is not enough to capture the variation in renewable power generation caused by weather to fully test an energy model [11]. Therefore, this project will use 40 years of historic weather. Sources of weather data are discussed in the next section.

Seven plans for the UK to reach a net zero energy system [19] produced by four different groups use different modelling approaches. Two of the groups: energy Systems Catapult and Climate Change Committee use a model called ESME. It is an optimisation model that searches for a least cost combination considering emissions targets, resource availability and deployment rates. National Grid FES consider each sector separately according to factors such as the uptake of efficiency measures, economic projections, historic demand, and feed the results into an optimisation model called UK TIMES. The Centre for Alternative Technology (CAT) do not explicitly calculate economic cost, but instead are guided by a set of principles such as net zero and 100% renewable energy. They use a model including historic weather to prove that the system they propose is viable.

Optimisation models search for an optimal design, usually based on costs. Whereas simulation models compare several different designs. A study comparing different modelling approaches [27] discusses the differences between the first two approaches and the latter one. They say that the advantage of the latter approach is that the public can be involved in a decision between several alternatives, whereas the optimisation approach is based on market values themselves subject to implicit political choices.

The models considered by this study are a simplified subset of simulation models which only consider energy when allocating sources of generation to satisfy demand. They

consider the national energy system as a single node and do not take into account that it is a complex network connecting sources of supply and demand with varying transmission capacities. For example, wind generation in the north of the UK, might be needed to supply demand in the southeast and the network needs the capacity to do this. In rural areas, there may not be enough transmission capacity for houses to have both electric vehicles and heat pumps. The results of the models would be less accurate if the transmission network were not upgraded to have the necessary capacity. These simplified models will be referred to as energy balance models.

1.2.6 Weather Data

Weather data are needed to model both the energy demand and the energy supply. Temperature is used to estimate heat demand and hence electricity demand. Wind speed and solar irradiance determine the power generated from wind turbines and solar panels respectively. Weather measurements have been collected at UK weather stations for many years. These include hourly values of parameters such as temperature, solar irradiance, precipitation, humidity, and wind speed at the earth's surface. UK weather observations data is recorded in the Met Office Integrated Data Archive System (MIDAS) [28]. However, this data has the disadvantage that it is only available at the locations of weather stations, and only has surface parameters. This means for example that the wind speed at the height of a wind turbine is not available.

An alternative to surface measurements is weather reanalysis data which provides these parameters at different heights. Reanalysis uses a forecasting model of atmosphere, winds, ground (including surface roughness), and ocean to assimilate and compare data from different sources [29]. This includes observed data such as temperatures at weather stations, and wind speeds from satellites. Additional parameters not measured at certain locations can be derived such as soil moisture and cloud properties in such a way that all the parameters are consistent with physics. The result is a global atmospheric model constrained by the values of actual physical measurements at specific times and locations. Reanalysis data has the benefits that:

- It has values at height (e.g., wind turbine hub height), not just at the surface.
- The values are available on a regular grid, rather than the locations of weather stations which makes computation easier. This is because the population grid is mapped onto the weather grid to establish how much of the national heat demand is caused by a particular set of weather parameters.
- The data is consistent over time and geographical location (whole world)
- All measurement sources are consistent with each other and the laws of physics.

The disadvantages of reanalysis data are that some smoothing occurs and the influence of local terrain is not always captured. The data may not match actual measured values. However, most recent studies are choosing to use reanalysis data. Two reanalysis data sources commonly used for energy modelling are:

- Modern Era Retrospective Reanalysis for Research and Applications (MERRA2)[29] produced by NASA used in these energy system studies [30-36]
- ERA5 [37]– European Reanalysis produced by the European Centre for Medium Range Weather Forecasts (ECMWF) used by these energy system studies [26, 38, 39]

As well as historic weather data, weather predictions are available. These can be either hindcast: weather that could have occurred, or future predictions of weather that may happen. It is difficult to know what future weather might look like and therefore this project will confine itself to using historic weather.

ERA5 was used to generate electricity demand time series in chapters 2 and 3. MERRA2 was used to generate wind and solar power time series discussed in the following sections 1.2.7 and 1.2.8 respectively.

It would have been desirable to use the same reanalysis data to model both the demand and generation. However, this would have required more work because the program to generate the heat demand was adapted from an existing program which used ERA5 whilst the available generation data used MERRA2.

1.2.7 Modelling Wind Power Generation

Although historic wind power generation time series are available for recent years, they do not cover the whole 40-year period of this study, and they are based on a constantly increasing generation capacity. Simulated wind generation time series are often used as they can keep the capacity constant and incorporate wind farms that have not yet been built. National wind power generation time series can be simulated by combining the contributions of individual wind turbines. To assess the potential power generation from one wind turbine, wind speed measurements at a particular site can be used with the turbine manufacture's power curve to create a generation time series [40]. Some previous studies [34, 41, 42] have used this approach with wind speed measurements from weather stations to model the national onshore wind power time series. Generation time series are created as though a particular type of turbine existed at the geographical location of a weather station. They argue that this can be scaled up to represent the national fleet. However, for weather station data, the wind speed is only available at the surface, so it has to be estimated at the hub height of a wind turbine. This is commonly done using the log law [43], equation (1) to calculate the wind speed U at one height Z from the wind speed at a reference height Z_{ref}

$$U(Z) = \left(\frac{\ln \frac{Z}{Z_0}}{\ln \frac{Z_{ref}}{Z_0}} \right) U(Z_{ref}) \quad (1)$$

Where $U(Z_{ref})$ is the wind speed at reference height Z_{ref} and Z_0 is the surface roughness. Typically offshore turbines are much higher (up to 300m [44]) where the log law is not valid on its own [45-47] for extrapolating surface wind speed. Most studies therefore use reanalysis data so that they can model offshore wind. In one such example [34] MERRA2 is used to model national time series of wind power generation based on wind power at 97 different geographic locations around the UK, both onshore and offshore.

However, rather than generate their own wind power data, some studies use publicly available time series. Renewables Ninja [48] provides hourly time series of wind generation for the UK based on historic weather from 1980 to 2020. Wind speeds from MERRA2 weather reanalysis at 2m, 10m and 50m are used with the log law to estimate Z_0 and wind shear to create a regression equation to extrapolate wind speed to hub height. The values at weather grid points are used to get the windspeed at the specific

geographic location of the wind farm using LOESS (Locally Estimated Scatter plot Smoothing) regression (a generalization of polynomial regression and moving average). Individual turbines are combined using a virtual wind farm model. These are created based on the actual locations of UK wind farms. The virtual wind farm converts wind speed to power using manufacturers power curves and smooths individual turbines to represent a farm. Separate time series of capacity factors are available for onshore and offshore based on near- and long-term projections of actual wind turbines and their locations servicing the UK. This dataset has been validated extensively against the actual power output of wind turbines and corrected for biases [33]. It has been used in several previous studies [30-36]. Separate time series for current, near-term future, and long-term future are available. The near-term future series includes wind farms that are newly built, under construction or approved and has been used in the study. The long-term future series also includes planned wind farms but was not used because it does not separate onshore and offshore wind.

1.2.8 Modelling Solar Power Generation

National solar PV electricity generation time series can be simulated by modelling individual solar PV panels and scaling up to represent the whole country. Standard methods [49] using solar irradiance time series can be used to create solar power generation time series. They use the orientation of the panel and the angle of the sun based on the hour of the year to estimate the power generated. For example, in one study [34] hourly solar PV time series are generated at 11 regions in the UK using MIDAS data on the assumption that the power generated is proportional to the solar irradiance. In another [41], daily time series are generated based on 4 geographic locations in the UK chosen as sunny locations where the most energy might be generated.

However, some studies use publicly available time series of solar power generation. Renewables Ninja [48] provides hourly time series of capacity factors of UK solar generation from 40 years weather. They are generated by modelling a solar power plant at each MERRA2 grid point in the UK [32]. Each panel has a latitude dependent tilt angle and azimuth distributed according to actual installations. They include a correction for bias because otherwise the mean capacity factor of the simulated PV generation does not match that at actual sites. Unlike the two studies mentioned above they also use hourly temperatures to model the increase in efficiency of solar panels at lower temperatures using panel efficiency curves. The Renewables Ninja solar time series will be used in this study.

1.2.9 Time Series Metrics

Methods to compare two time series are needed in the validation of electricity demand and of power generation time series. The three metrics used for comparison of time series in this project are shown in table (1-4): nRMSE, R^2 , and R.

Metric	Description	Calculation Method
nRMSE	normalised Root Mean Square Error. A_i is the actual (normalised) time	$nRMSE = \sqrt{\frac{1}{n} \sum (A_i - F_i)^2}$

	series and F_i the modelled time series. n is the mean value of A_i	
R^2	Coefficient of determination	[50]
R	Pearson's Correlation coefficient	[50]
MAPE	Mean Absolute Percentage Error	$MAPE = \frac{1}{n} \sum_{i=1}^n \left \frac{A_i - F_i}{A_i} \right $

Table 1-4- Time Series Metrics

nRMSE is a measure of the error when comparing a series of actual values A_i with a forecast value F_i . It is used in preference to other error metrics such as Mean Absolute Percentage Error (MAPE) in this project because the squared term penalises large errors. Large errors in an electricity system model can have high consequence possibly leading to too much power (wasted costs) or too little power (outages).

The coefficient of determination R^2 is a measure of how well a regression model explains the observed data. It is used because it is desirable for the variation of the time series to be as accurate as possible as the amount of energy storage required depends on the variation of supply and demand. Using R^2 also allows a comparison to be made with other studies. What is considered as a good value of R^2 varies for different domains of study. For example, a study comparing heat demand time series [38] states that “Both time series and load duration curves show a high consistency ($R^2=0.95$)”. Similarly, a study comparing a regression equation using temperature to the National Grid gas time series [51] says “ R^2 of 0.95 shows the model predicts with good accuracy”. Some inaccuracy is tolerable because storage is measured at high granularity of days and generation capacity in multiples of the mean daily demand. Everywhere in this report where a value of R^2 , is quoted the residuals plots have been checked for bias. The residual is the difference between the predicted value and the observed value. An example residuals plot is shown in figure (2-8) in chapter 2. It could be for example that the model accuracy varies seasonally or at high or low values.

Pearson's Correlation coefficient R measures a linear correlation between two variables. It is used here in addition to R^2 because when it is negative it shows an anti-correlation, whereas R^2 is always positive. R is also useful for comparison with other studies.

1.3 Novelty of the research question

Whilst most researchers agree that a net zero energy system [4] is possible, there is much debate on how best to achieve it [5]. Seven plans for achieving a net zero UK from four different groups, are reviewed in [19]. All contain high proportions of electricity generation from wind and solar PV, but all vary in their proposed mix of technologies. All the plans propose energy storage to cope with periods of low renewable generation and high demand, both on a short-term basis at the scale of hours and days and on a long-term basis of seasons or years. Heating is provided by electric heat pumps, hydrogen boilers or by district heating. The plans model all sectors, not just heating and transport.

The plans mentioned above are either prescriptive, ie they propose a certain technology mix and prove that it will work, or they do some optimisation, but only using a single

year of data. However research has found that 10 years or more is required to capture the variation in renewable power generation caused by weather to fully test an energy model [11]. One UK study considering all sectors, that used 10 years of data [34] only considers one mix of technologies and proves that it is viable. There are two UK studies that look at different amounts of storage required for long term weather fluctuations. One study uses 9 years weather data [52] and one uses 30 years [41]. However, both these studies use only the historic electricity demand and do not include changes to demand such as electrification of heat. One study that did consider varying amounts of wind, solar and storage, and also included weather dependent electrification of heating and transport [53], concentrated only on a 3-year period between 2009 and 2011

In summary, most previous studies fall into two groups:

- Those that try to model the whole energy system or electricity system for a small number of years and prove that a certain configuration is feasible.
- Those that model a smaller subset of the system for a large number of years looking for optimum configurations of energy storage.

Those studies that look at energy storage for a large number of weather years have not generally considered electrification of heating. And those that do consider electrification of heating have either used a small number of weather years or did not consider storage. Also, they look at the feasibility of a complete 2050 scenario, rather consider the impact of one sector, such as heating. But to make a policy decision in one sector it is important to understand the impact of a change to it on the whole system. This study addresses that gap. This project uses 40 years of historic weather to study how the future decarbonization of heat and transport will impact the mix of solar, wind and storage in a power system with a high penetration of these technologies.

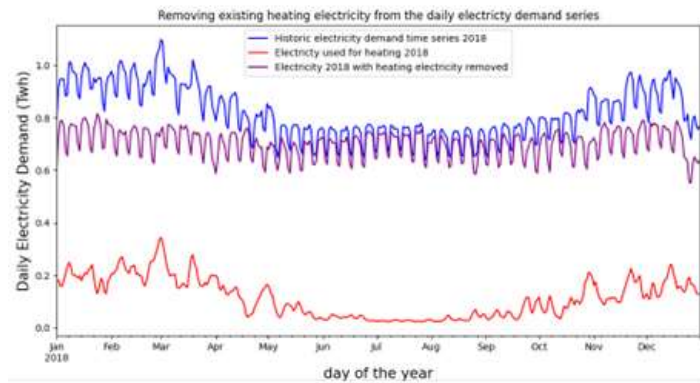
More detailed discussions on some of the references mentioned above are available in other parts of the thesis as listed below:

- A study on how the UK could be powered by 100% renewable energy [34] is also discussed in section 2.1 in the background to heat demand and the HDD 12.8 method.
- A study of seven plans for a UK net zero energy system [19] has already been mentioned in table (1-3) in the context of energy storage. It also features in a discussion on energy modelling in 1.2.5 and the relative proportions of wind and solar generation in 5.1.
- The two previous studies on the wind/solar/storage mix for the historic demand [41] and [52] are discussed in detail in 5.1 and chapter 7.

1.4 Brief Introduction to Thesis Methods and Results

To provide a context for the next chapter on the novelty of the work, a very brief summary of the main work of the thesis is presented. This also serves as a guide to the reader as to where the first 6 chapters are headed. Figure (1-1) provides a concise introduction to the main process in this thesis to identify the impact of heating electrification alone on shares of wind, solar and energy storage. It shows the main steps which are:

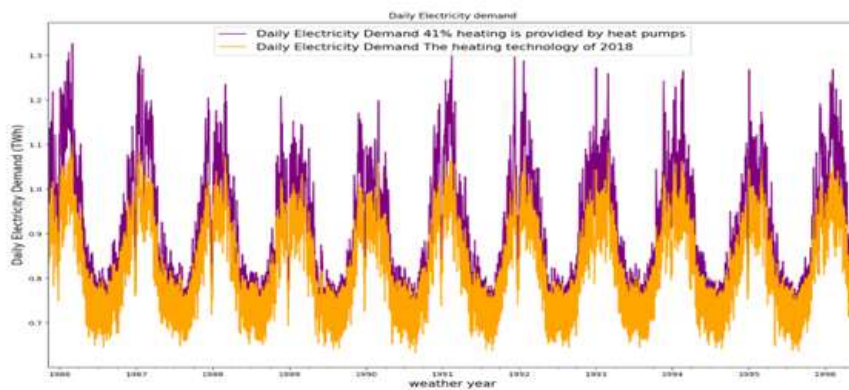
- Remove the heating electricity from the 2018 historic electricity demand time series illustrated by the graph on the top left. This gives a base line electricity demand without heating so that technology and socioeconomic factors are fixed at 2018 levels. This will allow us to study the impact of heating alone.
- Add in the heating electricity based on 40 years historic temperatures, illustrated by the weather reanalysis grid on the top right.
- Create two 40-year UK electricity demand time series. Everything other than heating is the same as for 2018. One time series includes heating based on today's heating technology and 40 years weather. The other includes 41% of heating provided by heat pumps for 40 years weather. These two time series are shown in the middle plot of figure (1-1)
- Feed these two electricity demand time series into a model that balances the demand with generation from wind, solar, base load and dispatchable power sources. For a range of wind and solar generation capacities the minimum required energy storage is calculated. This is shown by the two 3D plots at the bottom of figure (1-1) for a future electricity system with generation consisting only of baseload, wind and solar PV.
- Perform a detailed comparison of the data behind these two 3D plots to enable part of the main research question of the thesis to be answered: how the future decarbonization of heat and transport will impact the optimum mix of solar, wind and storage in a power system with a high penetration of these technologies. This comparison is based on the amount of storage and the wind energy fraction. Wind energy fraction is the proportion of the combined wind and solar energy generation which came from wind.



40 years temperatures



Two 40-year UK electricity demand time series: one has the heating technology of 2018, one has 41% heat pumps



Minimum storage for different wind and solar capacities

Base load 0.4 existing heating

Base load 0.4 electrified heat 41% heat pumps

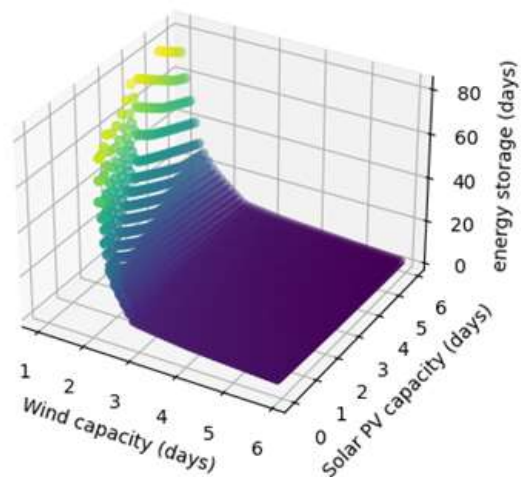
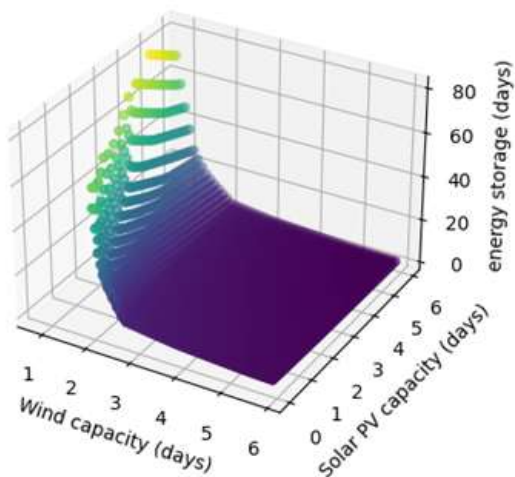


Figure 1-1 Modelling the impact of heating electrification on wind, solar and storage in this thesis.

1.5 Novelty of the approach

The novel aspects of this work are:

- a comparison of heat demand methods, linear regression on the gas time series to identify what portion is heat and validation against measured data not previously used for this purpose.
- a modification of the when2heat heat demand method using hourly temperatures and UK COP curves
- the inclusion of hybrid heat pumps
- the method of generation of electricity demand time series from the heat demand via proportions of heat pumps
- derivation of a heat pump hourly profile from trial data
- using a generated heating electricity time series to remove the heating electricity, rather than linear regression.
- analysis of the seasonal and interannual variation, rather than peak demand.
- investigation to establish if heating is the only significant weather dependency in the electricity demand time series.
- the algorithm to find the minimum storage, and the use of more accurate model inputs than those used in previous studies.
- investigation of the impact of heating and transport electrification on optimum UK wind energy fraction and energy storage capacity.
- updates to the findings of previous studies into UK energy storage mix
- a sensitivity analysis of the required storage to different model inputs from this and two previous studies.
- assessing the impact on wind energy fraction of green hydrogen boilers under long term weather variation.

1.6 Thesis Structure

Some of the chapters make use of results from previous chapters. See figure (1-2) for a diagram of this relationship. The three chapters that follow the introduction, shown in red on the diagram are concerned with how to generate an electricity demand time series incorporating the change to heat pumps alone. Most of this material is also published as a paper [54] in the Applied Energy journal.

- Chapter 2 is concerned with creating national heat demand time series. The heat demand is used in chapter 3.
- Chapter 3 – is concerned with creating a heating electricity time series using the heat demand from chapter 2. This heating electricity time series is then used in chapter 4.
- Chapter 4 – uses the heating electricity demand from chapter 3 to generate national electricity demand time series including the impact of heating alone. The resulting time series are then used to study the impact of heating electrification on UK electricity demand. They are also used in the remaining chapters to study the impact on storage and generation.

Chapters 5 and 7, shown in green, consider the energy storage model itself and chapter 6, shown in blue uses the model to find the impact of heating electrification on the mix of wind, solar and storage capacities.

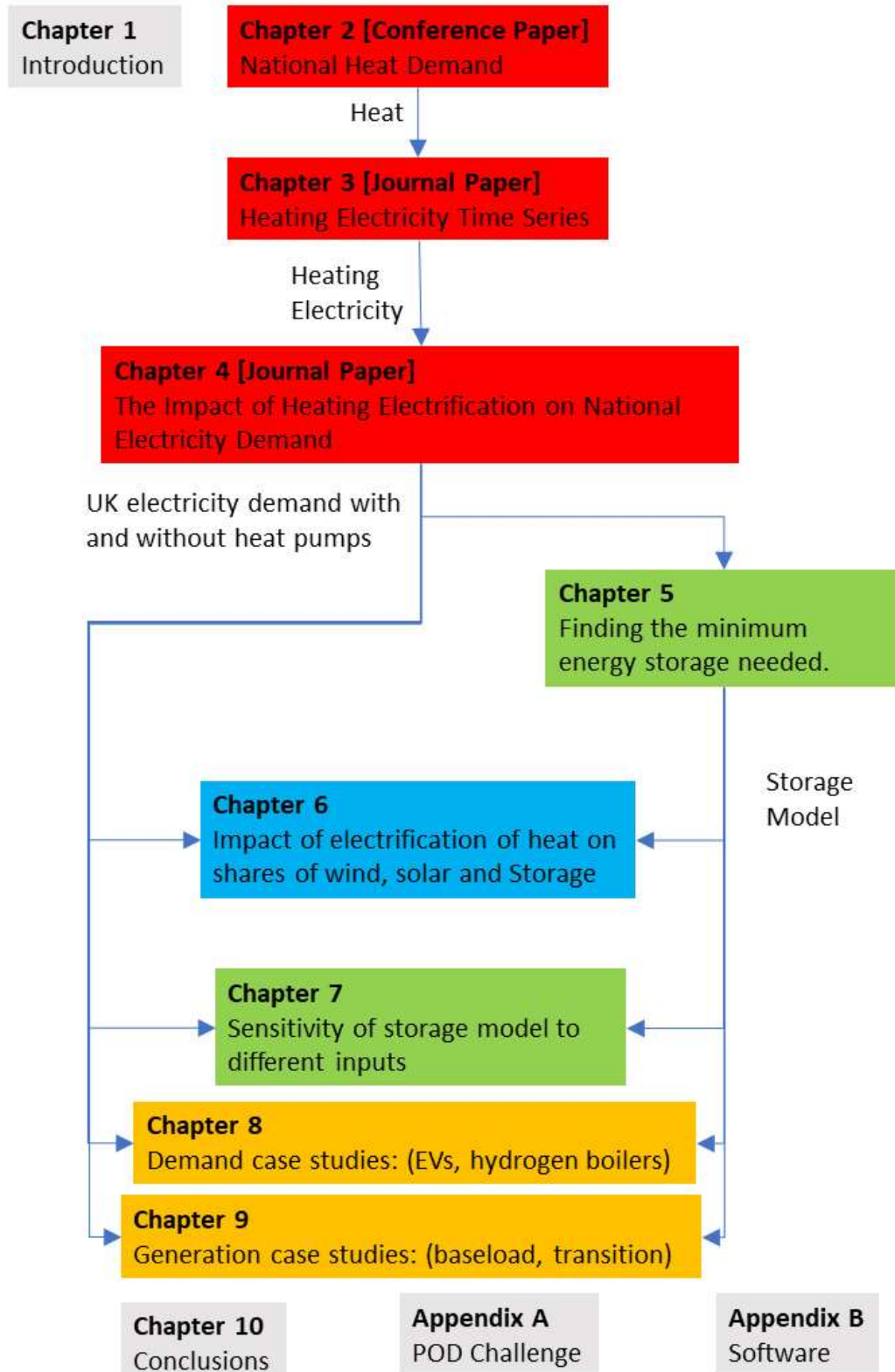


Figure 1-2 Thesis Chapter Relationships

- Chapter 5 defines the methods used to find the required energy storage from different generation capacities. The model is validated against that used in a previous study and against today's energy system. The model is then used to show that many configurations of wind and solar capacity with energy storage can satisfy the UK electricity demand with the existing heating technology from chapter 4. Energy and cost are used to identify which of these configurations to study in more detail. Section 5.3.1 contains a standard way of summarising experiments used throughout the thesis.
- Chapter 6 combines the electricity demand from chapter 4 and the storage model from chapter 5 to investigate the impact of the electrification of heat. Different ways of comparing results are discussed and illustrate this impact.
- Chapter 7 uses the energy storage model and improved model inputs defined in chapter 5 to perform a sensitivity analysis of these different model inputs on capacities of storage, wind and solar. Some investigations on the impact of length and resolution of time series are done.

The final chapters consider the impact of other changes to demand and generation on storage and shares of wind and solar.

- Chapter 8 investigates the impact of two changes to demand on generation and storage. The first is Electric Vehicles with the novel aspect of weather dependent EV charging. The second introduces a modification to the storage model to compare the impacts of heating using hydrogen boilers or heat pumps.
- Chapter 9 includes some case studies on power generation with the model:
 - The transition from a system with a high proportion of dispatchable generation to one with a high wind and solar penetration.
 - The relationship between storage and wind and solar.
 - Baseload and storage
 - Lost Energy
 - Long term pattern of energy store state of charge
 - Alternative ways of estimating the optimum wind energy fraction

Chapter 10 presents the overall conclusions. All the models are programmed in the Python programming language by the author. Some of the software developed during the project is described in appendix A. Appendix B describes participation in a competition to forecast electricity demand peaks and troughs from historic demand and weather data. Appendix C lists the corrections requested by the examiners.

2 National Heat Demand

A national heat demand time series is the first step towards the generation of heating electricity demand. This will help answer one of the subsidiary research questions: How should an electricity demand time series incorporating heating electrification alone under long-term weather fluctuations be generated? This national heat demand time series must vary from day to day and year to year only according to weather. All other factors such as population, internal temperatures, insulation, and the number of buildings should be kept constant. Generating this heat demand time series is the subject of this chapter.

The chapter will start by reviewing previous work. Four different methods of generating 40-year daily heat demand time series will be described. They will be compared and validated against historic national gas time series and measurements from gas smart meters and heat pump trials. The chapter concludes by identifying the best heat demand method from the four which will be then used in the following chapter to generate electricity demand time series.

2.1 Background

Whilst estimating the heat demand of one building is possible by measuring internal and external temperatures and the input fuel energy, knowing the heat demand of an entire country is very difficult [51]. Various methods of modelling heat demand have been used in previous work. For example, a regression model based on district heating measurements in Norway [55] was used to aggregate the heating loads of several buildings to represent a region within a city, but not an entire country. In a UK study [56], national gas demand for the years 1998-2010 was used to create a linear regression model to predict gas usage and hence heat demand from external temperature. Gas smart meter trial data from over 6000 homes from May 2009 to July 2010 were used to create a model to predict UK half hourly domestic gas demand [51]. However, these bottom-up statistical models all represent the housing stock as it was at the time of the measurements, limiting their use. An alternative approach is to use simulations. A building thermal model [57] was used to simulate heat pumps at 2-minute intervals for 960 buildings which were then aggregated to represent the national demand based on 2011 climate data. However, bottom up aggregated thermal models have uncertainty over the many different parameters that need to be specified [58] and have difficulty capturing diversity on a national scale[59] .

Multi-year daily national heat demand time series are typically generated top down as part of the procedure to generate a synthetic electricity demand. In one study of a 100% renewable UK electricity system [34] a specific heat space loss of 4.4 GW/K and a base temperature of 12.8 °C combined with UK national temperatures were used to create 10 year daily heat demand. Heating degree days with a base temperature of 15.5 °C with UK population weighted temperatures were used to generate 30 years heat demand time series in [30]. The when2heat dataset [38] contains time series of heat demand for 2008-2013 created using population weighted temperatures and a method based on German gas usage. Nothing was found in the previous literature comparing these different heat demand methods against each other. Therefore, a comparison of four heat demand methods based on the three references above and a regression equation from

[51] in the previous paragraph was undertaken. These four methods of generating daily heat demand time series were compared for the years 2016 to 2019 and reported in a conference paper[60]. For convenience the heat demand methods have been given the names **BDEW**, **Watson**, **HDD 15.5** and **HDD 12.8**. They are listed below, along with a reference to the previous work they were based on.

- **BDEW** The German gas company's equation to estimate consumers gas usage from the when2heat dataset [38].
- **Watson**: a method based on a regression equation based on UK building measurements from Watson et. al. [51] .
- **HDD 15.5**: Heating Degree Days (HDD) with a base temperature of 15.5° as used in two previous studies [30, 61].
- **HDD 12.8**: HDD with a base temperature of 12.8° as used in a study of a 100% renewable UK energy system [34].

The comparison and validation of these methods performed in this study uses not only historic national gas time series, as typically done in previous works [38], but also measurements of heat and gas usage from actual buildings, data sets that have not been used previously for this type of validation. The next section describes the methods used to create these time series.

2.2 Methods

A standard method of assessing heating demand is the concept of heating degree days (HDD). HDD are a measure of how long in days and how much in degrees the outside temperature was below a certain level called the base temperature. The definition is given by equation (2).

$$HDD = \sum_{d=1}^{ND} \begin{pmatrix} T_{base} - T_d : T_d < T_{base} \\ 0 : T_d \geq T_{base} \end{pmatrix} \quad (2)$$

Where T_d is the mean temperature for day d , T_{base} is the base temperature (generally 15.5 °C for the UK), ND is the number of days in the year. HDD will be used in the following sections.

The procedure to create the heat demand time series is split into two parts expanded on in the next two sub-sections.

1. Calculate the annual heat demand for Great Britain from fuel use.
2. Split this annual demand geographically amongst weather grid squares and temporally between days. Sum up all the grid squares to generate a daily national heat demand time series.

2.2.1 Calculate annual Great Britain heat demand.

The first step is to calculate the Great Britain annual heat demand. Annual energy demand for space heating and hot water broken down by fuel use was taken from table U2 in energy_2019_end_use_by_fuel.xlsx [8]. This data is based on consumer surveys, annual fuel sales and monitoring. For the years 2016 - 2018 the data includes a more

detailed breakdown of space and water heating by fuel. This enables a more detailed validation of the gas time series. Therefore, the year 2018 was chosen as the most recent of these years to represent the existing heating technology. This data is shown in table (2-1) converted to heat energy assuming the following efficiencies: gas 80%, electricity 100%, other made up of: oil 85%, solid fuel 76%, heat (eg combined heat and power) 100%, bioenergy and waste 87%.

Table 2-1 Annual UK Heat Energy for 2018

Heat Use	A_a	$\alpha(a)$	Annual Heat Energy by Fuel (TWh)			
			Gas	Electricity	Other	Total
Domestic Space	A_{ds}	space	191	18	50	259
Services Space	A_{ss}	space	56	16 (*)	27	99
Domestic Water	A_{dw}	water	56	5	6	67
Services Water	A_{sw}	water	7	2	4	13
Total			310	41	87	438
(*) Note that the services space also includes industrial space because this is included in the historic electricity time series (whereas industrial gas is not)						

This gives a UK annual heat demand for 2018 of 438 TWh. However, the process of generating a daily heat demand time series in the next section will use the individual values for each heat use A_a determined by $\alpha(a)$. The column of values from table (2-1) that is used depends on the objective:

- For generating a heat demand time series for the whole country, values from the **total** column would be used.
- For generating a heat demand time series for validation against daily gas demand, the **gas** column would be used.
- To generate a heat demand time series representing the heating in the historic electricity demand, the **electricity** column would be used.

To get the values of these annual demands for years other than 2018, they are factored by the ratio of heating degree days to that year. This fixes heating and insulation levels at 2018 levels but keeps the impact of weather.

$$A_{a,y} = \frac{HDD_y}{HDD_{2018}} A_{a,2018} \quad (3)$$

Where HDD_y is the number of heating degree days for year y calculated from the UK population weighted temperature and $A_{a,y}$ is the annual heat demand for heat use a for year y . The parameter $A_{a,2018}$ is one of (A_{ds} , A_{ss} , A_{dw} , A_{sw}) taken from table (2-1).

2.2.2 Calculate Daily Heat demand.

The next step is to calculate the heat demand for each UK weather grid square. The $0.25^\circ \times 0.25^\circ$ grid is defined by the ERA5 weather reanalysis [37] and contains hourly 2m ambient air temperatures for the UK for the years 1980 to 2019. The population for each of these grid squares was taken from Eurostat [62] for 2011. The four annual heat demands for the UK calculated in the previous section in table (2-1) were split up amongst these weather grid squares by population weighting as follows.

$$A_{a,g} = \frac{A_a \cdot P_g}{\sum P_g} \quad (4)$$

Where $A_{a,g}$ is the annual heat demand for grid square g for heat use a . The parameter a is used to look up A_a the annual heat demand from table (2-1) and P_g is the population in grid square g . Note that this is repeated for each year, but the y subscript from equation (3) is not shown for clarity. This annual demand was then split into days using equation (5).

$$H_{a,d,g} = \frac{A_{a,g} \cdot f_{d,g,\alpha(a)}}{\sum_{d=1}^{ND} f_{d,g,\alpha(a)}} \quad (5)$$

Where ND is the number of days in the year, $f_{d,g,\alpha(a)}$ the daily demand factor for heat use a , day d and grid point g . Each of the four methods of calculating daily heat demand has two versions of $f_{d,g,\alpha(a)}$ one for space heating and one for water heating. The parameter $\alpha(a)$ indicates which of the two equations for the method in table (2-2) is used to calculate the demand factor $f_{d,g,\alpha(a)}$ for heating use a . For $a=ds$ or $a=ss$ the space heating version $f_{d,g,space}$ is used. For $a=dw$ or $a=sw$ the water heating version $f_{d,g,water}$ is used. There are different sets of these two equations, one set for each of the four methods as shown in table (2-2).

Table 2-2 Temperature dependent equations to factor annual heat demand

Method	Demand factor equation (f)	N
BDEW space [38]	$f_{d,g,space} = \frac{A}{1 + \left\{ \frac{B}{T_{d,g}^{Ref} - T_0} \right\}^C} + D + \max \left(m_{space} - T_{d,g}^{Ref} + b_{space}, 0 \right)$	4
BDEW water [38]	$f_{d,g,water} = \begin{cases} D + m_{water} \cdot T_{d,g}^{ref} + b_{water} & T_{d,g}^{ref} > 15^\circ C \\ D + m_{water} \cdot 15 + b_{water} & T_{d,g}^{ref} \leq 15^\circ C \end{cases}$	4
Watson space [51]	$f_{d,g,space} = \begin{cases} -6.71 T_{d,g}^{Ref} + 111, & \text{for } T_{d,g}^{Ref} < 14.1^\circ C \\ -1.21 T_{d,g}^{Ref} + 33, & \text{for } T_{d,g}^{Ref} > 14.1^\circ C \end{cases}$	2
Watson water [51]	$f_{d,g,water} = -0.0458 T_{d,g}^{Ref} + 1.8248$	2
HDD 15.5 space [30]	$f_{d,g,space} = \begin{cases} 15.5 - T_{d,g}^{Ref}, & \text{for } T_{d,g}^{Ref} < 15.5^\circ C \\ 0, & \text{for } T_{d,g}^{Ref} > 15.5^\circ C \end{cases}$	1
HDD 15.5 water [30]	$f_{d,g,water} = 1.0$	
HDD 12.8 space [34]	$f_{d,g,space} = \begin{cases} 12.8 - T_{d,g}^{Ref}, & \text{for } T_{d,g}^{Ref} < 12.8^\circ C \\ 0, & \text{for } T_{d,g}^{Ref} > 12.8^\circ C \end{cases}$	1
HDD 12.8 water [34]	$f_{d,g,water} = 1.0$	

Where T_0 is 40°C and $A, B, C, D, m_{space}, m_{water}, b_{space}, b_{water}$ are factors taken from the code download for [38]. These factors depend on:

- UK 40-year mean wind speed – a different value for the factor is used depending on weather the grid point is classed as windy (90 grid points) or normal (12 grid points). This classification comes from the German gas company. Monthly mean 10m wind speeds for 1979 to 2018 from ERA5 weather reanalysis [63] were used to identify these windy and non-windy locations.
- Type of building which is determined by $a=ds$ or $a=dw$ (domestic: multi-family house 30% / single family house 70%) or $a=ss$ or $a=sw$ commercial building.

The reference temperature $T_{d,g}^{Ref}$ in table (2-2) was calculated using equation (6) based on the mean daily ambient temperatures of the N previous days to account for the thermal inertia of buildings.

$$T_{d,g}^{Ref} = \frac{\sum_{n=0}^N 0.5^n T_{d-n,g}^{amb}}{\sum_{n=0}^N 0.5^n} \quad (6)$$

Where $T_{d,g}^{Ref}$ is the reference temperature for day d at grid point g and $T_{d,g}^{amb}$ is the mean ambient air temperature for that grid point and day. The value of N depends on the heat demand method used as shown in table (2-2) (for $d < N$, $N=d$). For each of the four heat demand methods there will be four heat demand time series $H_{a,d,g}$ from equation (5) where a represents the heating use from table (2-1). The domestic and services series were added together to end up with two series, one for space heating:

$$H_{space,d,g} = H_{ss,d,g} + H_{ds,d,g} \quad (7)$$

and one for water heating

$$H_{water,d,g} = H_{dw,d,g} + H_{sw,d,g}. \quad (8)$$

Where $H_{space,d,g}$ is the space heating time series for day d and grid point g , and $H_{water,d,g}$ is the water heating time series. These two daily heat time series at each weather grid point are used as input to the process of generating a heating electricity demand time series in chapter 3. However, for validation, the contributions from each grid point are added together to create a daily heat demand time series H_d for the whole country.

$$H_d = \sum_{g=0}^{NG} (H_{space,d,g} + H_{water,d,g}) \quad (9)$$

Where NG is the number of grid points. The process defined by equations (2-8) is repeated for each of the 40 years of weather.

Two limitations of this method should be noted:

- It assumes that all regions of the country have similar standards of buildings and thus heat demand for a given temperature.
- Population distribution is not changed significantly from 2011.

2.3 Validation of Heat Demand Generation Methods

This section describes how the four methods of generating heat demand time series listed in section 2.1 were validated. The four heat demand methods were compared and validated against:

- National gas time series
- Heat demand measurements from domestic houses
- Gas usage measurements from public buildings in a smart meter trial.

2.3.1 Validation against national Gas

The objective of this section is to validate the four heat demand methods against UK national gas demand. Natural gas provides a large proportion of UK heating. Measurements of gas usage in over 6000 UK homes [51] showed that it is highly correlated with heat demand and can be used to predict it. Some studies [7] have even used it to generate their heat demand time series, using the simplifying assumption that all gas is used for heating. Therefore, gas usage can provide a validation of the heat demand time series generated here from weather.

Various historic gas time series are available from national grid gas data explorer [64]. The Non-Daily Metered (NDM) daily gas demand time series comes closest to including all heating. It was therefore used in this study to validate heat demand time series. However a previous study [38] which used the 2013 UK gas demand for validating heat demand time series identified that there is some uncertainty about how much of this is actually used for heating. This is because the time series also contains an unspecified amount of non-heat uses, as reported in government figures [65]. This discrepancy is shown as unknown use in table (2-3) for 2018. Using the unmodified gas time series as a ground truth for validation is potentially inaccurate. Therefore, the gas time series was investigated to ascertain how much of it is used for heating.

Table 2-3 - portion of the 2018 historic gas time series for which it is not known if it is used for heating or not

Sum of the 2018 gas time series converted to heat using an efficiency of 0.8 [64]	435 TWh
Gas heating energy for space and water heating derived from government surveys and sales figures [8], table(2-1)	310 TWh
Unknown use	125TWh

Figure (2-1) shows a strong correlation for 2018 between gas energy use and heating degree days. It was assumed that the part of the gas demand that is dependent on heating degree days is used for heating and that the remainder is not.

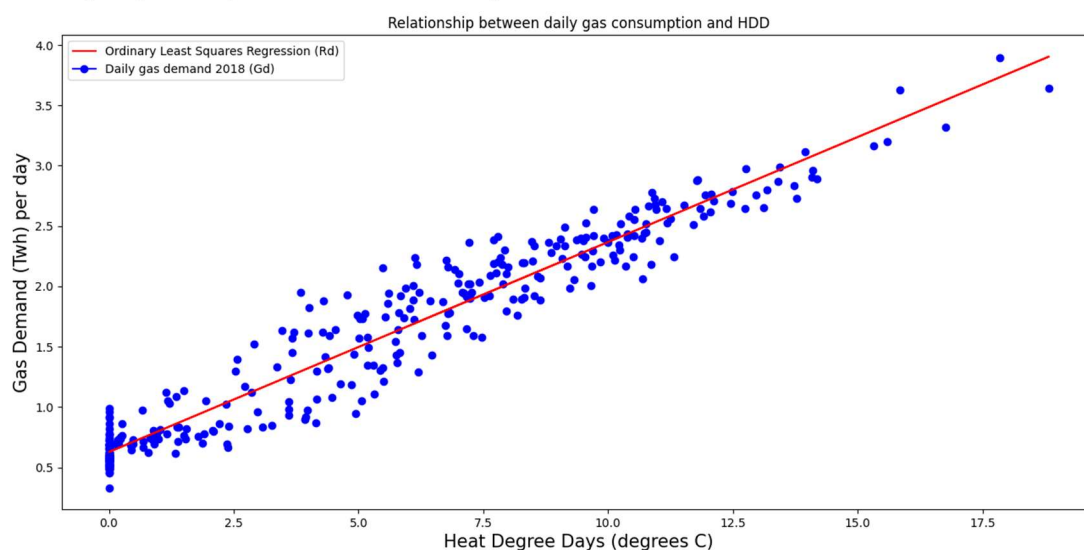


Figure 2-1 Relationship between daily Great Britain gas consumption and heating degree days 2018

A standard method of estimating the proportion of the electricity demand time series used for heating is to use linear regression on heating degree days [13, 66]. The same

procedure was used here on the daily gas time series, to find the constants a_0 and a_1 in equation (10). This was done separately for 2016, 2017 and 2018, the years for which detailed gas data is available.

$$R_d = a_0 + a_1 hdd_d \quad (10)$$

Where R_d is the daily (d) gas time series found by the regression, and hdd_d is the heating degree days for day d calculated using a population weighted mean daily UK air temperature and a base temperature of 15.5°C. The time series of gas used for heating is therefore given by $a_1 hdd_d$ so the gas not used for heating can then be estimated as equation (11)

$$D_d = G_d - a_1 hdd_d \quad (11)$$

Where D_d is the daily gas time series without the gas used for heat and G_d is the historic daily gas time series, which are plotted in figure (2-2) showing that its use as a method of removing the heating energy looks plausible.

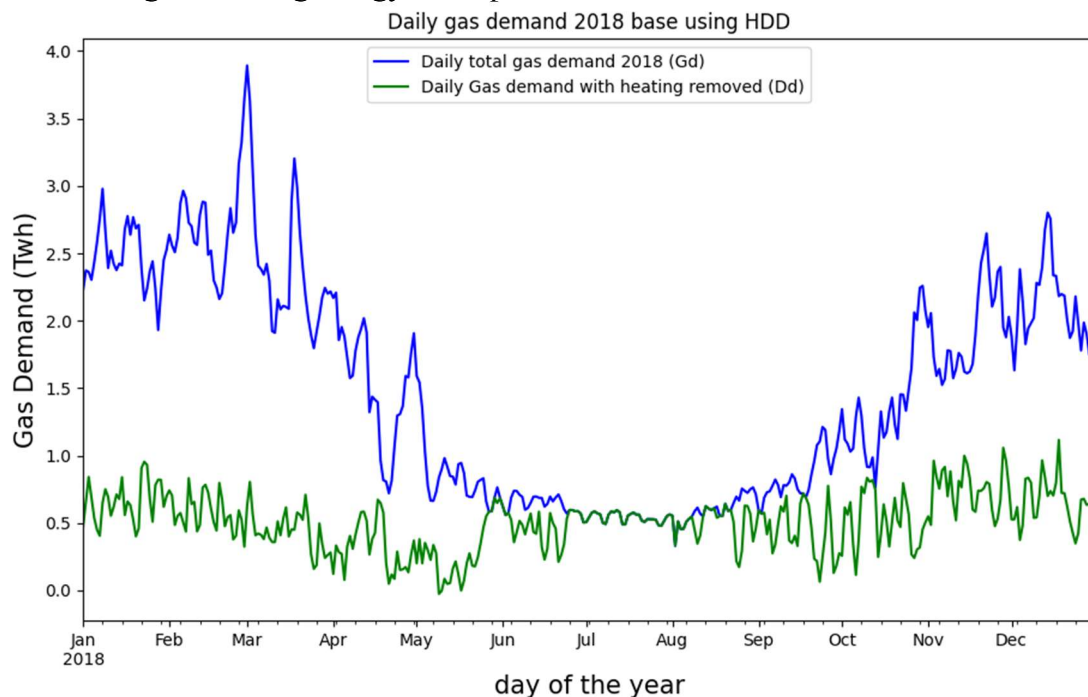


Figure 2-2 Daily gas demand and daily gas demand with gas used for heating removed

The sum of D_d from equation (11) is 162 TWh for 2018 and provides an estimation of the non-heat gas. To convert to heat demand, it is multiplied by 0.8, consistent with table (2-1) for gas boiler efficiency giving 129.6 TWh. This is close to the unknown 125 TWh from table (2-3) therefore, it was concluded that this unknown use portion is not used for heating. A similar result was found for 2016 and 2017 with the percentage of heat in the gas time series varying by 2% between the years 2016-2018 and the linear regression having a coefficient of determination R^2 between 0.90 and 0.94.

It should be noted that HDD are used to estimate space heating, not water heating. Some of the methods being validated listed in table (2-2) assume that hot water is constant throughout the year. However, some of the methods assume hot water is dependent on external temperature, but not HDD. This does cast some doubt on the justification for assuming that all the unknown portion is not heating. But since only 20% of gas heating use is for hot water (table 2-1), it does not compromise the validation too much, and is certainly more accurate than assuming it is all used for heating.

Using this result that the unknown use portion of the gas is not used for heating, a time series of heat for 2016-2018 was generated from the gas time series using equation (12)

$$H_d = 0.8G_d - \frac{125}{ND} \quad (12)$$

Where H_d is heat demand from gas for day d , G_d is the daily gas demand, 0.8 is the conversion efficiency of gas energy to heat, 125 is the amount of gas not used for heating, which was deduced above, and ND , the number of days splits this equally amongst days of the year. This heat demand series was then used to validate and compare the four methods described in section 2.2.2

Figure (2-3) shows all four methods of splitting the annual heating energy into days for 2018 along with a blue line for the gas heat demand time series. It can be seen that the HDD 12.8 method matches the gas time series less well, overpredicting at periods of high demand. In contrast, the other three heat demand methods over predict in summer and consequently under predict in winter. The graphs for 2016 and 2017 (not shown here) show a similar pattern.

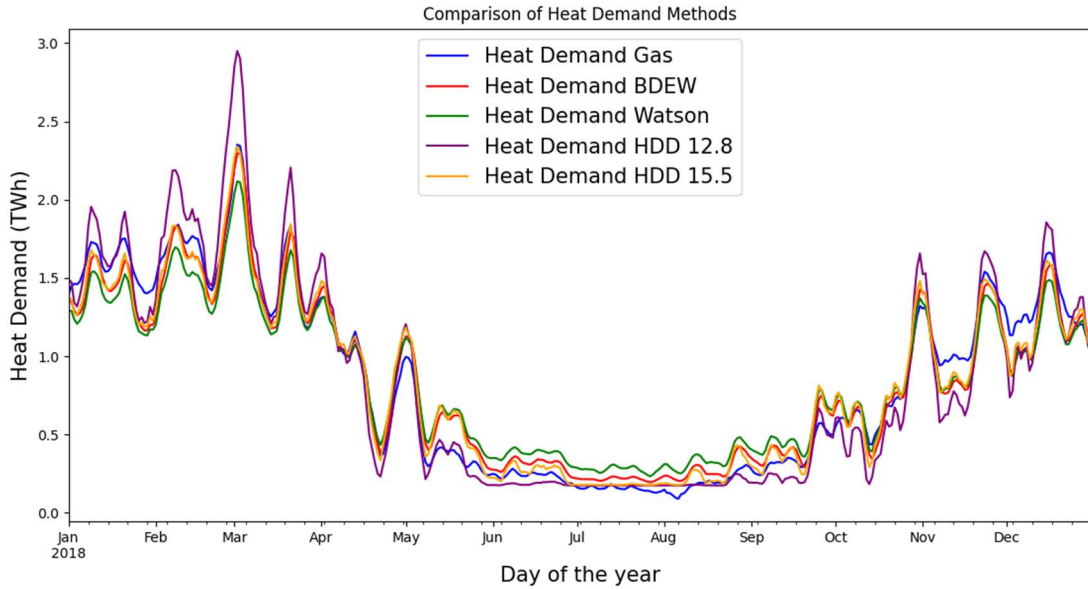


Figure 2-3 Heat demand methods compared to heat demand from gas for 2018

The quantitative results of this validation against the gas time series are discussed further in section 2.3.4 following the validations against the other data sources.

2.3.2 Validation of heat demand vs heat pump trial data

Measured heat pump heat demand was used to validate the four heat demand methods. The heat demand measurements were taken from the Renewable Heat Premium Payment (RHPP) Scheme [67] which monitored 418 UK houses in the period 2012 to 2015. The heat demand was the heat to the hot water cylinder added to the heat from the pump (if not already included in the heat to the hot water cylinder). It was measured by a heat meter consisting of sensors to measure flow of the heat transfer fluid and temperature rise at 2-minute intervals. The original trial report [68] found data quality problems, so only those houses which were part of the validated “B sample (cropped)” were included in this analysis. There were monitoring problems with the trial data where the space heating and water heating values were switched round, so space heating and water heating are considered together in this analysis. The houses were monitored

at different time periods so that at any time a different number of houses were being monitored. Figure (2-4) shows how many houses were being monitored each day over the period of the trial. Each horizontal line in figure (2-5) represents the period over which one house was monitored.

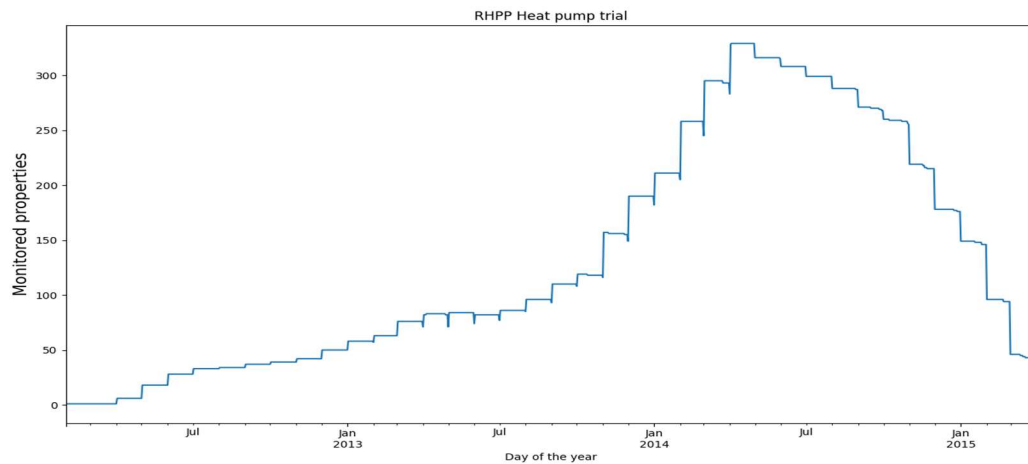


Figure 2-4 Number of monitored houses in the RHPP trial against time

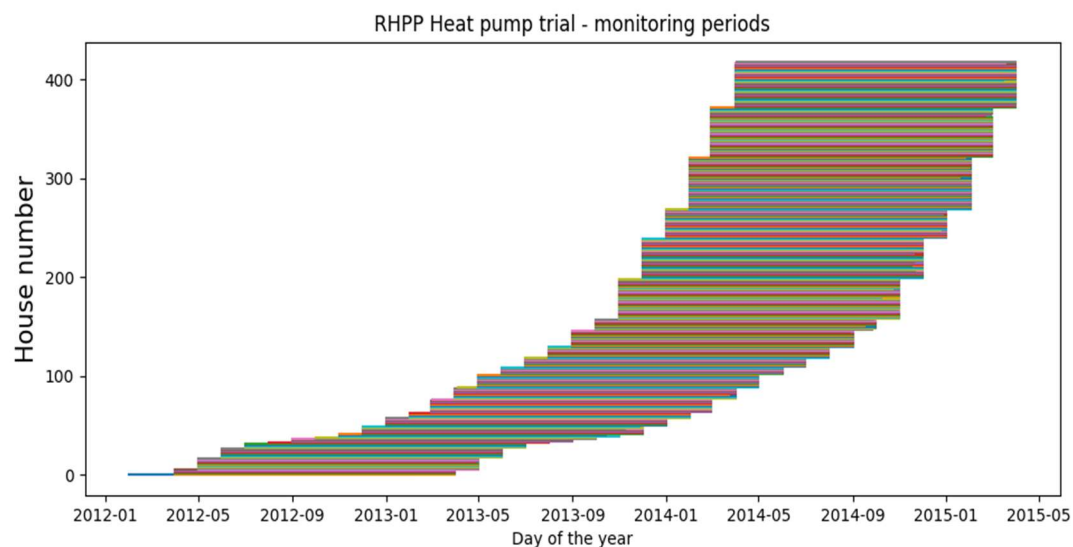


Figure 2-5 Monitoring period for each house in the RHPP trial

Instead of splitting annual demand of the whole country into days, the 4 methods are used to split the total heat demand for each house into days. The total heat demand is calculated by summing the houses' heat time series over the period that particular house was monitored. The objective is not to use these houses to estimate the UK annual demand, but rather to use them to compare how well the different methods work at generating a time series by splitting a total demand over a period into days. Population weighted average air temperature for the whole UK are used from ERA5 reanalysis as the exact location of these houses is not available. This provides five time series for each house: a measured heat demand time series and a synthetic time series for each of the 4 methods in table (2-2). The individual heat demand time series of the houses were merged and aggregated to daily. These time series represent different numbers of houses at different points over the 4-year period.

Figure (2-6) shows the measured heat demands of all the houses from the heat pump trial over the monitoring period compared to that predicted by the four methods of splitting the annual heat demand into days. All the methods predict the pattern of the measured heat demand well. The HDD 12.8 method has some large differences in winter. Note that although some seasonal variation is visible, there is also variation due to the number of houses being monitored at that time. Quantitative results are shown in section 2.3.4 along with the other heat demand validations.

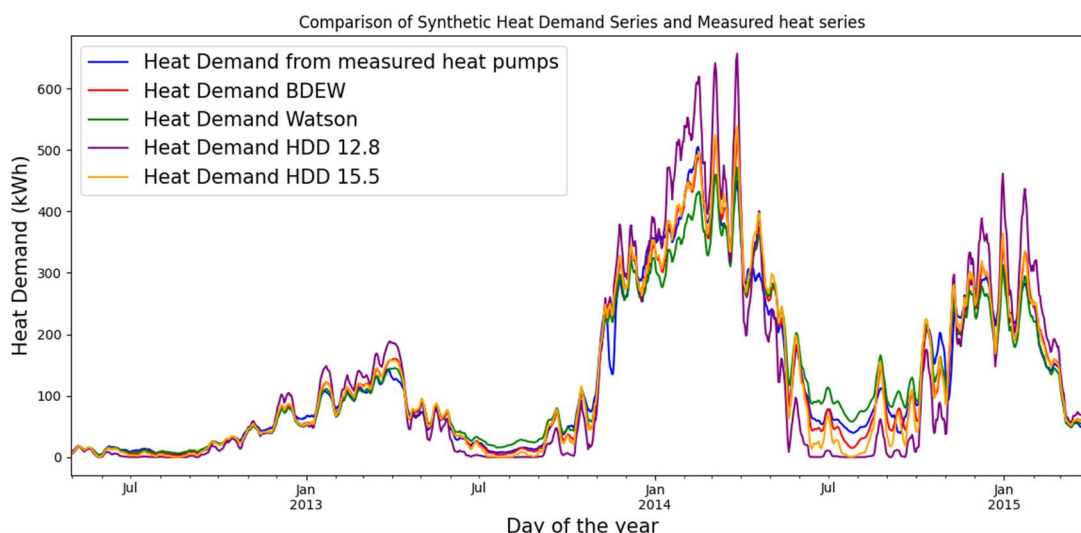


Figure 2-6 Comparison of methods of splitting total heat demand for a group of houses over a period into days using measured heat pump data (7 day rolling average).

Two limitations with this trial data should be noted:

- Some older heat pumps contain a backup immersion heater for hot water to ensure the temperature stays above 60°C for health reasons [21] which would reduce the COP.
- Some of the properties involved in the RHPP had log burners. This would not change the total heat demand measured by the heat pumps. However, it could lead to the heat pump being used less on certain days which would make splitting the annual demand into days based on the weather incorrect.

2.3.3 Validation of heat demand vs gas smart meter data

The four methods of heat demand were also validated using gas meter readings for commercial and public UK buildings. The data comes from a Smart Meter trial [69] by The Carbon Trust. It consists of half hourly gas meter readings in kWh for the period 2004 to 2006 from 51 gas meters in public and industrial buildings. The purpose of the trial was to get customers to try out smart meters and to see if it prompted energy saving behaviour.

The data was processed to remove duplicate values and replace missing values by linear interpolation from surrounding values. The gas meter data from the different public buildings was combined in the same way as the heat pump data in 2.3.2. The gas demand time series from each building were combined and converted to heat demand assuming that all their gas boilers have the same efficiency (0.8) and that all the gas is used for space heating, which is mostly the case[69].

Figure (2-7) shows the heat demand time series derived from the commercial buildings' gas smart meters compared to that predicted by the four methods of splitting the annual heat demand into days. The 2nd winter shows a higher heat demand as more buildings were monitored during this period.

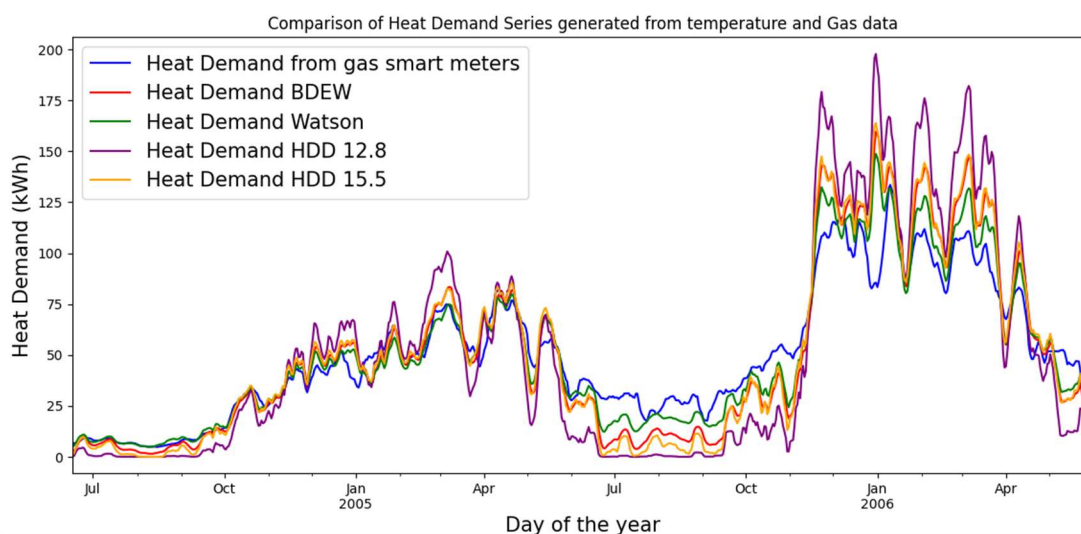


Figure 2-7 Comparison of methods of splitting heat demand over a period into days using gas smart meter data (7 day rolling average).

Two limitations from the study report [69] should be noted:

- The participants in the trial were self-selected and had a greater than average gas demand, and so were not entirely representative of the whole country.
- Some of the buildings were not used at weekends, yet it has been assumed for this analysis that they were.

2.3.4 Summary of heat demand validation

The results of the heat demand validations from the previous 3 sections are summarised in table (2-4). The BDEW method is shown to be better in all cases apart from the gas smart meter validation where the Watson method has the best R^2 . However, it should be noted that neither the group of houses in the heat pump trial nor the commercial buildings in the gas smart meter trial are fully representative of the national stock which may explain discrepancies between the modelled results and those from trials.

Table 2-4 Validation of 4 heat demand methods using 3 different data sources

	National Gas Heat 2016-2018		RHPP Heat Pumps 2013-2015		Gas Smart Meters 2005-2006	
	nRMSE	R^2	nRMSE	R^2	nRMSE	R^2
BDEW	0.12	0.989	0.25	0.977	0.57	0.880
Watson	0.13	0.987	0.26	0.974	0.59	0.896
HDD15.5	0.16	0.982	0.33	0.964	0.63	0.859
HDD12.8	0.30	0.953	0.59	0.912	0.87	0.789

Figure (2-8) shows the residuals plots for the comparison against gas demand. The green line of best fit compared to the red horizontal line shows that the BDEW fit has the least bias.

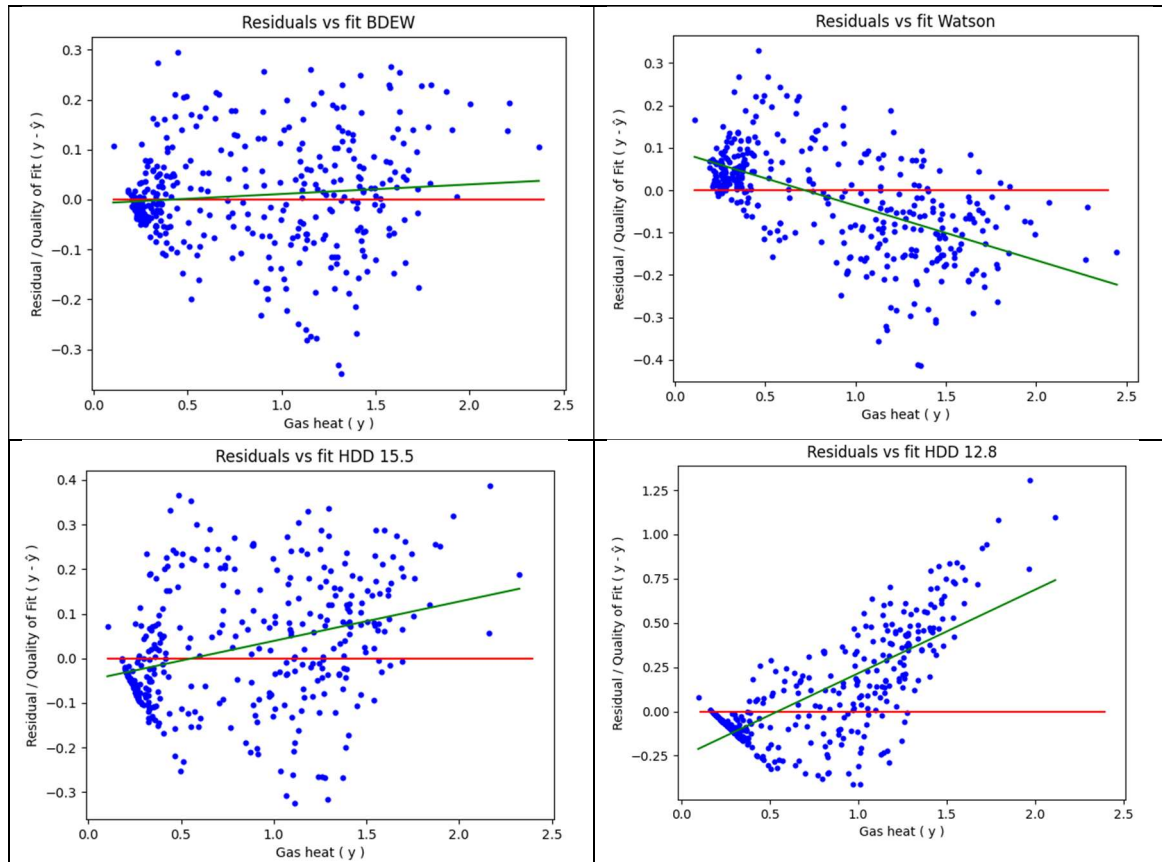


Figure 2-8 Residuals plots for the 4 heat demand methods validated against heat demand from historic gas

2.3.5 Sensitivity to modelling changes.

An experiment was done to compare heat demand time series created using the most accurate ERA5 weather grid of $0.25^\circ \times 0.25^\circ$ with a grid of $0.75^\circ \times 0.75^\circ$ which was that available on the ERA5 interim reanalysis as used in the original paper [38] for the when2heat dataset. It was found that in general the R^2 was unchanged, but that in some cases the nRMSE reduced by about 0.01, showing a small benefit in using a finer grid. The $0.75^\circ, 0.75^\circ$ was grid was used because the benefit of the finer grid was not considered to be worth the additional computational resources required.

Experimental time series were also created with simplified models using no population weighting and using no previous days of temperature. These resulted in a decrease in accuracy (R^2 reducing from 0.982 to 0.970 when validated against gas). It was therefore decided to retain these parts of the model.

2.4 Summary and Conclusions

Daily heat demand time series have been created using four different heat demand methods. The methods have been validated against national gas demand time series, including a regression to show that the unknown portion of the time series is not heating. The methods were also validated against heat pump measurements and gas smart meter data, data sources not previously used for this purpose. The BDEW method

based on the when2heat dataset [38] performed best and was therefore chosen. This is an important result because this method has already been used to provide the UK heat demand input for several previous studies by other authors [70-73]. It was also found that using a finer weather grid did not bring significant improvements. However, using previous days temperatures to account for thermal inertia of buildings and population weighting all improved the results and should be included in the method.

The heat demand time series for the chosen BDEW method will be used in chapter 3 to generate heating electricity demand time series.

3 Creating Heating Electricity Demand Time Series

This chapter concerns the generation of heating electricity time series. Daily heat demand time series from chapter 2 will be used to generate hourly heating electricity time series. The objective is to help answer one of the subsidiary research questions: How should an electricity demand time series incorporating heating electrification alone for long-term weather be generated? The aim is to generate time series for both existing resistive heating and heating provided by heat pumps.

The rest of the chapter is structured as follows. Some background on generating electricity time series, is followed by a description of the method and the assumptions used. The validation against electricity measurements from a heat pump trial is described followed by conclusions.

3.1 Background

Converting a daily heat demand to an hourly heat pump electricity demand involves two steps:

- Use an hourly profile which specifies what proportion of the daily demand occurs during each hour to convert the daily demand to hourly.
- Use heat pump COP to convert heat demand to electricity demand.

Previous work such as the when2heat dataset [38] have used hourly profiles based on gas usage. However, heat pump hourly electricity profiles have lower peaks and a more even spread than gas usage profiles [59]. For this reason, a heat demand profile was derived from UK measurements of heat pump demand and used instead.

Heat pump COP is used to convert heat demand to electricity demand. For example, in a study of a 100% renewable UK energy system [34] a constant COP of 3.0 is assumed. The DESSTINEE model [6] uses a more sophisticated approach with a quadratic based on population weighted daily temperature. The when2heat dataset [38] uses German manufacturers' COP curves to calculate the COP using four temperatures a day at weather grid points. COP is dependent on ΔT , the difference between the temperature of the source (from which the heat energy is taken) and the temperature of the sink (to which the heat energy is delivered). COP curves are produced by measuring COP values at different ΔT s and deriving a quadratic regression equation from the points. In contrast with previous work, COP will be calculated using hourly temperatures at weather model grid points and using UK COP curves.

3.2 Methods

This is the second part of a process that follows on from chapter 2 and finishes with chapter 4. Figure (3-1) shows the whole process.

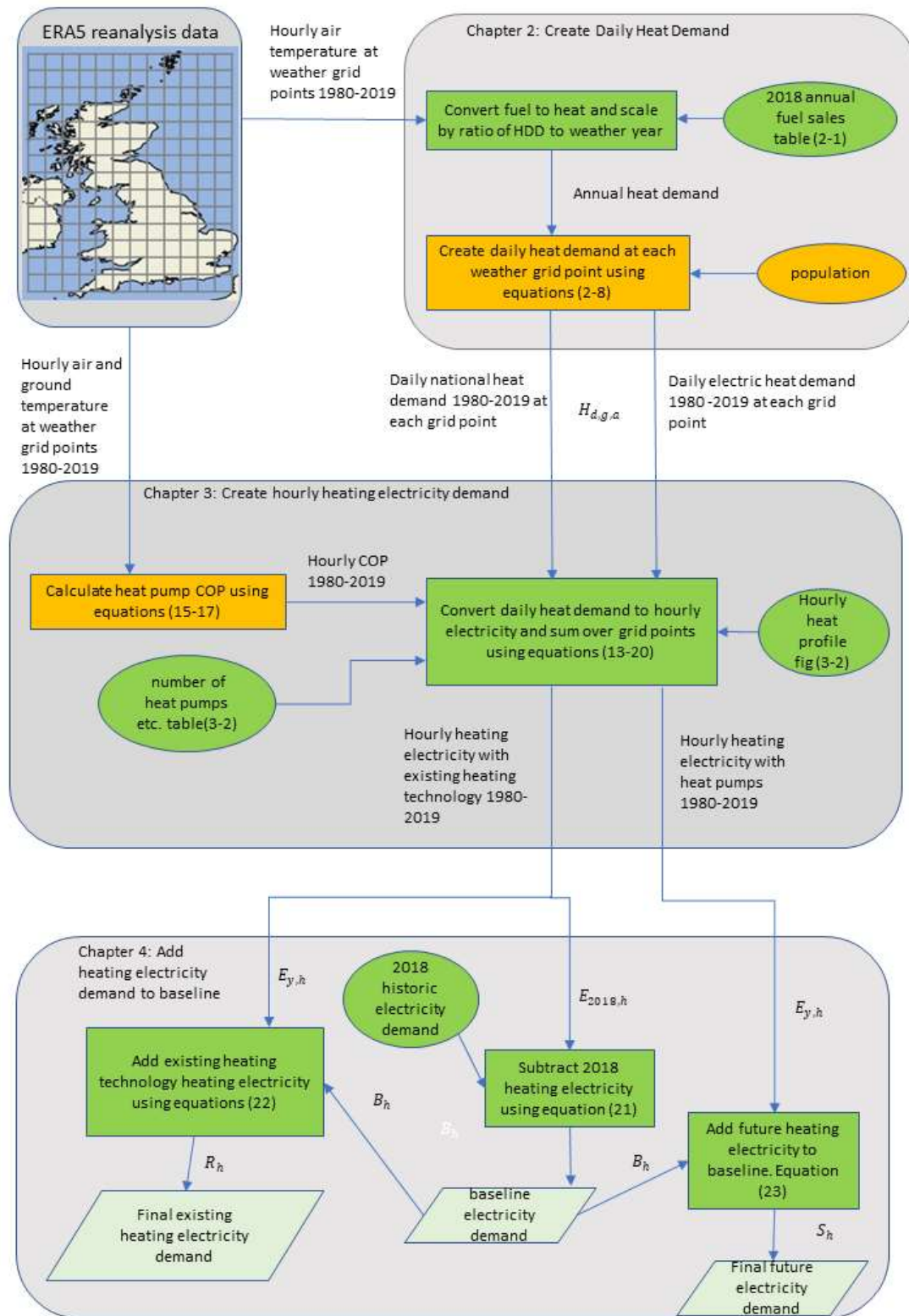


Figure 3-1 Process to incorporate heating electricity for different years into the 2018 historic demand

The process covered in this chapter to convert the daily heat demand to hourly electricity demand consists of five steps:

1. Convert daily heat demand to hourly demand.
2. Calculate hourly heat pump COP for each grid point.

3. Using the results from (1) and (2), calculate heating electricity demand time series due to historic weather at each grid square for both (a) the existing heating and (b) future heating with many more heat pumps. Sum up the contribution from all the grid squares, weighting by population.
4. Calculate the contribution from hybrid heat pumps.
5. Combine all the electricity time series.

3.2.1 Convert the daily heat demand to hourly heat demand.

An hourly profile which specifies what proportion of the daily demand occurs during each hour is used to convert daily heat demand to hourly heat demand. A UK heat pump profile was created using the RHPP heat pump trial data [67]. The heat demand measurements at 2-minute intervals for each individual house were aggregated up to hourly. The data for all houses was then combined into one time series along with the hourly mean population weighted UK temperature. This enabled each heat demand value to be added to a bin representing one of the 24 hours of the day and one of the thirteen 5° temperature bands from -15°C to 40°C. The values were converted to percentages by dividing by the total heat demand for each temperature band. This profile is referred to as the RHPP profile and $J(i, T_h^{amb})$ in equation (13) below.

The RHPP profile and the BDEW profile from the when2heat dataset [38] for the temperature bands -5 °C to 0°C are shown in figure (3-2) and those for 10 °C to 15°C are shown in figure (3-3). Both these profiles are a combination of space and water heating. It can be seen that the BDEW based on gas shows a higher peak in the first half of the day. Since there are other studies on German heat pumps showing a similar pattern [74] it would seem reasonable to assume that this is a difference in consumer behaviour between the UK and Germany, rather than a difference between heat pumps and gas boilers. The impact on the final demand of using a different profile is investigated in 4.5, including the flat profile shown below.

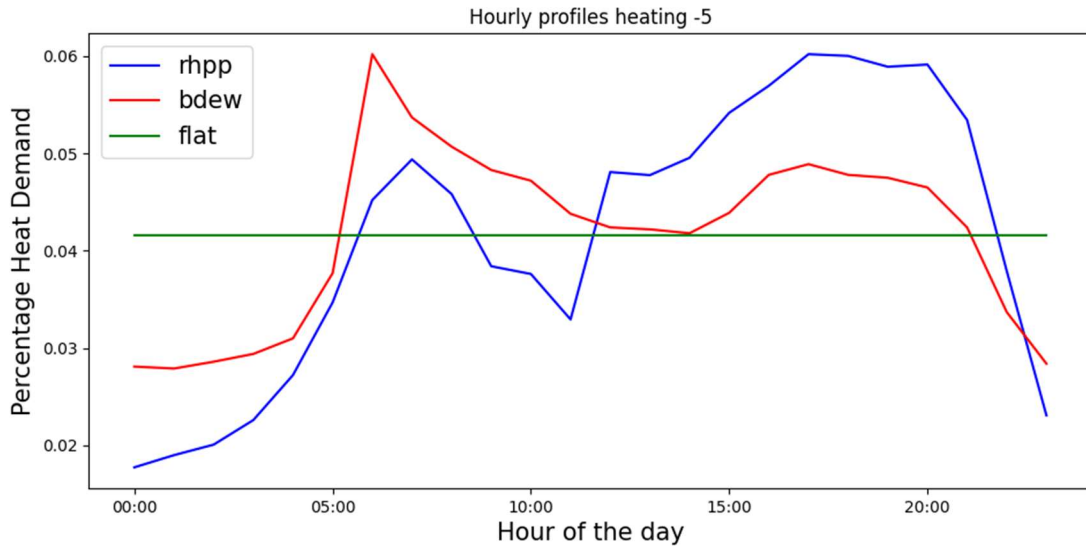


Figure 3-2 Hourly heat demand profiles for external temperature between -5°C and 0°C

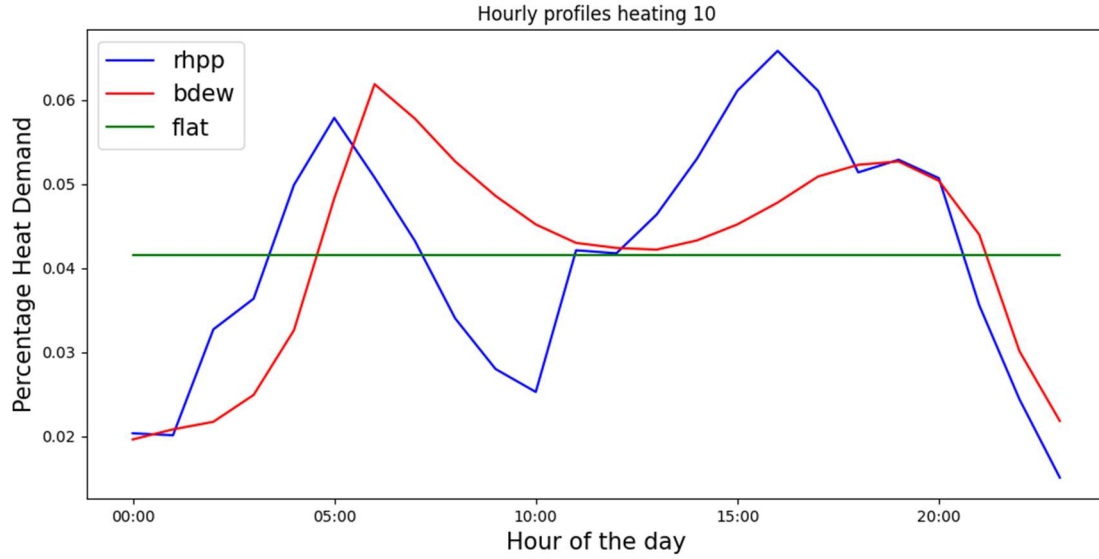


Figure 3-3 Hourly heat demand profiles for external temperature between 10°C and 15°C

These hourly profiles are used to convert the two daily heat demands to hourly. The hourly heat demand time series at each weather grid point (g) are calculated using equations (13) and (14).

$$H_{space,h,g} = H_{space,d,g} \cdot J(i, T_h^{amb}) \quad (i = 1, 24) \quad (13)$$

$$H_{water,h,g} = H_{water,d,g} \cdot J(i, T_h^{amb}) \quad (i = 1, 24) \quad (14)$$

Where $H_{space,h,g}$ is the hourly space heating demand time series for hour h at grid point g , $H_{space,d,g}$ is the daily space heating demand time series from chapter 2 equation (7) for day d and grid point g . The function J is the proportion of the daily demand for hour i based on the ambient temperature T_i^{amb} for that hour ($i=0,1,2 \dots$ ie i is the remainder from $h/24$). Similarly, $H_{water,h,g}$ is calculated using $H_{water,d,g}$ from equation (8).

3.2.2 Calculate Hourly COP at each weather grid point

An RHPP COP curve was derived using UK heat pump trial data [67]. The heat demand measurements at 2-minute intervals for each individual house were aggregated up to hourly. The hourly COP for each house was calculated by dividing the measured heat demand from the heat pumps by the measured electricity demand. The temperature difference ΔT for each hour was calculated as the difference between the measured temperature of the hot water leaving the heat pump and the population weighted UK temperature calculated using the ERA5 reanalysis 2m ambient temperature. In the case of GSHP this was the soil temperature and in the case of ASHP this was the 2m ambient air temperature.

Figure (3-4) shows these RHPP COP curves (in yellow) compared with the COP curves from other studies.

- Staffell [21] equations (15) and (16) which were chosen for the final model because they are representative of the UK
- Kelly [75],
- Fischer [76] based on industry standard data (2011, 2014, 2016)
- Ruhnau [38] from industry standard data
- RHPP derived in this study from UK heat pump trial data [67].

In general, GSHP (dotted lines) perform better than ASHP and since ground temperature tends to be higher and more constant than air temperature so the ΔT tends to be lower.

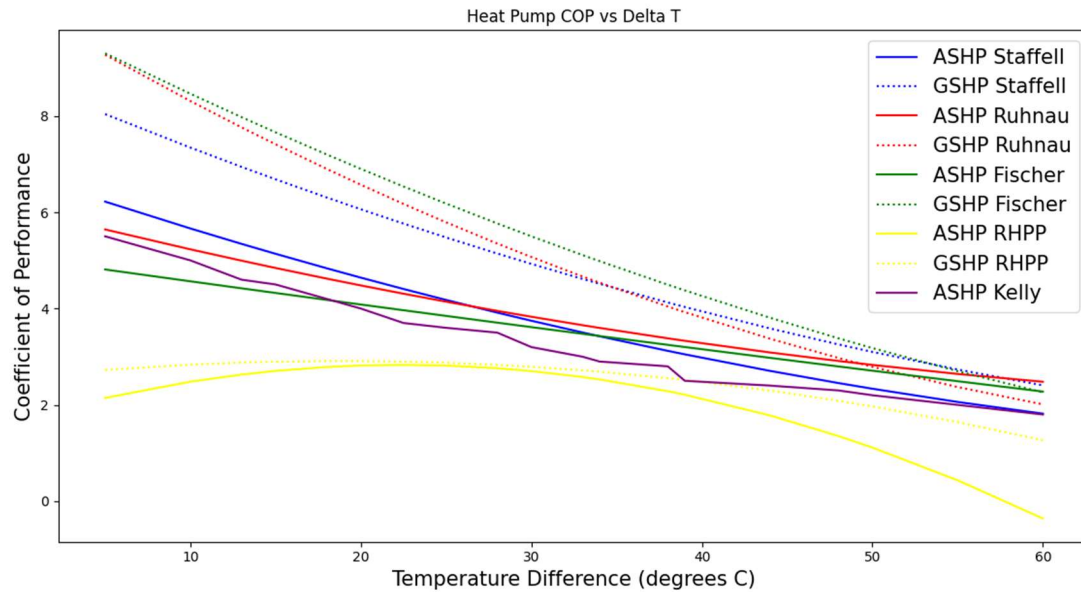


Figure 3-4 Relationship between heat pump COP and difference between source and sink temperatures from different studies.

As can be seen in figure (3-4) the shape of the RHPP derived COP curve (yellow) is different from the other curves. The COP should increase as the temperature difference declines, but this does not happen for lower temperature differences. Therefore, the RHPP curve was not used in the analysis. Instead, in this study, the COP curves from Staffell [21] shown on figure (3-4) in blue were used. These were calculated at each weather grid point using equations (15) and (16). For ordinary resistive heating the COP is assumed to be 1.0, equation (17)

$$COP_{h,g,ASHP} = 6.08 - 0.09\Delta T_{h,g}^{amb} + 0.0005\Delta T_{h,g}^{amb^2} \quad (15)$$

$$COP_{h,g,GSHP} = 10.29 - 0.21\Delta T_{h,g}^{soil} + 0.0012\Delta T_{h,g}^{soil^2} \quad (16)$$

$$COP_{h,g,RH} = 1.0 \quad (17)$$

Where $\Delta T_{g,h}^{amb} = S - T_{g,h}^{amb}$, $T_{g,h}^{amb}$ is the ambient air temperature for grid point g at hour of the year h, $\Delta T_{g,h}^{soil} = S - T_{g,h}^{soil}$, $T_{g,h}^{soil}$ is the 10m ground temperature for grid point g and hour of the year h. Both temperature values were taken from the ERA5 weather reanalysis [37]. S is the sink temperature from table (3-1).

Table 3-1 - Source temperature and sink temperature assumptions [38]

Sink	Sink temperature (S)
Radiators	$40^{\circ}\text{C} - T_{h,g}^{amb}$ (or 15°C if $T_{h,g}^{amb} > 25^{\circ}\text{C}$)
Underfloor heating	$30^{\circ}\text{C} - 0.5T_{h,g}^{amb}$ (or 15°C if $T_{h,g}^{amb} > 3^{\circ}\text{C}$)
Hot water	50°C

It should be noted that here COP is used to represent the whole system and not just the heat pumps. The electricity used to pump water to radiators is not considered

because it is similar to that used by a gas boiler and so will not affect the impact of heat pumps on the size of the electricity demand.

3.2.3 Calculate heating electricity demand for the whole country.

The hourly heat demands from equation (13,14) and the COP from equations (15-17) are now used to calculate a heat demand for the whole country.

For the purposes of this model, it is assumed that heating is supplied by either traditional resistive heating where the COP is assumed to be 1.0, an air source heat pump or a ground source heat pump. This heat is used for water heating or for space heating via radiators or underfloor heating. This gives 9 possible heating configurations (s) for which the heating electricity needs to be calculated as shown in table (3-2). The 9 different heating configurations arise from the different combinations of source and sink shown there. In table (3-2) the 2018 fraction represents 2018 proportions from National Grid[24] and the simplifying assumption is that all existing heating not provided by heat pumps is provided by resistive heating with efficiency 100%. The future fraction is based on the assumptions that all electric heating is provided by heat pumps (90% ASHP, 10% GSHP based on current proportions [24]) and that 90% of heating is provided by radiators and 10% by underfloor heating.

Table 3-2 - Assumptions and COP equations for different types (s) of heating electricity demand

Heating Configuration: use-source-sink				Indices		Proportions of heating configurations	
s	Heat Use	Source	Sink	$\alpha(s)$	$\beta(s)$	2018 Fraction (K_s) [24]	Future Fraction (K_s) [24]
1	Space Heating	Ground	Radiator	space	GSHP	0.0045	0.09
2	Space Heating	Ground	Floor	space	GSHP	0.0005	0.01
3	Space Heating	Air	Radiator	space	ASHP	0.0378	0.81
4	Space Heating	Air	Floor	space	ASHP	0.0042	0.09
5	Space Heating	Resistive	Radiator	space	RH	0.8577	0.0
6	Space Heating	Resistive	Floor	space	RH	0.0953	0.0
7	Hot Water	Ground	Water	water	GSHP	0.005	0.1
8	Hot Water	Air	Water	water	ASHP	0.042	0.9
9	Hot Water	Resistive	Water	water	RH	0.953	0.0

The daily heat demand time series at each weather grid point from equations (13,14) was converted to an hourly electricity time series and summed using equation (18) over the whole country.

$$E_{h,s} = \frac{K_s}{\eta_{HP}} \sum_{g=0}^{NG} \frac{H_{\alpha(s),h,g}}{COP_{h,g,\beta(s)}} \quad (18)$$

Where $E_{h,s}$ is the heating electricity demand for hour of the year h and heating configuration s representing different types of heating as shown in table (3-2), η_{HP} is a correction factor set to 1 for resistive heating or 0.85 for heat pumps to account for real world inefficiencies as per [38] and K_s is the proportion of heating configuration s in

the country as shown in table (3-2) $H_{\alpha(s),h,g}$ is the heat demand for hour h at weather grid point g for heating configuration s , $COP_{h,g,\beta(s)}$ is the heat pump COP for hour of the year h , grid point g . The parameter $\beta(s)$ indicates which of the equations (15-17) is used to calculate COP for heating configuration s in table (3-2). The parameter $\alpha(s)$ indicates weather equation (13) or (14) is used for $H_{\alpha(s),h,g}$.

3.2.4 Hybrid heat pumps

Hybrid heat pumps are envisaged to provide 13% of heating by UK National Grid Future energy scenarios [24]. Hybrid heat pumps combine a smaller heat pump with a boiler for the coldest days. Initially this would be a boiler powered by natural gas. In their net zero scenario, from which the figures used in this study are taken, a transition from natural gas to hydrogen is envisaged. The hydrogen would be generated by electrolysis from water using excess renewable energy and pumped into the existing gas network. The objective of a hybrid heat pump is to reduce peak electricity demand by switching entirely to hydrogen below a threshold temperature (set here as 4.15°C in order to meet the requirement of the proportion of energy specified in [24]). The hourly heating electricity $M_{h,s}$ for hybrid heat pumps is calculated using equation (19).

$$M_{h,s} = \begin{cases} E_{h,s} : T_h^{amb} \geq T_F \\ 0 : T_h^{amb} < T_F \end{cases} \quad (19)$$

Where $E_{h,s}$ is the heating electricity from equation (18) for heating configuration s from an ordinary heat pump, T_F is 4.15°C the hybrid heat pump threshold temperature and T_h^{amb} is the population weighted ambient air temperature.

The operation of a hybrid heat pump using this model is shown in figure (3-5). The red horizontal line shows the threshold temperature below which the hydrogen boiler is used instead of the electric heat pump. The other red line shows the outdoor temperature. The green line shows the electricity demand for ordinary heat pumps and the blue line that of a hybrid heat pump which goes to zero as the hydrogen boiler (yellow line) kicks in. Note that the blue line exactly follows the green line so is not visible when the temperature is above the threshold when the boiler kicks in.

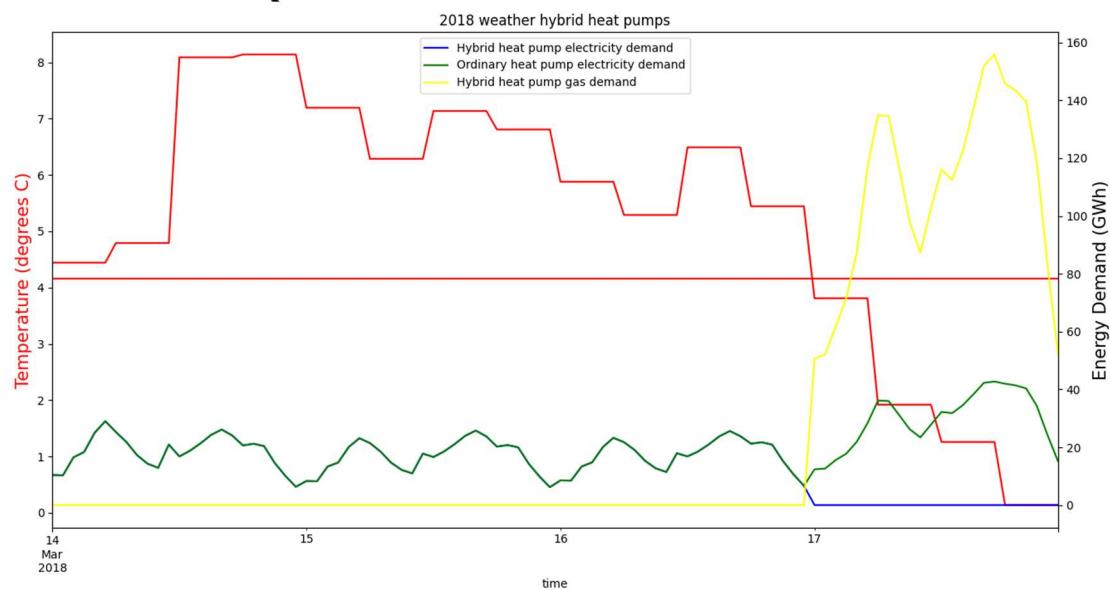


Figure 3-5 Hybrid heat pumps compared to ordinary heat pumps – electricity demand and gas demand.

The graph above (for 2018) shows a similar pattern to figure (4.14) from National Grid Future Energy Scenarios 2019 [24] (not shown here) for 2017 data, providing some validation for the model. One of the objectives of Future Energy Scenarios is as a starting point for academic studies. However, no previous mention of hybrid heat pumps being included in long term national energy models has been found in the academic literature.

3.2.5 Combine heating electricity demand for all configurations

All the heating configurations from table (3-2) and equation (18) and (19) are then added together as per equation (20)

$$E_h = P_E \sum_s E_{h,s} + P_M \sum_s F_{h,s} \quad (20)$$

Where P_E is the proportion of heating from ordinary heat pumps and P_M is the proportion of heating from hybrid heat pumps. $P_E = 0.29$, $P_M = 0.13$ from national grid Future Energy Scenarios 2019 [24].

This process described in equations (13-20) was repeated for each weather year y , giving $E_{y,h}$ as the electricity demand for year y and hour h . This gives a multi-year electricity demand time series including heating, using either the heating technology of 2018 or future technology using heat pumps. These two electricity demand time series created for use in chapter 4 are shown in table (3-3).

Table 3-3 Summary of the simulated electricity demand time series

Time Series ($E_{y,h}$)	years	Annual demand from table (2-1)	Fraction K_s table (3-2)
a) 40 years heating electricity with 2018 technology	1980 - 2019	Electricity column	2018
b) 40 years heating electricity with 41% heat pumps	1980 – 2019	Total column	Future

3.3 Validation of heat pump electricity demand time series

Electricity demand measurements were used to validate the method of simulating heating electricity time series. The electricity demand measurements were taken from the same RHPP trial used in 2.3.2 to validate heat demand. Two time series were generated:

- An electricity demand time series created by merging the 2-minute electricity measurements from each house in the trial and aggregating to hourly.
- A heat demand time series created using the BDEW heat demand method to split the total heat demand from 2.3.2 into days. Population weighted ERA5 reanalysis temperatures from the years of the trial data were used. This heat demand was then converted to an electricity demand time series using the methods from section 3.2.3. For each house in the trial, the appropriate heat pump type (GSHP or ASHP) was used according to the trial data [67]. The sink temperature was determined by whether the heating was provided by radiators or underfloor heating which is also specified in the trial data. In the case of those

having both heating types, 50% underfloor heating is assumed. The time series for all houses were then merged.

These two time series were then compared. Figure (3-6) shows that the actual electricity demand measured from the heat pump trial data is higher than that predicted.

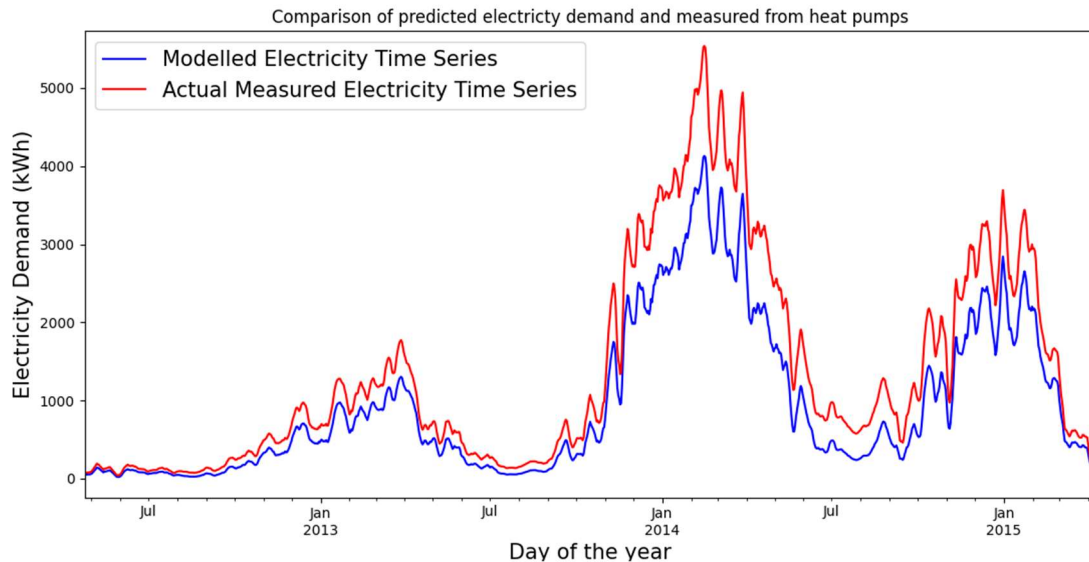


Figure 3-6 Comparison of predicted electricity demand from weather with actual hourly electricity demand from measured heat pumps in the RHPP trial (7 day rolling average)

The modelled electricity demand time series compared to the measured one with $R^2=0.994$ reflecting the fact that both time series follow a similar pattern, but the high nRMSE of 0.70 reflects the under prediction in the model.

The reason for the higher heat pump electricity demand from the heat pump trial data could be the fact that the sample of housing in the trial is mostly social housing [67] not representative of the UK housing stock and containing heat pumps not representative of the typical heat pumps sold. Another reason could be that UK heat pumps perform less well than German installations [21] possibly due to lack of experience amongst installers. Another possible explanation is inaccuracy of the RHPP trial data, although a previous study [59] expressed doubts about the accuracy of the heat measurements rather than the electricity measurements. Finally, another cause could be that the method used here assumes that all the hot water is provided by heat pumps alone, but this is not the case for at least 4% of the houses [67].

It is clear from figure (3-4) that the temperature dependent COP calculated here from the RHPP heat pump trial data is very poor compared to those used in other studies. For ASHP an average COP of 2.4 was calculated from the trial data, compared to the annual population weighted COP of 2.9 calculated using equations (15) and (16) based on the weather of 2010 to 2019. For comparison, a review of available heat pump data [77] notes a large variation in COP from 2 to 4, and that one trial of retrofitted homes in Northern Ireland reported a COP as low as 1.4. This variability in heat pump performance obtained from heat pump trials suggests that heat pump trial data should be used with caution in research.

3.4 Summary and Conclusions

A method has been developed to convert daily heat demand time series into an hourly national heating electricity demand. The electricity demand can be generated either on assumptions of future heat pump penetration or the existing 2018 heating technology. Validation against measured heat pump trial data shows the method underpredicts. However, there is uncertainty about the accuracy of the trial data. This chapter includes the following novel contributions:

- An hourly heat pump electricity profile derived in this study using trial data.
- A modification of the when2heat method using hourly temperatures and UK COP curves
- The inclusion of hybrid heat pumps
- Method of generation of electricity demand time series from the heat demand via proportions of heat pumps
- Derivation of RHPP COP curve.

Two electricity demand time series have been generated which will be used in the next chapter:

- 1980-2019 heating electricity (based on 2018 technology)
- 1980-2019 heating electricity (based on 41% heat pumps)

4 The impact of heating electrification on national electricity demand

This chapter completes the process of creating an electricity demand time series incorporating heating electrification alone for long-term weather. It is the third step shown in figure (3-1). The heating electricity time series created in chapter 3 will be incorporated into the historic 2018 time series, to keep technology constant at 2018 levels, so that the impact of heating electrification alone can be studied for 40 years weather. The resulting time series is analysed to assess the impact that heating electrification will have on Great Britain's electricity demand.

The remainder of the chapter is structured as follows. The background section reviews other studies on the impact of heating electrification and introduces the concept behind the method to be used. The method itself is described. The validation section uses the method to generate a different year's time series and compares them with those obtained using linear regression and historical demand. There is also a sub-section justifying the assumption that temperature is the only weather parameter that needs to be used in this model. The generated electricity demand time series are used to assess the seasonal and interannual impact of heat pumps. Finally, there is a sensitivity analysis followed by overall conclusions.

4.1 Background

Previous research has assessed the future impact of heating electrification on UK electricity demand in several different ways. One study [78] used the historic gas series as a proxy for heat demand to predict the impact on electricity demand if all gas heating were electrified. A regression model with historic gas demand and weather was used in [7] to modify the historic electricity demand time series. In another study, heat pump simulations of 960 buildings [57] were used to predict net peak demand. Heat pump trial data was upscaled in [59] to represent the national housing stock. These studies focus mainly on the peak hourly demand with little attention given to the impact on the seasonal and interannual variation. A study that investigates such effects on electricity demand [15] incorporating long term weather effects too, is based on projections of demand into the future and does not isolate the effect of heat electrification from other developments. It is this impact of heat electrification alone on seasonal and interannual electricity demand that is the focus of this chapter. It is analysed and quantified for the case of Great Britain.

Some studies linearly scale one year of hourly historic electricity demand [42, 61, 79] to account for future changes to demand such as electric heating and vehicles. However, over the 40-year period used in this project to capture weather variation, changes in the demand pattern need to be considered. Figure (4-1) illustrates how the annual UK electricity demand has changed over the years.

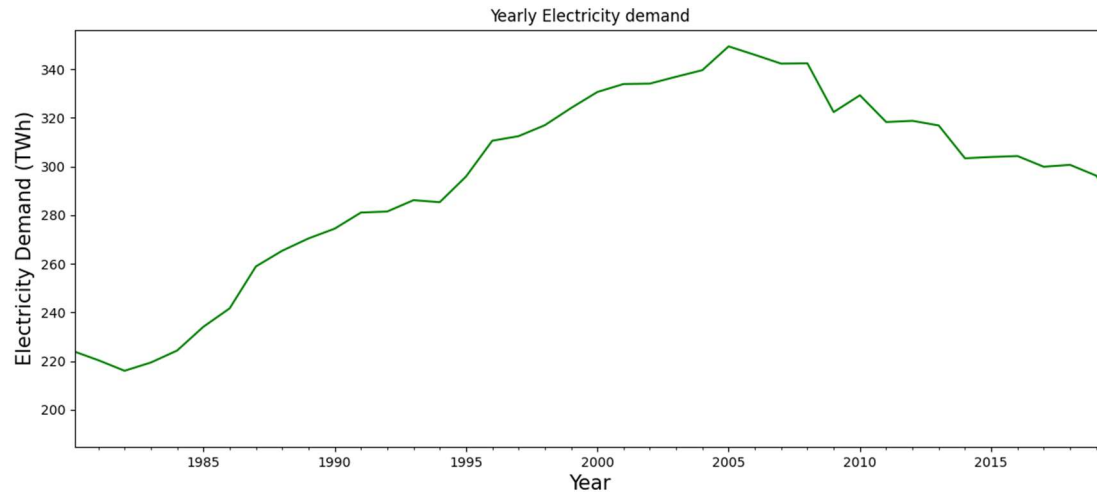


Figure 4-1 Change in historic annual electricity demand (TWh) over 40-year period from 1980 - 2019

Technological and economic changes over a long time period [80] have led to an overall reduction in the UK electricity demand in the last decade. An analysis of the impact of weather on the UK electricity demand from 1974 to 1990 [81] also found that the demand pattern has changed with correlation between demand and temperature weakening over time which might be explained by a move towards gas heating, or improved thermal insulation. Using historic electricity demand could make it difficult to distinguish these changes from those due to the model. Some studies scale historic electricity demand time series so that all years have the same annual energy [41, 52], but this has the disadvantage of removing the effect of weather: cooler years generally have higher demand due to heating.

This work introduces a method to isolate and study the impact of a specific change to the electricity demand. It will be used to keep current technological and socioeconomic conditions constant and account only for the anticipated implementation of electric heat pumps. Rather than use the historic electricity demand, or generate a purely synthetic demand, an alternative approach will be used. The electricity demand is based on a single year, 2018 from which the significant weather impact of electric heating has been removed. This concept of removing the heat demand and assuming it to be the weather dependent demand has been used previously in research: for characterising the response of the power system to weather [66] and for identifying events of simultaneous high demand and low renewable generation [82]. The method relies on the assumption that removing heating electricity removes the dependency on weather, which has been shown by previous studies [7, 81]. However, the previous work has removed the heating electricity using linear regression from the time series. Instead of using linear regression, the novel aspect of the method used here is to generate the heating electricity from historic weather, annual fuel use and proportions of heating technology. The advantage of using this method is that it is only necessary to simulate the heating electricity and no other sectors. This heating electricity was generated in chapters 2 and 3. It will now be used to modify the historic 2018 electricity demand.

4.2 Methods

This section describes the method used to generate two forty-year national electricity demand time series: one with the existing heating technology of 2018 and one with 41% of heating provided by heat pumps. The method allows the impact of heating

electrification to be studied in isolation to changes due to other socio economic and technological factors. The process uses the electricity demands from table (3-3) in chapter 3 as follows:

1. Take only the year 2018 from the existing heating electricity table (3-3) (a) and subtract it from the 2018 historic time series to give a baseline electricity demand (without heating).
2. Add the heating electricity from table (3-3) (a) for each of the 40 years to the baseline demand from above. This creates a 40-year electricity demand time series with the existing heating electricity technology.
3. Add the heating electricity from table (3-3) (b) for each of the 40 years to the baseline demand from above. This creates a 40-year electricity demand time series with the future heating electricity technology.

This procedure will be referred to as *the baseline method*. These processes are further explained in the following sections.

4.2.1 Baseline electricity demand time series

A baseline electricity demand time series is created which represents 2018, but with no heating electricity. This is done by simply subtracting a time series of heating electricity for 2018 from the historic 2018 electricity demand using equation (21).

$$B_h = F_h - E_{2018,h} \quad (21)$$

Where B_h is the baseline electricity demand, F_h is the half hourly historic 2018 electricity time series for Great Britain from [83] converted to hourly by summing up pairs of half hourly values and $E_{2018,h}$ is the heating electricity for 2018. This 2018 heating electricity time series was calculated using the 2018 fraction from table (3-2) and the weather of 2018 using the methods from section 3.2 with equation (20). This baseline B_h represents sources of demand other than heating, allowing the study of the impact of heating alone by adding in the electricity demand for each year of weather including future heating with heat pumps.

4.2.2 40-year electricity demand for existing heating technology

An electricity demand time series with the existing heating technology is created. This is done using equation (22).

$$R_h = \bigcup_{y=1}^{40} (B_{y,h} + E_{y,h}) \quad (22)$$

The union operator signifies that the time series for each year y from 1 to 40 are concatenated end to end to form the 40-year hourly electricity demand time series R_h . Where $B_{y,h}$ is the hourly baseline time series for year y and $E_{y,h}$ the hourly heating electricity demand time series. $B_{y,h}$ is calculated from B_h in 4.2.1 by simply copying the values in each year, apart from leap years where a February 29th is made up by linear interpolation from the day before and the day after. $E_{y,h}$ is taken from section 3.2.5 equation (20) using the 2018 fraction K_s from table (3-2) and the 40 years weather.

Each year of this time series represents the electricity demand that 2018 would have had if it had had the weather of that year. It allows us to keep technology constant and look at the impact of weather alone.

4.2.3 40-year electricity demand for future heating technology

Similarly, to create an electricity demand time series with future heating technology, the future heating electricity is added to the baseline. This is done using equation (23).

$$S_h = \bigcup_{y=1}^{40} (B_{y,h} + E_{y,h}) \quad (23)$$

Where S_h is the 40-year hourly electricity demand time series with future heating technology and $E_{y,h}$ the hourly electricity demand time series from equation (20) using the future fraction K_s from table (3-2). $B_{y,h}$ is the baseline as in the section 4.2.1.

Each year of this time series represents the electricity demand that 2018 would have had if it had had the weather of that year and 41% of heating had been provided by heat pumps. It allows us to keep technology constant and look at the impact of weather alone.

4.3 Validation of adding in weather dependent heating electricity

The objective of this section is to validate the process of removing the heating electricity for the reference year 2018 and adding in the heating electricity for a particular weather year. First the baseline electricity demand method itself is validated. Then for comparison, the linear regression method from previous work is validate using the same method. Some investigations are done to justify the underlying assumption that removing heating electricity removes weather dependence. Finally, the baseline and linear regression methods are compared.

4.3.1 Validation of Baseline Method

As described in section 4.2.1, the baseline method removes the heating electricity from the 2018 historic electricity demand which should make it independent of the weather. The heating electricity based on a particular year's weather is then added back in as described in 4.2.2 and 4.2.3. Heating electricity demands for 2017 and 2019 were generated using this method. These generated demands were then compared to the historic ones. The investigation is restricted to just these two years to ensure similar technoeconomic conditions with 2018. The synthetic 2017 electricity demand time series is created by removing the 2018 heating electricity from the historic 2018 electricity time series and adding in the 2017 heating electricity. This approximates the historic 2017 electricity demand time series as per equation (24)

$$\hat{E}_{2017,h} = B_h + E_{2017,h} \quad (24)$$

Where $\hat{E}_{2017}$ is predicted 2017 historic electricity demand time series, B_h is the baseline electricity demand time series and $E_{2017,h}$ is the generated time series of heating electricity for 2017 from equation (20).

This predicted timeseries compares well with the actual 2017 electricity demand giving $R^2=0.994$. For the 2019 time series it was $R^2=0.995$. Both years have $nRMSE=0.08$. This has shown that the baseline method can generate recent years electricity demand from weather with high accuracy. Figure (4-2) shows how the electricity demand predicted by this method (red) compares to the historic electricity demand (blue) and

the linear regression method (green) described in the next section. It can be seen that although the baseline method is an improvement on linear regression, that there are a few times when it over predicts the historic electricity demand.

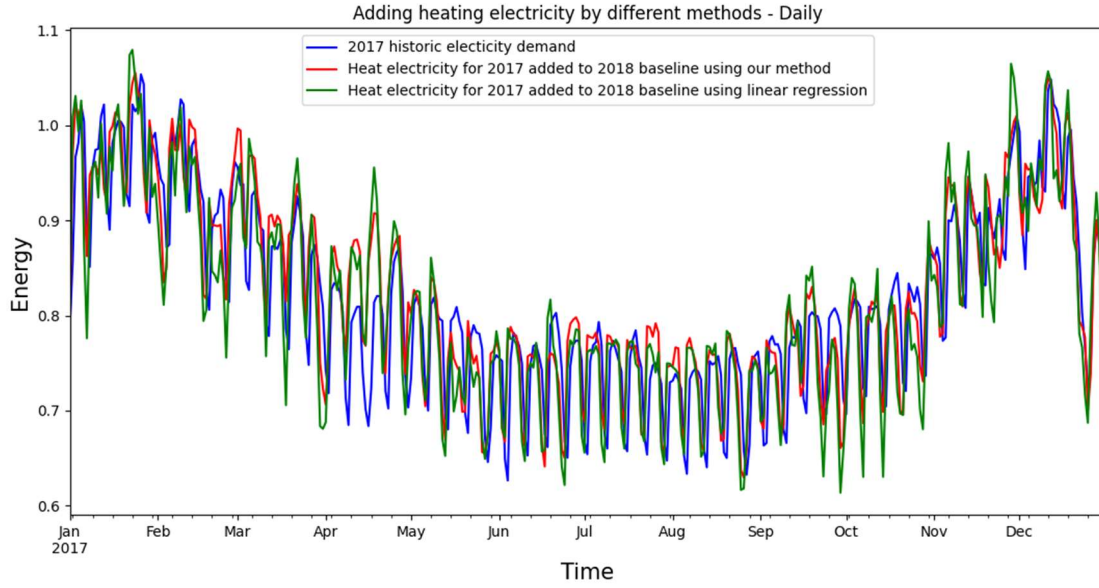


Figure 4-2 Comparison of predicting the 2017 electricity demand using the baseline method from this thesis and by linear regression.

4.3.2 Validation using linear regression.

Instead of using generated heating electricity demand time series as was done in the previous section, previous work has used linear regression. One previous study [66] found the heating electricity for all European countries using linear regression in a similar way to what was done with the gas demand in section 2.3.1 but including cooling degree days (CDD) as well as HDD. To compare the accuracy of this method with this study, linear regression was used to estimate the coefficients b , c , h in equation (25). This allows an estimate of the amount of heating and cooling in the electricity demand time series to be made.

$$E_i = b + cC_i + hH_i \quad (25)$$

Where E_i is the electricity demand time series, C_i is a time series of Cooling Degree Hours (CDH) using a base temperature of 20°C, H_i is a time series of Heating Degree Hours (HDH) using a base temperature of 14.8°C. Note that an hourly series is being used here, so that HDH and CDH are used rather than HDD and CDD. The heat demand from this standard linear regression was also used to validate the heating electricity demand: using equation (24) from the previous section, but with B_h and $E_{2017,h}$ being calculated using this linear regression model instead of using the generated heating electricity demand.

The electricity demand time series generated in this way compared to the actual historic one for 2017 with $R^2=0.993$ and $nRMSE=0.08$. This linear regression also provides an important additional validation of the heat demand method itself using the electricity time series, as relying only on the gas time series alone could lead to some doubt as to if we are validating heat demand or gas usage. The heat energy in the time series given by hH_i was 36.9 TWh which compares to 41 TWh estimate of annual heating energy for electricity from table (2-1).

4.3.3 Electricity demand regression coefficients

The previous work on which the above linear regression model is based [84] quote their linear regression coefficients. Therefore, as an additional validation, the regression of equation (25) was repeated for the years 2017-2019 as a comparison. The regression coefficients are shown in table (4-1) compared to the previous study.

Table 4-1 - comparison of electricity demand regression coefficients with another study [66]

Study	h (HDD)	Years
Supplemental material of [84]	0.75	2016-2017
This study	0.79	2017
This study	0.77	2018
This study	0.77	2019

The HDD coefficients compare quite well. The CDD coefficients for the UK were not quoted in the that study because there is only a small amount of cooling energy in the UK electricity demand. The number of HDD in 2018 was 1882, whereas the number of CDD was 22.

4.3.4 Prove heating is the most significant part of electricity demand.

The method of generating electricity demand time series being used in section 4.2 relies on the assumption that by removing heating electricity from the historic time series, the significant weather dependence (ie on temperature) has been removed. Although this method has been used in previous work using the UK electricity demand [66, 85] they do not say if they have validated the method in a UK context. The method is derived from US studies [86] using a limited number of variables at weather stations. However, this study is using UK not US weather and using reanalysis instead of weather stations. Therefore, an investigation was done to establish if:

- Any other weather variable is comparably significant to temperature.
- If the baseline electricity demand still has any weather dependence remaining which should be removed.

The literature contains several relevant studies.

A study using monthly regression models applied to the UK electricity demand time series from 1970 to 1995 [81] looked at heating degree days, cooling degree days, enthalpy latent days (which is an alternative measure of cooling), wind speed, rainfall and hours of sunshine. They found a strong correlation between temperature and demand, some correlation between humidity and demand in the summer months and a weak correlation with rainfall.

A previous study [7] used Lasso regression to investigate the relationship between net (of renewables) electricity demand and various parameters including weather variables. The Lasso method [87] is a common method of identifying important features for a machine learning model. It is a regression analysis method favouring the smallest number of features. In that study, they only look at the winter months and conclude that the only important weather variable is temperature (hourly and mean daily). They find that population weighted wind chill and cold spell uptick are not significant. Wind chill

is defined as a relationship between the wind speed being above a certain value at the same time the temperature is below a certain value. Cold spell uptick is defined as $\max(T-3,0)$, where T is temperature in °C.

To predict electricity demand, the UK National Grid use composite variables which are weighted averages from a few selected weather stations for effective temperature, cooling power of the wind (CP) and effective illumination (EI) [88]. EI used to be a complex function of radiation levels and types of cloud cover but has recently been replaced by a cubic function of the ground solar radiation. It should also be noted that government figures [8] show that lighting energy use in the UK has declined from 7375 ktoe in 2007 to 1215 ktoe in 2018, so its significance has probably declined also. CP is defined in [89] by equation (26).

$$CP_t = \sqrt{W} \begin{cases} 18.3 - TO_t & \text{if } TO_t < 18.3 \\ 0 & \text{if } TO_t \geq 18.3 \end{cases} \quad (26)$$

Where TO is the mean temperature for the previous 4 hours in °C and W is the wind speed in m/s.

To summarise, the previous work on which the method of removing the electricity for heating is based used hourly US electricity demand. Other studies looked at monthly regression on the UK demand or at just the winter months, but not at hourly UK electricity demand for the whole year. The purpose of this section is to fill that gap.

Various weather variables were taken from the ERA5 reanalysis 2017 - 2019 covering the same recent years used as the electricity demand baseline. Only three years are considered to avoid technological changes that would occur over a long period. The variables used were chosen based on the previous work referenced above as those considered most likely to influence electricity demand. They are listed in table (4-2), along with additional derived variables. A new variable ghi_w (weather dependent ghi) was derived, as the difference between the theoretical maximum “clear sky” Global Horizontal Irradiance (GHI) and the actual GHI. Clear sky GHI is the theoretical GHI based on the geometric position of the sun in the absence of any cloud cover. The square and cube of ghi_w were included because National Grid’s EI variable (see above) is defined as a cubic function of solar irradiance.

Table 4-2 - Correlation of weather parameters with electricity demand

Variable	Description	Daily R historic demand	Daily R baseline demand	Daily Lasso historic demand	Daily Lasso baseline demand
dailytemp	Mean daily temperature	-0.806	-0.605	0.14	0.148
tempyd	Yesterday's dailytemp	-0.787	-0.579	0.072	0.139
tempdb	2 days ago mean temp	-0.774	-0.585	-0.078	-0.067
temp_dp	Dew point temperature	-0.772	-0.576	0.0	-0.0
hdd	Heating Degree Days	0.831	0.631	0.241	0.246
wind	Wind speed	0.367	0.351	0.064	0.071
ghi	Global Horizontal Irradiance (GHI)	-0.597	-0.493	-0.024	-0.009
clear_sky	Clear Sky GHI	-0.662	-0.554	-0.065	-0.075
ghi_w	Weather Dependent GHI	-0.391	-0.34	-0.060	-0.056
ghi_w2	Ghi_w squared	-0.32	-0.297	0.006	0.052
ghi_w3	Ghi_w to the power 3	-0.28	-0.27	-0.07	-0.109
cp	Wind Cooling Power equation (26)	0.827	0.064	0.003	0.045
thermal	Thermal Irradiance	-0.625	-0.459	0.215	0.225
pressure	Surface atmospheric pressure	-0.340	-0.337	-1.046	-1.389
cloud	Cloud cover	0.195	0.151	-0.00	0.0
precipitation	Precipitation rain and snow	0.131	0.11	-0.040	0.05
cdd	Cooling degree days	-0.213	-0.13	0.073	0.038

Both the historic electricity demand and the baseline electricity demand (section 4.2) were analysed to determine the daily correlation (R) of each variable and its significance in Lasso regression. The results of this investigation are shown in table (4-2). The values of R range from -1 completely negatively correlated through 0 no correlation to +1 completely correlated. Lasso regression is similar, but those variables that are deemed not useful because they are correlated with something else are set to zero. Columns 3 and 5 show that the most significant parameters shown in **bold** affecting the historic demand are indeed those that are related to temperature, such as daily temperature, yesterday's temperature, and heating degree days. This supports the idea of heating degree days being the most significant part of the weather dependent demand.

For example, figure (4-3) shows a correlation between *hdd*, one of these temperature dependent variables and the 2017-2019 daily historic electricity demand.

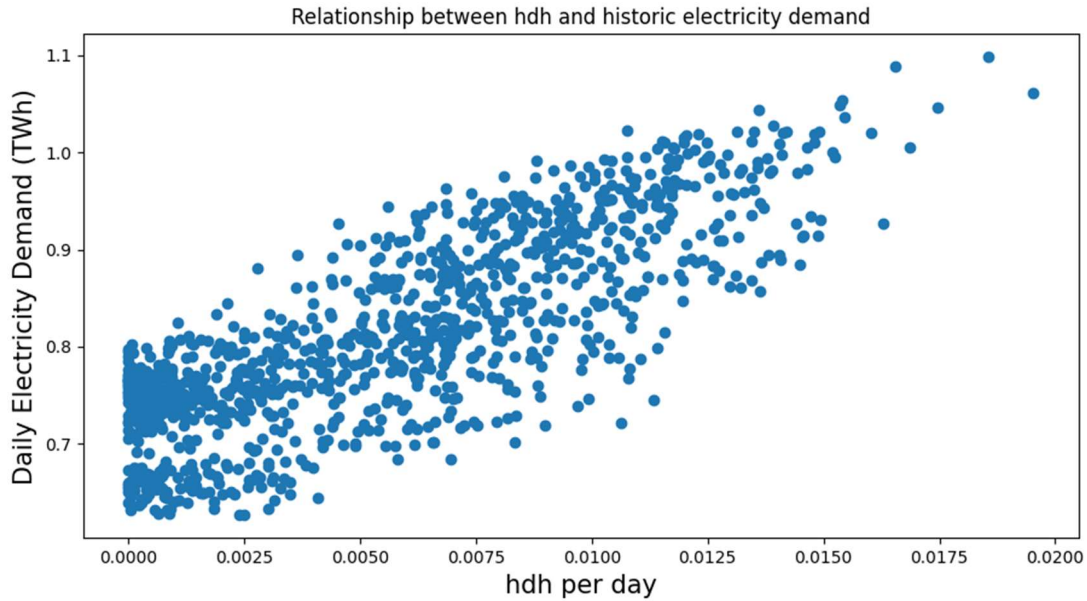


Figure 4-3 Correlation between HDH per day and 2017-2019 daily historic electricity demand

Columns 4 and 6 in table (4-2) relate to the baseline demand. From R, it appears that dew point temperature (which includes humidity) correlates well with demand, however the Lasso Regression shows that this parameter is not needed in a model because of correlations with other parameters, presumably temperature in this case. Similarly, GHI seems to correlate well, but the Lasso shows it is not important in a model, possibly because GHI also correlates with time. Surface pressure is highlighted as being significant by the lasso analysis of the time series after removal of heat. It might be thought that the high correlation of GHI indicates some relationship to lighting since annual lighting energy of 37.9 TWh is comparable to heat energy. However, it should be noted that the amount of sunlight is also correlated with the day of the year. Therefore, the variable *ghi_w* was included to investigate only the effect of weather and shows a weaker correlation to the electricity demand than *ghi*. Figure (4-4) does not show any obvious relationship between *ghi_w* and the baseline electricity demand (with electricity for heating removed).

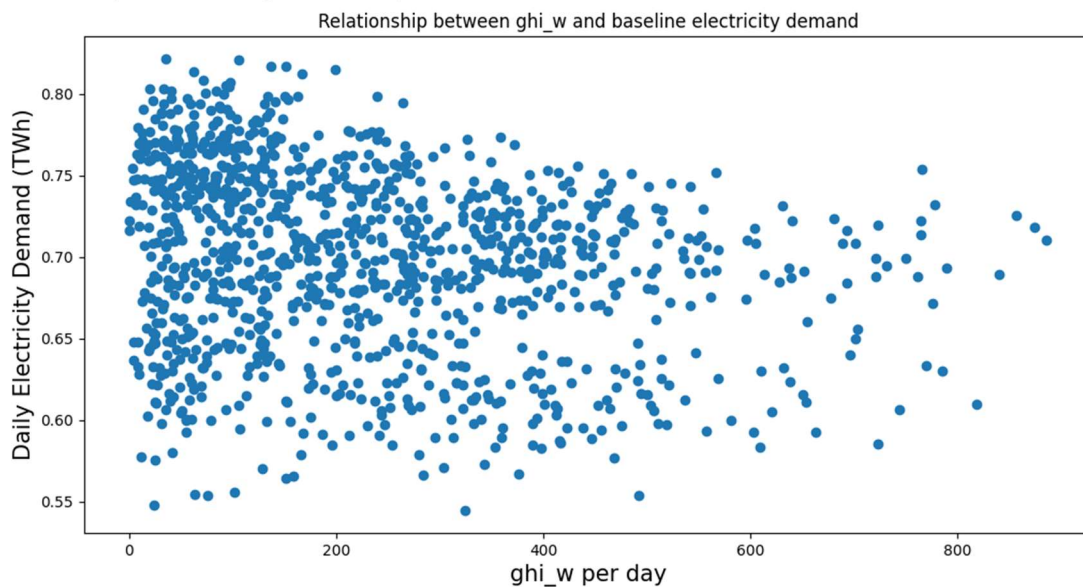


Figure 4-4 Correlation between weather dependent GHI and baseline electricity demand 2017-2019

With a linear regression, such as the model used in the previous section, the form of the model is fixed. This has the advantage that as in the case of the HDD and CDD model equation (25) that the portions of the time series that are heating, and cooling can be extracted. However, if the assumption about the form of the model were incorrect, then better results might be obtained from a model with a different form. Therefore, an investigation was done using the Random Forest (RF) machine learning method. RF is an ensemble method which takes the average of many decision trees [90]. A decision tree is a method of subdividing the data based on the values of certain variables. Individual decision trees tend to overfit, but RF overcomes this limitation by averaging the predictions of many trees. The objective of the investigation was to see if including any of the parameters identified as significant from table (4-2) improved a model to predict electricity demand from weather. This might indicate that the variable should have been considered in generating baseline electricity demand. The results of this analysis are shown in table (4-3). The variables used in the prediction are shown in brackets. These models do not perform better than the regression model from section 4.3.2 or the heat demand model from 4.3.1. However, it can be seen that the addition of *ghi_w* into the model made a small improvement in the R^2 values.

Table 4-3 Comparison of Random Forrest models for predicting electricity demand from weather

Comparison to the daily 2017 electricity demand of	R²	nRMSE
2017 Random Forests (RF) prediction (hdh,cdh)	0.993	0.09
2017 Random Forests prediction (hdh,cdh,ghi_w)	0.994	0.08
2017 RF (hdh,cdh,ghi_w,temp_dp)	0.994	0.08
2017 RF (hdh,cdh,ghi_w,temp_dp,surface_pressure)	0.994	0.08

If the baseline demand after the removal of heat, still contains some weather dependency then one possible improvement might be to train a model to forecast the baseline line demand from the weather, ie B_h from equation (21), instead of just using the baseline of 2018 directly. This was tried using the variables *ghi_w*, *temp_dp* and *surface_pressure*, but made no improvement to the assessment in table (4-3).

The conclusion is that we do not need to add any more weather parameters to the calculation of weather dependent demand. Removing heating electricity is sufficient to remove weather dependence.

4.3.5 Summary of validation

The previous section provides a justification for the assumption that removing heating electricity from the historic demand removes its weather dependency. Section 4.3.1 validated the method of using a baseline electricity demand. Section 4.3.2 investigated the alternative method of linear regression. These two methods are compared in table (4-4) and figure (4-5).

Table 4-4 Comparison of generated 2017 electricity time series to the actual historic data

Comparison to the 2017 electricity demand time series	R²	nRMSE
2017 synthetic time series using the heat demand method from section 4.3.1 to calculate H_{2018} and H_{2017}	0.994	0.08
2017 synthetic time series using linear regression model from 4.3.2 to calculate H_{2018} and H_{2017}	0.993	0.08

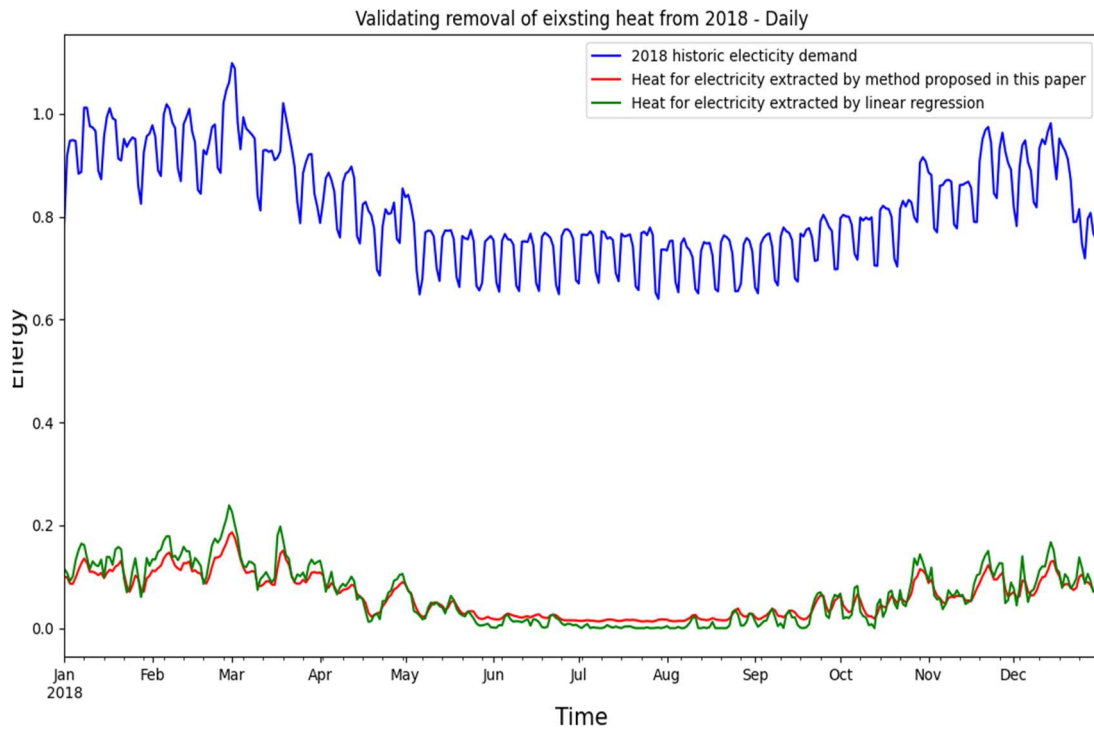


Figure 4-5 Removal of heating from weekly electricity demand time series

It can be seen that the method used in this study is slightly better than the linear regression method used in previous work. The method is also better than some methods which generate the whole electricity demand time series, rather than just replacing the heating electricity. For example, the DESSTINEE model time series for 2010 compares to the actual time series with $R^2 = 0.92$.

4.4 Results of Electrification of Heat

The previous section validated the methods of incorporating the electrification of heating via electric heat pumps into the electricity time series. This section will use these time series to look at the impact heating electrification will have. Two 40-year electricity demand time series were created using the methods from section 4.2: one representing the heating technology of 2018 and one representing future heating technology with 41% heat pumps. Although hourly time series have been generated, only the daily series are shown in the following plots for clarity.

Figure (4-6) shows the daily historic electricity time series for 2018 (in blue) with the portion of that which was heating (in red) subtracted from it to give the baseline electricity demand without heating electricity (purple). This demonstrates the method of creating a baseline electricity demand described in section 4.2.1.

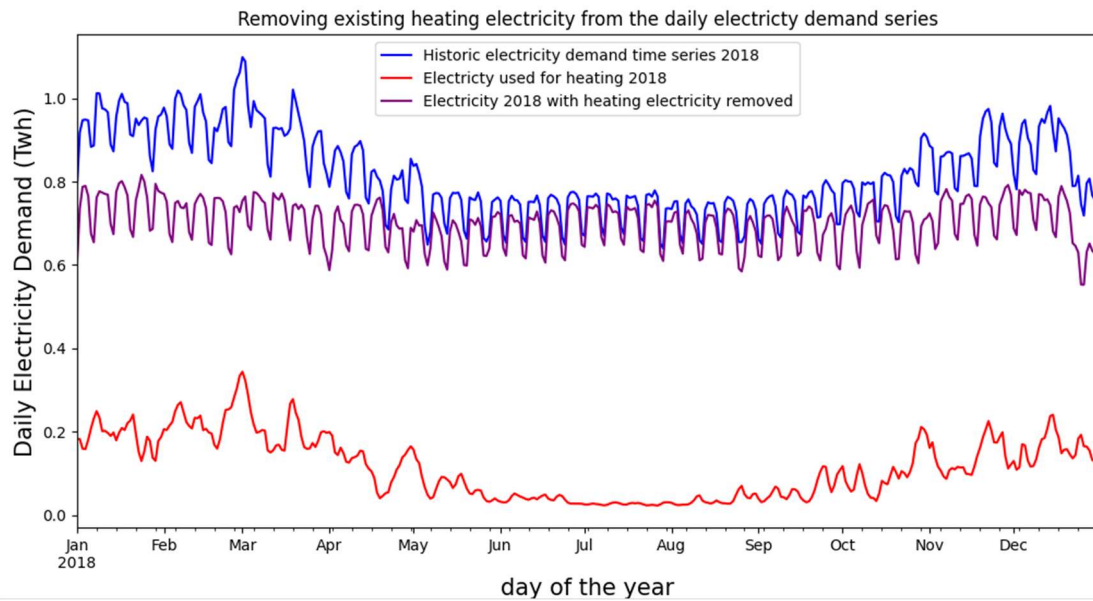


Figure 4-6 Removing the electricity for heating from the historic electricity demand of 2018 to obtain the baseline electricity demand.

Figure (4-7) shows generated electricity demand time series from 10 arbitrary consecutive years of weather from the total 40. The purple line of figure (4-7) shows the baseline electricity demand which is the same time series repeated as the influence of weather has been removed. The orange line shows the effect of adding in the electricity demand for heat pumps assuming all heating was provided by heat pumps. The heating is based on weather, so this line is different for each year. As expected, all heating provided by heat pumps would have a very large impact as currently most UK heating is provided by gas.

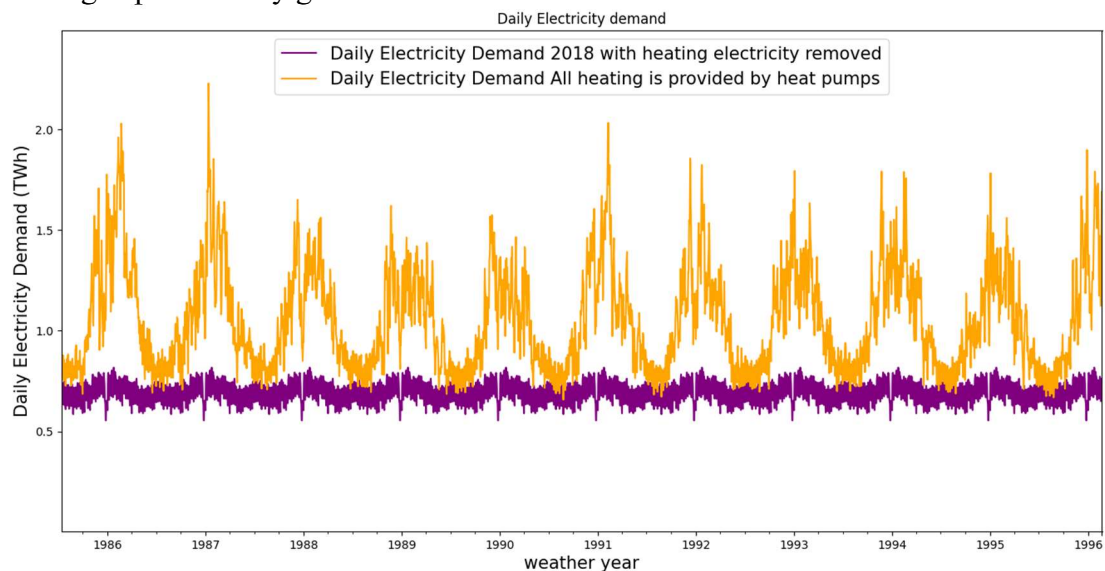


Figure 4-7 Baseline electricity demand (2018 time series without the electricity used for heating) compared with generated electricity demand assuming all heating is provided by heat pumps

Note that despite the removal of the weather dependence due to heating, the baseline electricity demand still shows some variation between months also visible in figure (4-6). December has a mean daily demand of 0.7 TWh where there is a noticeable dip in the holiday period at the end of month. The mean electricity demand of the other months varies between May with 0.67 TWh, July with 0.71 TWh and January with 0.75 TWh. A weekly cycle is also visible in figure (4-6), where demand varies within a week by

0.23 TWh compared to the variation between weeks of only 0.09 TWh. Section 4.3.4 showed that the baseline demand is only weakly correlated with heating degree days per hour and temperature, and no correlation with weather dependent GHI. Therefore, it seems reasonable to conclude that most of the weather dependency has been removed, and that the pattern is due to time dependent consumer behaviour.

Figure (4-8) shows a similar period with two different electricity demand time series that will later be used to investigate the impact on the required energy storage: the existing heating technology (4.2.2, orange) and 41% heat pumps (4.2.3, blue). The increase in winter demand seen here and its day-to-day and year-to-year variability will impact the required shares of weather dependent renewables and the storage found in chapter 6.

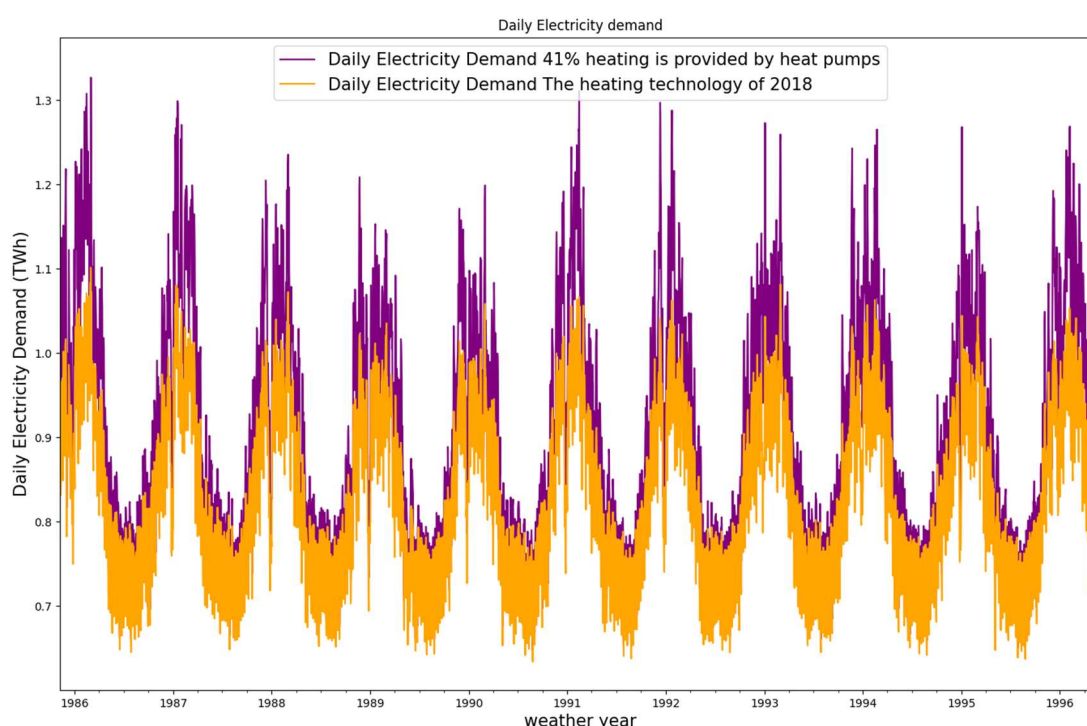


Figure 4-8 Existing Heating Technology compared to 41% heat pumps

Figure (4-9) shows the 2018 historic electricity demand (blue line) compared to what it would have been if all heating were provided by electric heat pumps (red line), where the annual electricity demand would increase from 299 TWh to 391 TWh. The green line represents a more realistic scenario of 41% heat pumps from the 2050 prediction from Future Energy Scenarios [24] where the annual electricity demand would be 323 TWh. As expected, there is a noticeable increase in winter demand and the day-to-day variability of this demand. However, it is also important to note the advantage of using heat pumps over traditional electric heating. The purple line in figure (4-8) shows the electricity demand for 2018 if the existing electric heating had been provided by heat pumps. This would have resulted in a reduction in the annual demand of 16 TWh and a reduction in hourly peak demand from 54GW to 48GW.

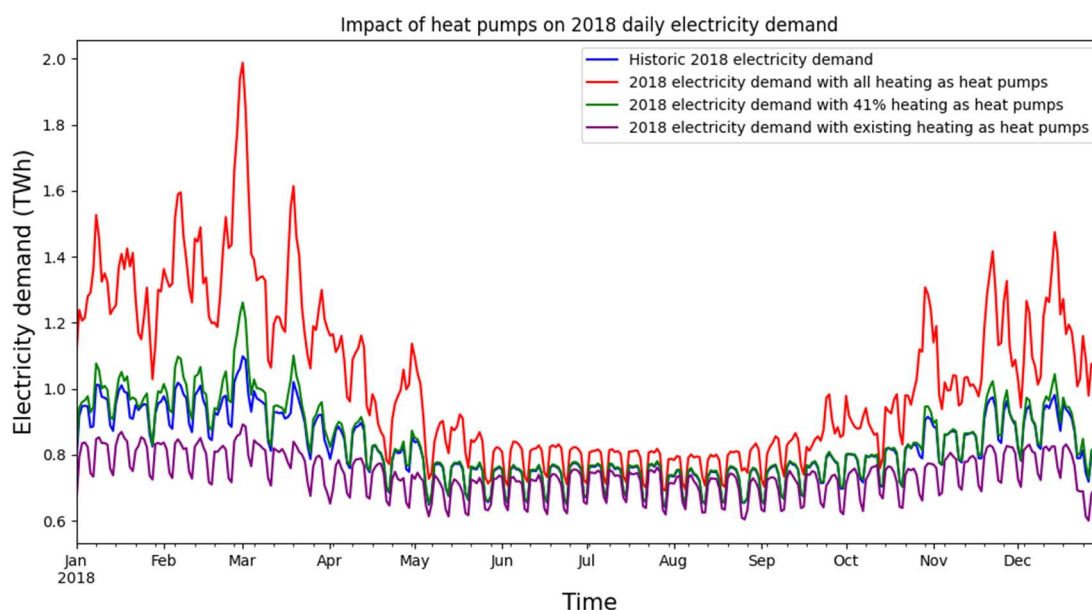


Figure 4-9 The impact on the 2018 electricity demand if all heating were provided by electric heat pumps

Figure (4-10) shows the daily electricity demands generated from 40 consecutive years weather all overlaid on the same graph. The case assuming 41% of heating provided by heat pumps is compared with the case when the electricity demand includes only the existing heating electricity. This shows a very large variation in the electricity demand in the winter months for different years and a much smaller variation in the summer for the case of 41% heating from heat pumps. The monthly electricity demand has doubled leading to an increase in about 30TWh for each winter month (December, January, February).

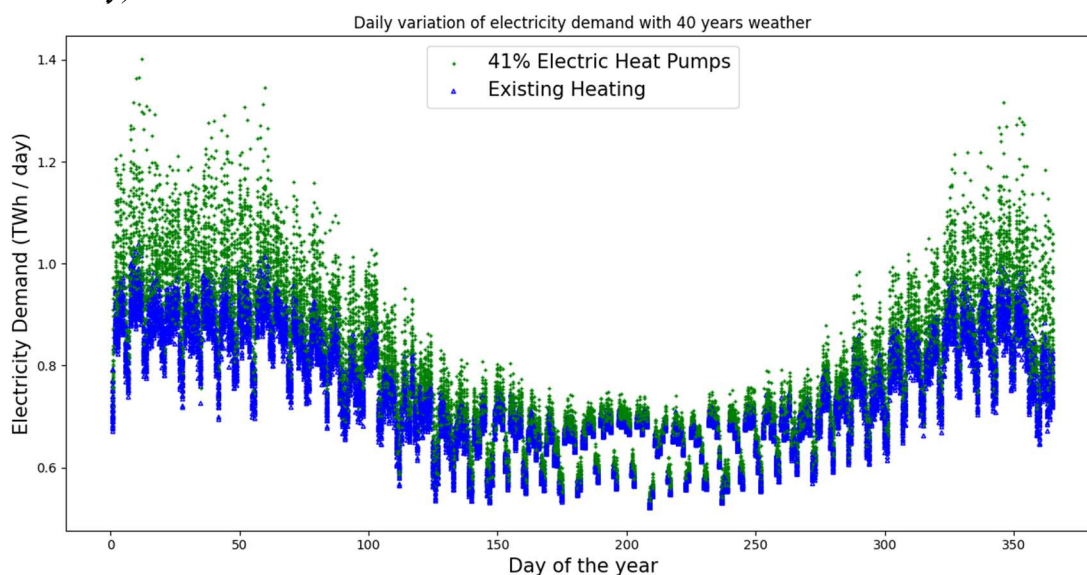


Figure 4-10 40 years generated daily electricity demand time series incorporating 41% of heating provided by heat pumps compared to existing heating

Figure (4-11) shows how the annual electricity demand varies amongst different years. With the existing heating technology, it varies over a range of 19 TWh, whereas with 41% of heating provided by heat pumps this variation increases by 37% to a range of 26 TWh.

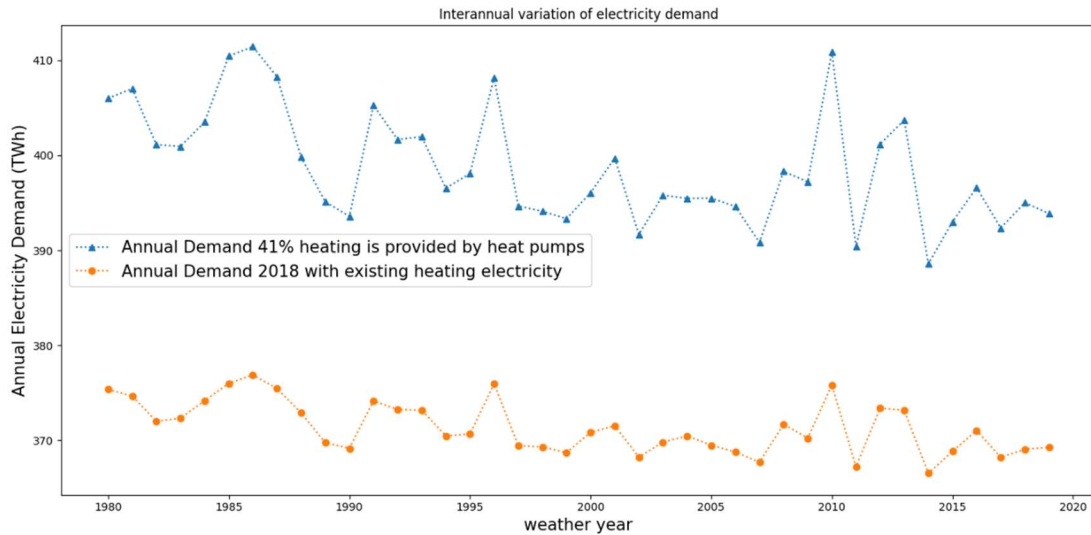


Figure 4-11 Annual demand with 41% heat pumps compared with heating electricity at 2018 levels

The decline in Great Britain's annual electricity demand with 41% of heating provided by heat pumps visible in figure (4-11) is caused by a decline in annual heat demand of 70 TWh over the 40-year period due to approximately 1°C increase in the population weighted Great Britain temperature over the years 1980 – 2019. No attempt has been made to correct for this because including more extremes of heat demand will better stress the energy system model ensuring that there is enough minimum storage. However, it was found that it is possible to correct for climate change by increasing the temperature at each weather grid point by about 1/40th of a degree per year as suggested in [91].

4.5 Sensitivity analysis of electricity demand.

Both the method used to generate daily heat demand time series from section 2.2.1 and the selection of the hourly profile of heat pump operation from figures (3-2) and (3-3) in section 3.2.1 will impact the final electricity demand time series. The objective of this section is to study their effect on peak demand, annual demand, and ramp rates. Peak demand is important for estimating the required generation capacity and ramp rates are important for the stability of the electricity system as it has to react to the sudden addition or loss of load. Although this study is primarily concerned with long-term variations, peak demand and ramp rates are examined in order to do a comparison with other studies.

Previous work on generating hourly heat pump electricity demand time series [6] has used hourly profiles derived from gas boilers. Flat profiles [92] have also been suggested assuming that heat pumps would be configured this way as the best way of reducing peak demand whilst ensuring thermal comfort. This study has used an hourly profile derived from actual heat pump data. However, different trials have shown heat pump profiles with different shapes [93] due to the way the heat pumps are configured. To investigate the impact the different choice of hourly profile can have on the final results, three different hourly profiles were tried with the same heat demand method. The results are shown in table (4-5). The higher peak demands for the RHPP profile will have been caused by its higher afternoon peak shown on figure(3-2) because the time of peak demand in the historic series also occurs in the later afternoon.

Table 4-5 Hourly electricity time series comparisons if 2018 had heat electrification

Electricity Time Series	Hourly Profile	Hourly Peak Demand	Hourly Ramp up	Hourly Ramp down	Annual Demand
Historic (existing heating)		54 GW	7 GW	6 GW	266 TWh
BDEW method (heat pumps)	BDEW	94 GW	12 GW	11 GW	397 TWh
BDEW method (heat pumps)	Flat	89 GW	7 GW	5 GW	380 TWh
BDEW method (heat pumps)	RHPP	100 GW	20 GW	15 GW	379 TWh

To investigate the impact of the choice of heat demand method, four heat demand methods were used with the same hourly profile. The results of varying the daily heat demand method but keeping the same hourly profile are shown in table (4-6).

The choice of heat demand method (splitting the annual heat demand into days) and hourly profile only have a small impact on the annual electricity demand. However, the hourly peak demand values vary over a range of 25 GW (25%) which is quite significant compared to estimates of what the future peak demand might be. For example a study into electricity demand and weather variability [94] predicts that electrification of heat will double peak demand from about 50 GW to 100 GW and in a study including other sectors as well as heat [30] hourly ramp rates of ± 15 GW are predicted by 2030. This suggests that estimates of peak demand are very inaccurate if they can vary so much depending on the method of generating the heat demand time series.

Table 4-6 - Sensitivity of the hourly electricity demand to heat demand method

Electricity Time Series	Hourly Profile	Hourly Peak Demand	Hourly Ramp up	Hourly Ramp down	Annual Demand
Historic (existing heating)		54 GW	7 GW	6 GW	266 TWh
BDEW method (heat pumps)	RHPP	100 GW	20 GW	15 GW	379 TWh
Watson method (heat pumps)	RHPP	95	16 GW	13 GW	378 TWh
HDD 12.8 method (heat pumps)	RHPP	120 GW	24 GW	18 GW	381 TWh
HDD 15.5 method (heat pumps)	RHPP	102 GW	19 GW	15 GW	380 TWh

Despite being based on the same annual heat demand, the annual electricity demands estimated from the different methods and shown in table (4-6), differ, because the methods assume both different hourly heat pump operation profiles and daily total heat demand. The intraday temperature variations mean different COP for each hourly profile of heat pump operation and hence the total amount of electricity required to generate the same heat varies accordingly.

4.6 Summary and Conclusions

Two UK electricity demand time series have been created based on 40 years' weather: one with the existing heating technology of 2018 and one with 41% of heating provided by heat pumps. These time series allow us to study the impact of heating electrification with heat pumps alone on electricity demand, independently from all other factors. Previous work has done this either by using linear regression to replace the electricity for the heating sector in one year's historic electricity demand based on multiple years weather or has simulated all sectors. In contrast the method used here replaces the electricity for the heating sector with a heating electricity time series from chapter 3 based on detailed calculations for current or future heating. The new method can generate time series for recent years more accurately than those used in previous work. Analysis of the dependence of the historic electricity demand justifies the assumption that removing the heating electricity removes its weather dependence.

The research reveals that the difference between the largest and smallest annual electricity demand for weather years 1980-2019 increases from 19 TWh to 26 TWh. It also reveals the sensitivity of generated peak electricity demand to the hourly profiles used in modelling leading to uncertainties in the estimations of peak electricity demand which vary over a range of 25 GW. This is quite significant compared to estimates of future peak demand of between 40 and 100 GW reported in research. Such inaccuracies have not been quantified in previous work.

It was found that the electrification of heat expected by 2050 with the introduction of heat pumps, modifies the seasonal profile of electricity demand doubling the monthly demand for electricity leading to an increase in about 30TWh for each winter month. The evidence of the generated time series shows that year to year variability of electricity demand due to weather will increase by 37%.

The impact of these two factors on the role of wind generation, solar generation, and energy storage requirements in a future highly renewable electricity system are the subject of chapter 6. But first the method by which energy storage is modelled is described in chapter 5.

5 Finding the minimum energy storage needed

This chapter will aim to answer one of the subsidiary research questions posed in section 1.1: How should the required energy storage be found? A model is needed to find the minimum energy storage required for a given electricity generation capacity. This can then be used to study the impact of changes to electricity demand on storage and generation capacities.

The chapter starts with a review of previous work. The method used to find the minimum storage is then described. To help identify which configurations are important a method of calculating the cost of electricity generation taken from another paper is described. The results section describes how the method can be applied to a system with today's demand but a supply with a high renewable energy penetration. The model is validated by comparison to that used by another study and against today's energy system. The chapter concludes with a summary of how the model will be applied in the remainder of the thesis.

5.1 Background

Previous studies on future UK energy systems have proposed different capacities of wind generation, solar generation, and energy storage to achieve a net zero UK. For example, seven different plans from four different groups, are reviewed in [19]. All contain high proportions of electricity generation from wind and solar PV, but all vary in their proposed mix of technologies. The ratio of wind energy to solar energy generation capacity ranges from 0.80 in the plan with least wind capacity to 0.99 in the plan with most wind capacity. Several previous studies have investigated the ideal mix of wind and solar needed to satisfy the historic electricity demand. These studies make different assumptions about what the energy storage might be and hence its efficiency. For example a study assuming a round trip efficiency of 80% for pumped storage [95] found the ideal mix for Europe was 55% wind. Another study which assumed a round trip efficiency of 36% for hydrogen storage [96] and assuming an excess generation of 50% found the ideal mix for Europe was 70% wind. A UK study looking at efficiency of 75%-85% for pumped storage [41] found that for a system with 25 TWh storage that 30% more energy generation above the demand was required for a system which had 81% wind. The proportion of wind energy for a purely wind and solar system for the UK was found to be 84% assuming a round trip efficiency of 70% for compressed air storage [52] by finding the minimum cost configuration at today's prices. Despite the electricity system being a complex network of interconnected consumers and generators, these studies use a simplified model to capture the essential features needed to study the interaction of demand, generation, and storage at a high level.

Some energy models have energy stores of fixed capacity, and it is up to the user to optimize the system by varying the storage capacities. Energy Plan [97] has a thermal store and an electricity store which can be pumped storage, batteries, V2G or CAES. The electrical energy store starts 50% full, and an iterative procedure is used until the amount of energy stored at the end is at least that stored at the start. A model of a 100% renewable UK [34] has multiple fixed sized stores used in a merit order of heat, V2G, electrical, hydrogen and synthetic fuel.

Other models using a single energy store attempt to find the amount of storage required. Energy is taken from the store during periods of high demand and low generation and added to it during periods of high generation and low demand. Fragaki et. al [41], discussed below, assume that the energy store is full at the start, and define the required store size by the maximum amount of energy taken from it. A study of the optimal wind solar mix for Europe [95] uses a similar algorithm but the energy store is allowed to overfill, and the initial state of charge is determined by increasing the energy generated to ensure that it contains more energy at the end than it did at the start. In a later study by the same author [96] the algorithm is modified to constrain the capacity. A study for Germany [18] iteratively moves the storage pattern up and down to find the minimum storage where the store ends up with more energy than it started with. Cardenas et. al. [52], discussed below, use a similar algorithm, but make no assumption about how full the store is to start with. The initial state of charge is determined using an iterative procedure which ensures that the amount of energy in the store at the end is at least equal to how full it is at the start. This “no free lunch” assumption of the store having more energy than it started with is common to most studies [52, 95, 97]. Some studies vary the generation to achieve this. Some assume an initial state of charge, and for some it emerges from the algorithm. It is not clear if all these different algorithms find the same optimum storage which is possibly a question for future study.

Previous studies on the amount of energy storage needed have yielded a wide range of results. A review of such studies [98] found that for renewable energy penetrations of greater than 80% storage requirements varying between 0.2-6 TWh for the US, 0.2-22 TWh for Europe and 0.05-83 TWh for Germany. These variations are 187%, 196% and 91% respectively. No firm conclusions were drawn on the reasons for the wide variation in results, although they found that high PV penetration tended to lead to high storage requirements. No UK studies were included in that review. However, two previous studies into running the UK on purely wind and solar have been found and investigated here. The aim is to improve on their methods. The differences made by these new methods is investigated in chapter 7.

Fragaki et al. [41] show that the historic electricity demand can be satisfied by wind and solar generating 30% more energy than the existing system complemented by 30 days storage. Wind speeds from MIDAS were used to model a typical wind turbine at 6 onshore weather stations using standard methods. A solar panel was modelled at the location of 4 weather stations. These daily time series were scaled up to represent power generation for the whole UK for the weather of 1984 – 2013. Electricity demand was modelled using the historic electricity demand scaled by adding a different constant for each year to each day’s demand, so that each year had the same annual demand. The required energy storage was found assuming round-trip efficiencies of 75% - 85% representing pumped storage. This study was examined because the original idea of this research was to build on it to include the impact of the electrification of heat.

Cardenas et. al. [52] show that 15% excess energy minimizes the total cost of electricity generation and requires a minimum storage size is of 43.2 TWh (which equates to 35 days) and has 84% of energy from wind. The cost is based on CAES with a 70% round trip efficiency at today’s prices. They use the simulated PV generation from Renewables Ninja, but the actual wind generation from Elexon / National grid and normalise it on a quarterly basis to account for the increase in generation capacity over the years. For the years 2011-2019, the hourly historic electricity demand for each year

is multiplied by a different constant so that it has a total demand of 335 TWh, the annual demand for 2018. This approach is questioned in another study looking at peak demand [6] because it changes the pattern of the demand curve. This study was examined because the cost model used in this project was taken from it.

Cardenas used a different algorithm to find the required amount of storage. First, they define the amount of excess generation allowed. Then for different proportions of wind energy and solar energy they create power generation series from the time series of wind and solar capacity factors that generate this amount of energy. A net demand time series was then produced to which losses due to the store round-trip efficiency have been applied. So, the round-trip efficiency is applied once, rather than separate charge and discharge steps. Iterative procedures were used to find (i) the required energy, (ii) the required storage (by increasing it from zero until the energy curtailed equals the excess generation allowed) and (iii) the initial state of charge (by generating more energy) until the store ends up with the same energy as it started with. This means that the initial amount of energy in the store is an output of the model.

Both these studies tried to keep the economic changes constant by scaling the historic electricity demand time series so that each year uses the same amount of energy. However, this removes the difference in the heating energy requirement between warmer and colder years. Both studies try different proportions of energy generation from wind and solar to find the energy storage needed.

To improve on these two previous UK studies, this study will:

1. Use wind generation time series from Renewables Ninja because being based on all UK wind farms they should be more accurate than using just 6 MIDAS weather stations and will not change over time like the current national grid wind.
2. Use PV generation time series from Renewables Ninja which would be expected to be more accurate as they are hourly, rather than daily.
3. Use hourly time series, rather than daily throughout for improved accuracy.
4. More accurate electricity demand time series combining National Grid generation and the balancing mechanism from Elexon.
5. Use electricity demand time series from chapter 4's baseline method which include the different heating energy between years, rather than scaling which removes it.
6. Use an algorithm to find the minimum storage which ensures that the SOC at the end of the period is at least that at the start, but without adding additional generated energy to achieve it, which might lead to finding a non-optimal solution.
7. Cover a complete range of generation capacities in a grid which allows interpolation of in between points and avoids having to guess at the excess energy generation needed.
8. Use 40 years of weather data to capture more variation.
9. Consider cost, rather than just energy.

A summary of the differences between this project and these two studies is shown in table (5-1).

Table 5-1 Comparison of methods of two previous studies with those used here

Method or data	Study		
	This Project	Fragaki	Cardenas
Wind generation	Renewables Ninja combined offshore and onshore	6 MIDAS weather stations onshore	National Grid onshore and offshore
Solar PV generation	Renewables Ninja	4 MIDAS weather stations	Renewables Ninja
Frequency	Hourly	Daily	Hourly
Electricity demand data	Pre-processed from [83]	National grid	National grid
Electricity Demand	Baseline with heating electricity added for the weather	Historic: each year scaled to the same energy by adding a constant	Historic: each year scaled to the same energy by multiplying by a constant
Algorithm to find storage	Iteratively try store capacities	Store capacity is maximum deficit	Iteratively find energy, capacity and initial SOC
Configurations chosen	Range of capacities on a regular grid	Range of wind energy fractions and over sizing factor	Range of wind energy fractions and over sizing factor
Initial SOC	70%	100%	Emerges from algorithm
Final SOC	$\geq$ Initial SOC	No limit	$\geq$ Initial SOC
Cost	As Cardenas	None	Cardenas
years	1980-2019	1984-2013	2011-2019
1 day energy	818.386 GWh	835.616 GWh	917.808 GWh
Mean daily power	34 GW	34.8 GW	38 GW

5.2 Methods

This section contains the methods for:

- Finding the energy storage for a given capacity of wind and solar generation
- Calculating the cost of electricity for a configuration

5.2.1 Finding the minimum required energy storage

This section describes how time series of renewable generation are combined with an electricity demand time series to estimate the required energy storage capacity. One 40-year hourly time series models the electricity supply, and one time series models the electricity demand. The model calculates the minimum energy storage that is needed to balance it, so that the electricity demand is supplied without interruption. The electricity supply is generated from time series of wind and solar power generation capacity factors. These represent what power would have been generated for historic weather and are scaled up to represent different generation capacities. The electricity demand is

an hourly time series generated for the whole country based on the same historic weather. For each generated electricity demand time series, a whole set of possible electricity supply time series were investigated. Each supply time series is based on a configuration having a different capacity of wind and solar power. The objective is to identify the minimum energy storage required for the system to balance without loss of load. The model consists of a simplified system where the energy generated consists solely of wind, solar PV, base load and dispatchable generation. A time series of demand net of generation is created using equation (27)

$$N_t = D_t - W_t - P_t - X_t - V_t \quad (27)$$

where N_t is the net electricity demand at time t , and W_t , P_t , X_t , V_t are the energy generated at time t from wind, solar PV, base load and dispatchable sources respectively. D_t is the electricity demand. The time period t is typically hourly, for example S_h generated in section 4.2, or in some experiments it is converted to daily by aggregation.

For convenience, and in line with previous studies, generation capacities and storage capacities are specified in units of days related to the mean daily energy in the 2018 historic electricity demand time series of 818.38 GWh per day. Thus, a wind generation capacity of 1 day means 34 GW ($=818.38/24$) and 1 day of storage is 818.38 GWh.

The base load X_t is defined as a constant daily amount C_b , with the simplifying assumption that it is always on. Base load could be nuclear power. Or at a high-level tidal power could be considered as another form of baseload since it is independent of weather, although it varies according to daily and lunar cycles (not being modelled here). Geothermal could also be considered as constant base load although there is not very much potential for this in the UK.

The dispatchable generation V_t is power that can be brought online at the request of grid operators, in contrast to baseload (which cannot be turned off) and wind and solar whose availability is subject to weather. It encompasses all thermal power plants using fossil fuels such as natural gas, oil, coal, and biomass. To simplify the model, it is assumed that it will always be used in preference to stored energy up to its maximum capacity C_v . For time t , V_t is the amount of energy needed to make N_t zero up to a maximum specified value C_v .

$$V_t = \begin{cases} C_v + N_t, & (0 > N_t > -C_v) \\ 0, & (N_t \geq 0) \\ C_v, & (N_t < -C_v) \end{cases} \quad (28)$$

In this model this dispatchable generation is assumed to be brought online as needed although in practice some power stations must be on stand-by. Note that the distinction between dispatchable and storage is slightly nuanced, because although in theory natural gas could be created using electricity via the Sabatier process [34] and thus be a form of energy storage, it is only considered as dispatchable in the model used in this thesis.

The power generation time series for wind W_t is calculated by multiplying the input time series of capacity factors from section 1.2.7 by the generation capacity C_w as shown in equation (29)

$$W_t = W_t^{cf} C_w \quad (29)$$

Where W_t^{cf} is the time series of wind capacity factors from Renewables Ninja. The near-term future time series is used which includes wind farms which are under construction and planned in addition to those that already exist.

The power generation time series for solar PV P_t is calculated by multiplying the input time series of capacity factors from section 1.2.8 by the generation capacity C_p as shown in equation (30)

$$P_t = P_t^{cf} C_p \quad (30)$$

Where P_t^{cf} is the time series of PV capacity factors from Renewables Ninja.

The many different types of energy storage in the actual power system are all represented in the model by a single energy store of capacity C_m and round-trip efficiency of η .

Thus, we have a model of the UK energy system with energy storage defined by C_m and η with a net demand time series N_t defined by these four values: C_v , C_b , C_w , C_p . For fixed values of C_b and C_v the values of C_w and C_p are varied in steps by fixed amounts starting from zero creating a 2D grid of wind and PV capacities. For these different power system configurations, the task is to find the amount of energy storage C_m for a specific efficiency η . There must always be enough energy to supply the load D_t .

For one such system, this can be calculated using equation (31). Using a storage variable (S) modified according to the sign of N_t at each time point t , assuming a storage charge efficiency of η_c and discharge efficiency of η_d

$$S_t = S_{t-1} - \begin{cases} \frac{1}{\eta_d} N_t, N_t > 0 \\ \eta_c N_t, N_t \leq 0 \end{cases} \quad (31)$$

Where S_t is the amount of energy stored at time t . The algorithm marches through the net demand time series N_t . There are two cases:

- If N_t is positive, demand exceeds supply. Energy is removed from the store. More energy is needed to supply the demand, so divide by η_d .
- If N_t is negative, supply exceeds demand. Energy is added to the store. Less energy is put into the store due to storage efficiency so multiply by η_c .

S is subject to the constraints that $S_0 = C_i$ (the store starts off containing an initial amount of energy C_i) and that $0 < S_t < C_m$ where C_m is the maximum size of the store. The maximum charge rate was calculated as $\max(S_t - S_{t-1})$ ($t = 1, NT$) where NT is the number of points in the store history S . The maximum discharge rate similarly.

The model has several limitations. It is based on the energy balance alone with no account taken of losses due to transmission, start-up time and thermal power plants on standby. Wind and solar generation outages are taken account via the capacity factor. The only renewable energy curtailment is due to the energy store being full. There is no constraint on the rate at which the energy store can fill and empty (ie power curtailment). Delays to discharge are not modelled. For example, if the energy store were hydrogen, then there could be a delay for start-up time to the power station generating electricity from hydrogen, for discharge of the store. Also, loss of charge is

not modelled eg hydrogen leaking out. However, other work has shown that these models do provide a rough estimate of storage and provided a basis for comparison of different scenarios [25].

In contrast to the studies mentioned in 5.1 above, in this project an iterative procedure is used to find the minimum value of C_m so that the constraints are satisfied. The novel algorithm for finding the required storage capacity C_m for a given PV capacity C_p and wind capacity C_w is described below, where SL is a lower bound for the storage and SU is an upper bound. SU starts at 80 days, a value arrived at by trial and error as the largest storage required to capture the comparison points for the models used in this study. SL starts at zero. The lower bound is gradually increased if there is not enough storage. The upper bound is reduced if there is more storage than needed. When the upper and lower bounds are within a tolerance δ_s the minimum storage has been found. The algorithm is illustrated as pseudo code below and as a flow chart in figure (5-1).

Table 5-2 Algorithm for finding the minimum energy storage for a given net demand time series.

• Set SL=0, SU=80 • Repeat until the difference between SL and SU is less than a threshold value ($\delta_s = 0.01$): ○ check if we have enough energy with storage capacity $C = 0.5(SL + SU)$ by going through the N_t time series adding and removing energy as in equation (31) and stopping if the energy runs out (ie is not enough to satisfy the demand at any time point) ○ if we have enough energy, set $SU = C$ ○ if we don't have enough energy, set $SL = C$ At the end of this process C_m is set equal to SL

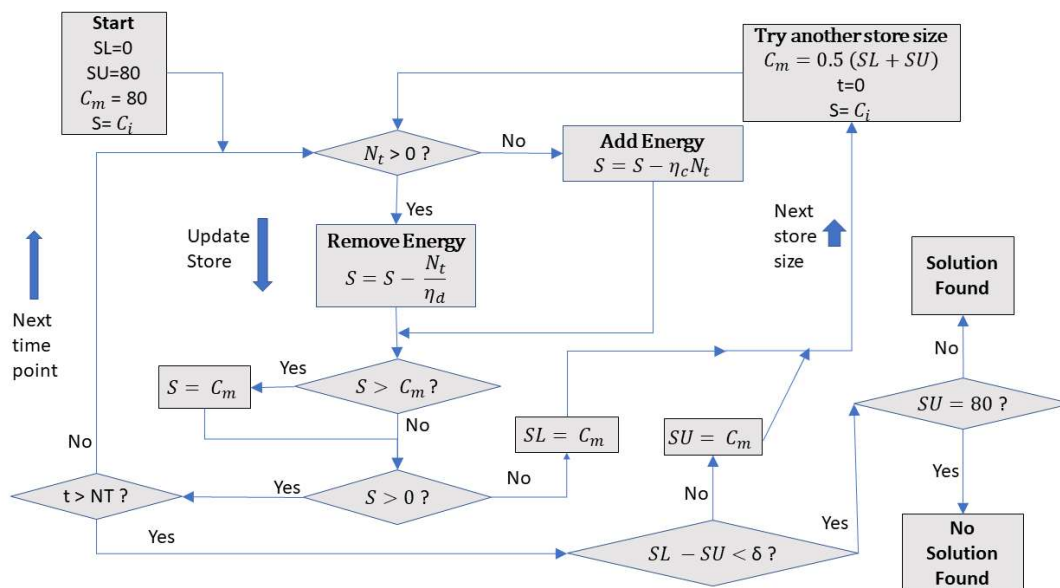


Figure 5-1 Flow chart showing the algorithm to find the minimum storage for a given net demand time series

5.2.2 Calculating the cost of electricity generation

To provide a guide as to which power system configurations might be important, a cost is calculated for each one. This section describes how the cost of electricity for a particular experiment is calculated. The cost model used here is exactly the same as that used in a previous study [52]. The cost is defined to be the total system cost of generating electricity. Each configuration is specified by a certain amount of wind generation capacity (C_w), an amount of PV generation capacity (C_p) and amount of energy storage C_s . The aim here is to not to predict the actual cost, but to provide a guide as to which configurations to use to assess the impact of changes to the demand pattern. One overall figure for the cost of the system based on today's costs was calculated and one for projected future costs.

Table 5-3 Cost model parameters with references to the studies they were taken from

Technology	Value	Unit	Variable	Future Cost
LCOE Offshore Wind	57.5 [52]	£/MWh	L_s	40
LCOE Onshore Wind	46 [52]	£/MWh	L_l	44
Offshore %	46.7 [52]	%	P_s	77
Onshore %	53.3 [52]	%	P_l	23
LCOE PV	60 [52]	£/MWh	L_p	33
LCOE Gas	66 [52]	£/MWh	L_g	120
Cost CAES capacity	3 [52]	£/kWh	α	15% reduction
Cost rated power	300 [52]	£/kW	$\beta \gamma$	15% reduction
Lifetime	30 [52]	Years	λ	
Hydrogen Store	0.67 [52]	£/kWh	α	
Hydrogen electrolysis	1100 [52]	£/kW	β	
Hydrogen electricity generation	450 [52]	£/kW	γ	
Pumped Storage capacity	66.4 [100]	£/kWh	α	
Pumped storage rated power	1188 [100]	£/kW	$\beta \gamma$	
LCOE Nuclear	95 [65]	£/MWh	L_n	

The values used in that cost model are shown in table (5-3). They define the cost metric using estimates from other studies derived from government figures or projections based on the Levelized Cost of Energy (LCOE). LCOE is the discounted lifetime cost of building and operating a generating asset expressed as a cost per unit of electricity generated [99] (£/MWh). It provides a simple way of comparing the costs of different technologies. The costs of the generation and storage capacities are then added up to

provide a total system cost that is expressed as a cost per MWh of the electricity demand, not the electricity generated. This is because we are comparing configurations where more energy may be generated to satisfy the same demand. This means that energy curtailment will result in a higher system cost.

The values for pumped storage in table (5-3) have been taken from a study on the levelized cost of storage technologies [100] and those for nuclear/base load from government figures [65]. For the purpose of calculating system cost, baseload is costed as nuclear. The rest of the values are taken from Cardenas et. al. [52] where this cost model was taken from.

The total cost of the system T_c is calculated using equation (32).

$$T_c = \frac{K_v + K_w + K_p + K_b + K_e}{E_d} \quad (32)$$

Where $K_v = E_g L_g$ is the cost of dispatchable (fossil fuel) generation, $K_w = E_w (P_s L_s + P_l L_l)$ is the cost of wind generation, $K_p = E_p L_p$ is the cost of PV generation, $K_b = C_b L_n$ is the cost of baseload based on nuclear, E_d is the total electricity demand, E_g is the dispatchable energy generation, E_w is the wind energy generated, E_p is the PV energy generated and K_s is the cost of storage given by equation (33)

$$K_e = \frac{N_y}{\lambda} (\alpha C_m + \beta P_c + \gamma P_d) \quad (33)$$

where P_c is the maximum storage charge rate, P_d is the maximum storage discharge rate, C_m is the capacity of the storage in kWh, N_y is the number of years of generation and λ is the lifetime of the asset (all assumed to be 30 years). α , β , and γ are the cost of storage capacity, storage charging power, and storage discharging power. They depend on the type of storage from table (5-3).

Note that this cost model has several limitations. The discount rate and life of the generating plants are accounted for in these figures for 30-years, although degradation due to the number of charge/discharge cycles for storage has been neglected. The cost for large scale solar has been used, but rooftop solar is more expensive. If future curtailment of wind and solar varies from today, for example because the energy is stored then this could impact the LCOE, and it is not clear how this is accounted for in the study from which the cost model was taken. However, rather than actually trying to calculate cost, the main interest here is to use it to define which configurations to compare.

5.2.3 Wind energy fraction

As well as looking at the amount of energy storage, we will assess the mix of solar using the *wind energy fraction* which is the proportion of the total energy generated from wind and solar that comes from wind. Wind energy fraction W_f is defined by equation (34).

$$W_f = \frac{E_w}{E_w + E_p} \quad (34)$$

Where E_w is the total energy generated from wind and E_p is the total energy generated from Solar PV.

5.3 Results and discussion

5.3.1 Standard way of summarising experiments in the thesis

To make it easier to keep track of what is changing in these experiments, a table of the form of table (5-4) is included at the start of each section. This format will be used in the remainder of the thesis.

Table 5-4 Example of an experimental objectives' summary table

Experiment Objective			The aim of the experiment			
Frequency	η	Demand	Storage	Wind	PV	Years
Hourly	50%	Baseline	New	ninja	Ninja	1980-2019

The values that can be contained in this table are explained briefly below:

- **Frequency:** of the time series – hourly or daily
- **η :** round trip efficiency of the storage
- **Demand:** electricity demand source and scaling method:
 - **Baseline:** adding in heat for the weather as per the model used in this project
 - **Historic Add:** historic electricity demand scaled by adding a constant amount onto the historic time electricity demand to make each year the same energy as per Fragaki et. al.
 - **Historic Mult:** historic electricity demand scaled by multiplying the historic electricity demand so that each year contains the same energy as per Cardenas et. al.
- **Storage:** algorithm for finding the minimum storage:
 - **Iterative:** storage algorithm from this project
 - **Max Deficit:** storage algorithm from Fragaki et. al.
- **Wind:** wind generation source
 - **Ninja on:** Renewables Ninja onshore wind
 - **Ninja S:** Renewables Ninja onshore wind scaled to the capacity factor of offshore.
 - **Ninja off:** Renewables Ninja offshore wind
 - **Ninja C:** Renewables Ninja combined wind (offshore and onshore)
 - **Fragaki:** Wind generation from Fragaki et. al.
 - **Fragaki S:** Wind generation from Fragaki et. al. scaled to Ninja offshore capacity factor.
 - **NGrid:** Wind generation from National Grid as per Cardenas et. al.
- **PV:** PV generation source:
 - **Ninja:** Renewables Ninja
 - **Fragaki:** Generation from Fragaki et. al.
 - **Fragaki S:** Generation from Fragaki et. al. scaled to Ninja capacity factor.
- **Years:** years of the analysis period.

5.3.2 Investigation to establish model parameter values

A preliminary investigation was done using only 4 years of weather to be able to consider a very wide range of generation configurations in a reasonable computing time. A 50% round trip efficiency and baseload of 0.4 was used, with the electricity demand from chapter 4 for the existing heating technology of 2018. The aim is not to draw any definite conclusions but to illustrate the range of possible solutions, and to decide where to look in more detail. This section also explains the values of some of the specific constants used in the model to define the experiments.

The single energy store in the model is defined using one round-trip efficiency. However, the future power system is likely to be made up of different types of storage, to cover different requirements. This study will consider Compressed Air Storage (CAES) with round trip efficiency $\eta=70\%$ [52], pumped hydro storage with round trip efficiency $\eta=75\% - 85\%$ [41] and hydrogen storage with round-trip efficiency of $\eta=50\%$ [61] (to specify $\eta_c = \eta_d = \sqrt{\eta}$ in equation (31))

For convenience, and in line with previous studies [41], generation capacities and storage capacities are specified in units of days related to the mean daily energy in the 2018 historic electricity demand time series of 818.38 GWh per day. Thus, a wind generation capacity of 1 day means 34 GW ($=818.38/24$) and 1 day of storage is 818.38 GWh. The daily energy from the generated electricity time series from chapter 4 is not used because it varies between years and between the existing heating technology and the 41% heat pumps.

A baseload capacity (C_b) of 0.4 days is assumed based on the sum of possible future UK nuclear and tidal power generation. The current UK nuclear capacity is 0.3 days [101], actual generation in 2018 was 0.2 days [102] and the potential future capacity ranges from 0.13 days to 0.42 days [103]. A figure of 0.3 for nuclear as assumed being between these two extremes. Potential UK tidal power generation is 0.8 days [19] consisting of tidal barrages, lagoons and stream generation. Here it is assumed that 0.1 days is built. Tidal is considered to be baseload because of its predictability and low seasonal and interannual variation. This gives a combined nuclear and tidal value of 0.4 days. The consequences of varying this baseload are investigated in section 9.4. The minimum demand for 2018 was 0.7 days so the model will never store baseload generated energy.

The experimental parameters are summarised in table (5-5) following the format described in section 5.3.1.

Table 5-5 Experiment to assess the whole range of possible configurations to satisfy the electricity demand with the existing heating technology (see 5.3.1 for terminology)

Experiment Objective: Investigate the whole range of possible configurations to satisfy the electricity demand with 2018 heating technology under 4 years weather variation. Baseload: $C_b = 0.4$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 11.9$ Solar $0.0 \leq C_p \leq 11.9$							
Electricity Demand	Frequency	η	Demand	Storage	Wind	PV	Years
Existing Heating technology	Hourly	50%	Baseline	Iterative	Ninja	Ninja	2016 - 2019

Figure (5-2) indicates the minimum amount of energy storage needed for each combination of wind capacity (C_w), and PV capacity (C_p). Each of these possible combinations will be referred to as a configuration. Each configuration will either be able to meet the demand with a minimum amount of storage which has been found using the model described in section 5.2.1 or will run out of energy and not be viable. They are coloured according to the capacity of energy storage required. Those configurations with low generation in the bottom left-hand corner have no colour because they were not viable and there was not enough energy to satisfy the load. The electricity demand could be satisfied by a wide range of configurations ranging from those in red with a large amount of storage to those on the right in yellow with very low storage, to those in grey with zero storage. The large amounts of renewable generation for the zero storage configurations are well within the potential for offshore wind of 6700 GW [19]. However, the optimal configurations will lie somewhere in between these extremes. It is noted that 30 days storage is approximately in the middle of the range of storage capacities and so it will be used as a comparison point later.

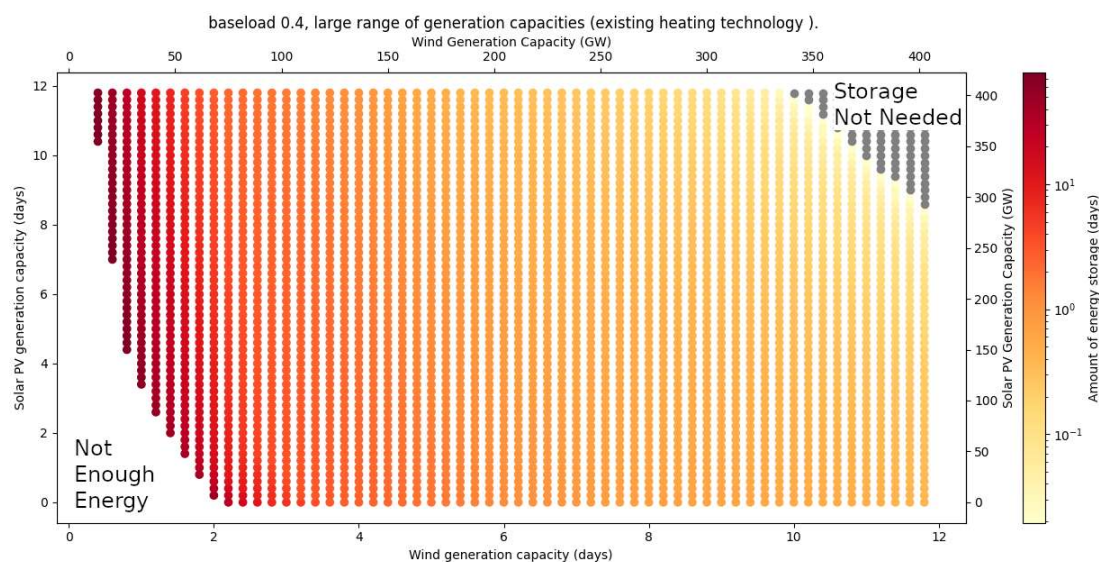


Figure 5-2 Minimum storage for full range of possible configurations of wind and solar to satisfy the load for 2018 heating technology for 40-years weather variation

Figure (5-3) shows the same combinations of wind and solar capacities but instead of showing the minimum storage, shows the cost of electricity at today's prices. Although cost is not the focus of this study, it is used as a guide as to which configurations should

be investigated. Those configurations with large capacities of wind and PV are clearly the most expensive, and the cost optimal configuration is in the bottom left-hand corner. The high cost of the configurations with large amounts of wind and PV is due to curtailment. This is used as a justification for concentrating the analysis on wind and solar capacities below 6 days. The minimum cost configuration is 43 days hydrogen storage for a wind generation capacity of 1.6 days and a PV generation capacity of 1.4 days. The minimum cost configurations for CAES are also well within this region.

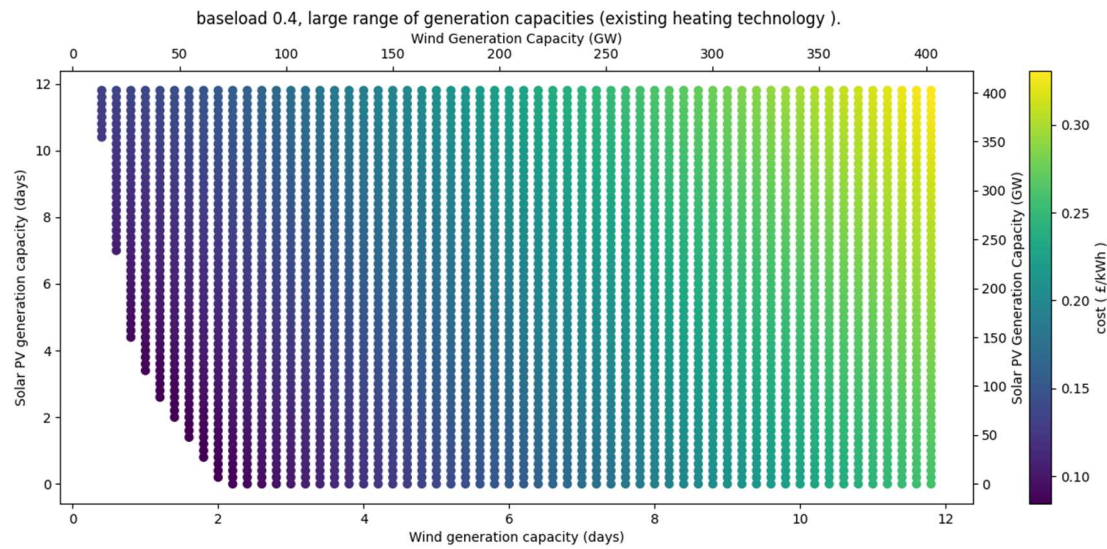


Figure 5-3 Cost of electricity generation for each combination of wind and solar capacity to supply electricity demand with the 2018 heating technology for 40 years' weather variation.

5.3.3 Parameter Values

Based on the discussion in the previous section. for the remaining experiments in this project, the minimum storage was calculated for a set of configurations on a 60x60 2D grid. These were defined by wind ($0 < C_w < 5.9$) and PV ($0 < C_p < 5.9$) in steps of 0.1. The lower computational requirement allows us to use the whole 40 years of data. Those configurations with very high generation, but low energy storage were ignored. This gives 360 points (C_w, C_p) for which the minimum storage required C_m has been calculated. Other quantities that were calculated for each of these points were the Renewable Energy generated (the sum of the Wind energy and PV energy generated), the wind energy fraction and the maximum charge and discharge rates.

The initial state of charge of the energy store was set to 70%. This value was chosen from an analysis of the model with the 40-year electricity time series with the existing heating technology from section 4.2.2. Considering all these possible combinations of wind and solar capacities it was found that the size of the store at the start of each year varies between 27% full and 100% full and that average value at the start of each year is 70% full. Therefore, it was assumed at the start of the 40-year period that the store was 70% full i.e., $C_m \cdot S_0 = 0.7C_m$.

Values which will be varied during the experiments are summarised in table (5-6).

Table 5-6 Model parameter values varied during the experiments.

Parameter	Symbol	Value	Equation
Round trip efficiency hydrogen storage	η	$\sqrt{0.5}$	(31)
Round trip efficiency CAES	η	$\sqrt{0.7}$	(31)
Round trip efficiency pumped storage	η	$\sqrt{0.8}$	(31)
Wind Capacity	C_w	$0 < C_w < 5.9$ days	(29)
Solar PV Capacity	C_p	$0 < C_p < 5.9$ days	(30)
Initial state of charge	S_0	0.7 days	(31)
Base load capacity	C_b	0, 0.2, 0.4 days	(27)
Dispatchable capacity	C_v	$0 < C_v < 1.2$	(28)

Values which remain fixed during these experiments are listed in table (5-7).

Table 5-7 Model parameter values fixed during the experiments.

Parameter	Symbol	Value	Where Used
Hybrid heat pump threshold temperature	T_F	4.15 °C	Equation (19)
Threshold for considering 2 values of storage as the same	δ_s	0.01	Table (5-2)
Initial Store Size	S_0	0.7 C_m (70% full)	Equation (31)

5.4 Validation

This section validates the storage model against the maximum deficit storage model used by a previous study. The first step is reproducing that study to prove that its storage model has been implemented correctly. This also allows one weakness of the previous model that it does not ensure a full energy store at the end of the analysis period to be investigated to prove that it does not impact its use as a validation. Then it is used to validate the iterative model used by this study.

5.4.1 Validate re-implementation of max deficit storage model

The results from the Fragaki et. al. study were reproduced using the same methods from table (5-1) and the same 30 year period. The objective of reproducing the results is to prove that the storage model of that study has been re-implemented correctly, so that it can be compared with the model used in this project. The daily time series of wind and solar generation and the historical electricity demand were made available by the author of the study. The algorithm to find the required storage was re-implemented independently. In contrast to the algorithm defined in 5.2 for this project, it assumes that the energy store starts full, and that the maximum deficit is the required size of the store. It is implemented as follows. The store capacity S from equation (31) is subject to the constraints: $S_0 = 0.0$, $S_t \leq 0$. The algorithm marches through the net demand time series adding and subtracting energy as per equation (31). At the end of the period, the capacity of the store is set $C_m = -S_t$. No check was made to ensure that the store was full at the end of the period. A range of different configurations is generated using different proportions of wind and solar energy combined with an over sizing factor.

Table 5-8 Experiment to reproduce Fragaki et. al exactly (see 5.3.1 for terminology)

Experiment Objective: Reproduce Fragaki et. al.						
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	75% 85%	Historic Add	Max Deficit	Fragaki	Fragaki	1984-2013

Figure (5-4) shows the results of this experiment presented in the same format as those of the original study which is shown in figure (5-5) below. Points on this graph represent the different proportions of wind and solar PV generation capacity. The lines join points with the same energy storage requirements (the minimum amount for storage needed for the system to supply the load). The size of energy store needed was normalised by the mean daily energy demand so that one day of energy storage is 835.616 GWh. The generation capacities for wind and PV are also normalised to this value, so that 1 on the Y axis is 34.8 GW. The dotted lines are for a round trip efficiency of 85% and the solid lines 75% representative of a range of values for pumped hydro storage.

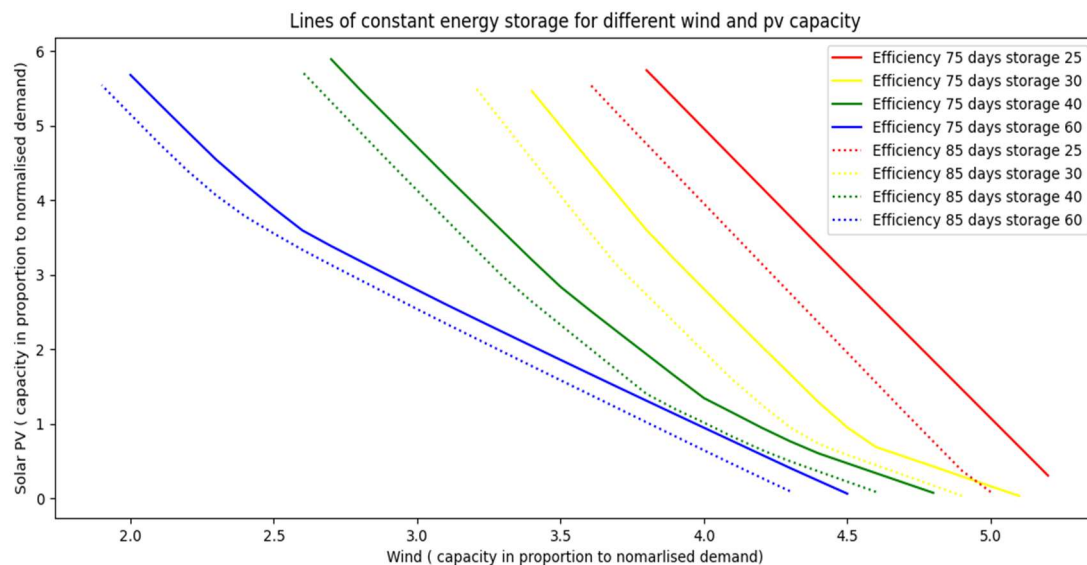


Figure 5-4 Recreation of Figure (8) from Fragaki et. al. using the same data inputs and model.

It can be seen from figure (5-5) which is taken from Fragaki et. al. that the same results have been reproduced. This provides confidence that the same data and methods have been used. The black star represents an illustrative configuration from that study which has 30 days storage and 30% excess energy generation. In contrast to the linear interpolation used to create the contours in figure (5-4), figure (5-5) used a threshold value where, for example 30 days storage means $29.95 \leq \text{storage} \leq 30.05$.

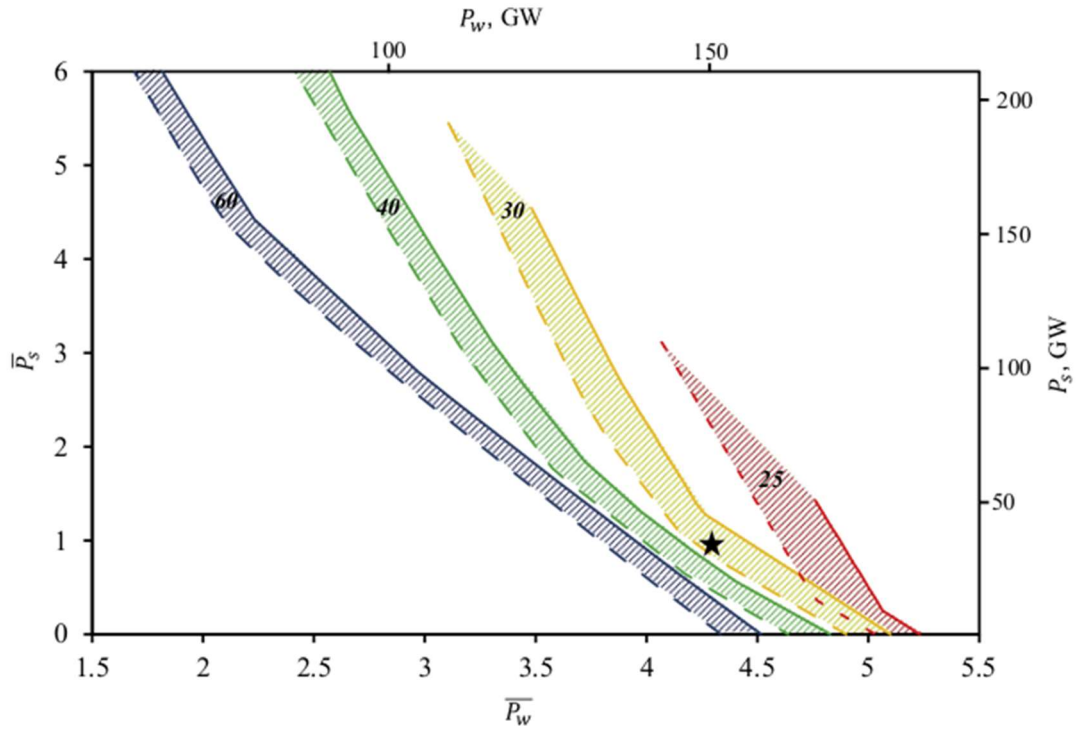


Figure 5-5 Figure (8) from Fragaki et. al. showing lines of constant storage for different wind (x-axis) and solar (y-axis) generation capacities.

Figure (5-6) shows the results from Fragaki et. al. (labelled as Storage KF) for 75% round trip efficiency plotted on the same graph as those from the reimplementaion of the algorithm in this project (labelled as Storage MP). It is clear that they match almost exactly.

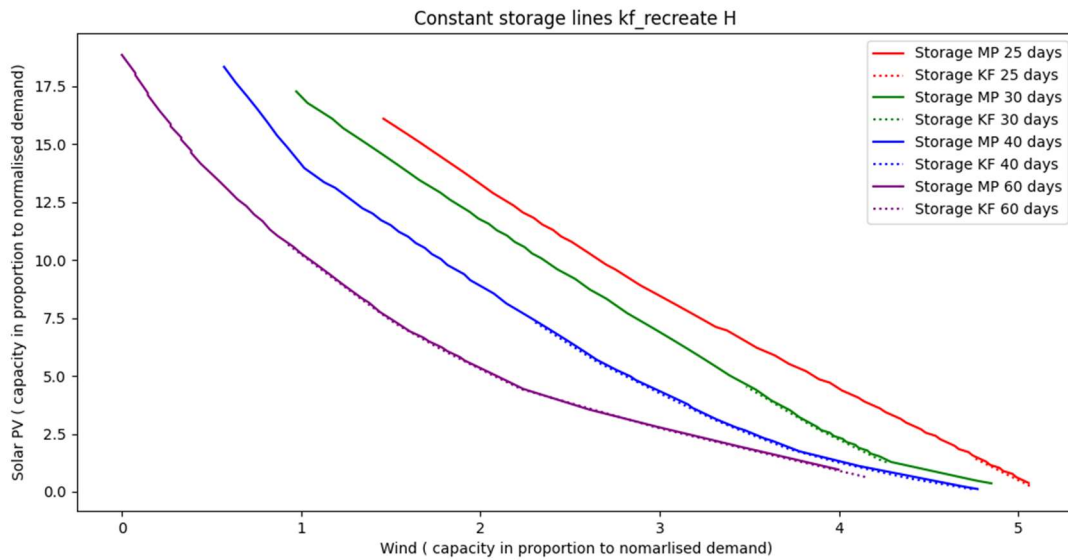


Figure 5-6 Lines of constant storage from the re-coded Fragaki et. al. model plotted on the same graph as the original results.

5.4.2 Validation of the method of finding the minimum storage

The model used in the Fragaki et. al. study assumes that the energy store starts full, and it is sized according to its maximum deficit. In contrast, the model used in this study assumes that the store starts 70% full and uses an iterative procedure to find the minimum storage such that the demand is satisfied and that the store ends up with more energy than it had at the start. This section looks at the difference made to the results depending on which of these models is used. All other aspects are kept the same, apart from the method of finding the storage required. The experimental parameters are summarised in table (5-9).

Table 5-9 Experiment to assess the impact of using a different method to find the storage capacity (see 5.3.1 for terminology)

Experiment Objective: What is the impact of the different method of finding the required energy storage capacity?						
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	85%	Baseline	Max Deficit	Ninja C	Ninja	1980-2019
Daily	85%	Baseline	Iterative	Ninja C	Ninja	1980-2019

Figure (5-7) shows lines of constant storage found using the maximum deficit method compared to the iterative method from this thesis (dotted lines). It can be seen that they are almost identical at most configurations, but that there are slight differences at high PV configurations. This is probably explained by the energy store emptying, as shown in figure (5-8) and discussed in the following section. The energy generated and wind energy fractions for the minimum energy points marked by a black star are all the same, apart from for the 25 days line where 82% wind is used for the maximum deficit method compared to 84% wind for the iterative method used here.

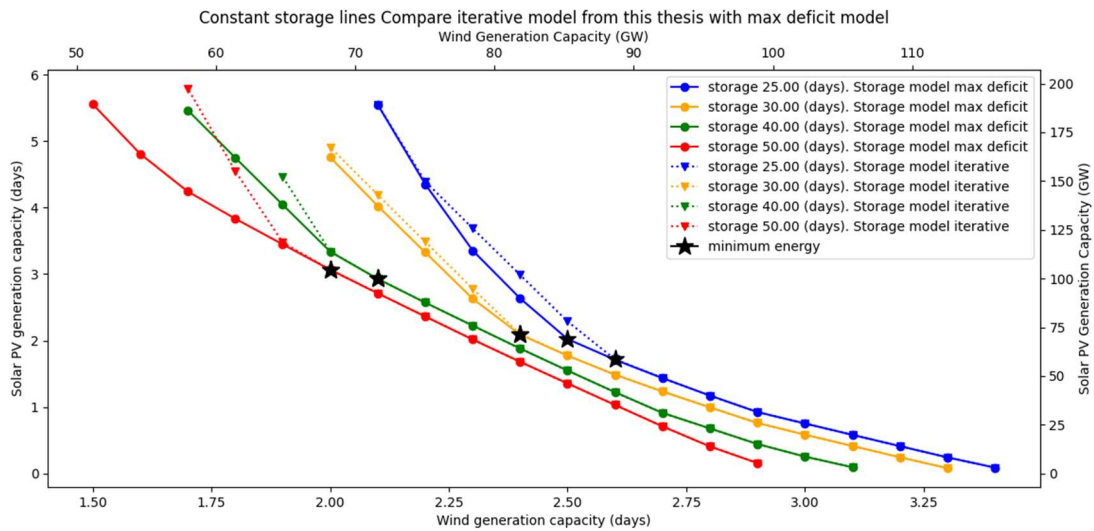


Figure 5-7 Comparison of the maximum deficit and iterative methods of finding the minimum storage using lines of constant storage.

5.4.3 Validation of final State of Charge

Most models of energy storage in previous studies [18, 52, 95, 97] ensure that the energy store contains at least as much energy at the end of the analysis period as it did at the start. In contrast to this “no free lunch” assumption, the model used by Fragaki et. al. does not enforce this condition. However, a small final store size could mean that the solution is not viable because the store started full, and just kept going down over time. In the extreme case with very large storage the system could run for 40 years with no generation at all. The objective of this section is to examine if the energy store does empty over time, and if the lack of this condition is causing a problem. This is to justify using the maximum deficit method as a validation of this project’s method.

Table 5-10 Experiment to check how full the energy store is at the end (see 5.3.1 for terminology)

Experiment Objective: How full is the energy store at the end?						
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	85%	Baseline	Max Deficit	Ninja C	Ninja	1980-2019
Daily	85%	Baseline	Iterative	Ninja C	Ninja	1980-2019

Figure (5-8) shows for different wind and solar capacities how full the energy store was at the end. It can be seen that whilst the energy store ended up full, or nearly full for those configurations to the right of the plot, the final state of charge is very low for low generation configurations in the bottom left-hand corner of the plot. For example, 1.7 days wind 4.5 days solar has 47 days storage and is in range of configurations we are looking at in figure (5-7) but has only 60% charge at the end. This could explain the discrepancies in figure (5-7) at high PV.

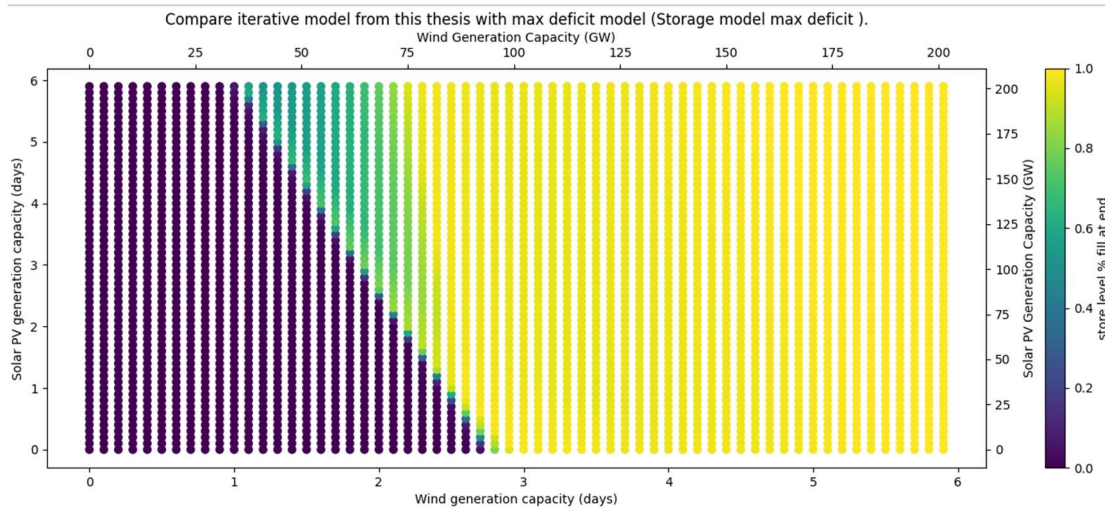


Figure 5-8 The fraction of the initial energy remaining in the store at the end of 40 years using the maximum deficit model.

To address this potential weakness, a different model was adopted in this study that ensure that there is more energy in the store than it started with. To achieve this the store does not start full. It starts 70% full. Figure (5-9) below shows a similar plot of the results using the model in this study. It can be seen that for some configurations the store ends up almost full whereas for others it can be as low as 70% full.

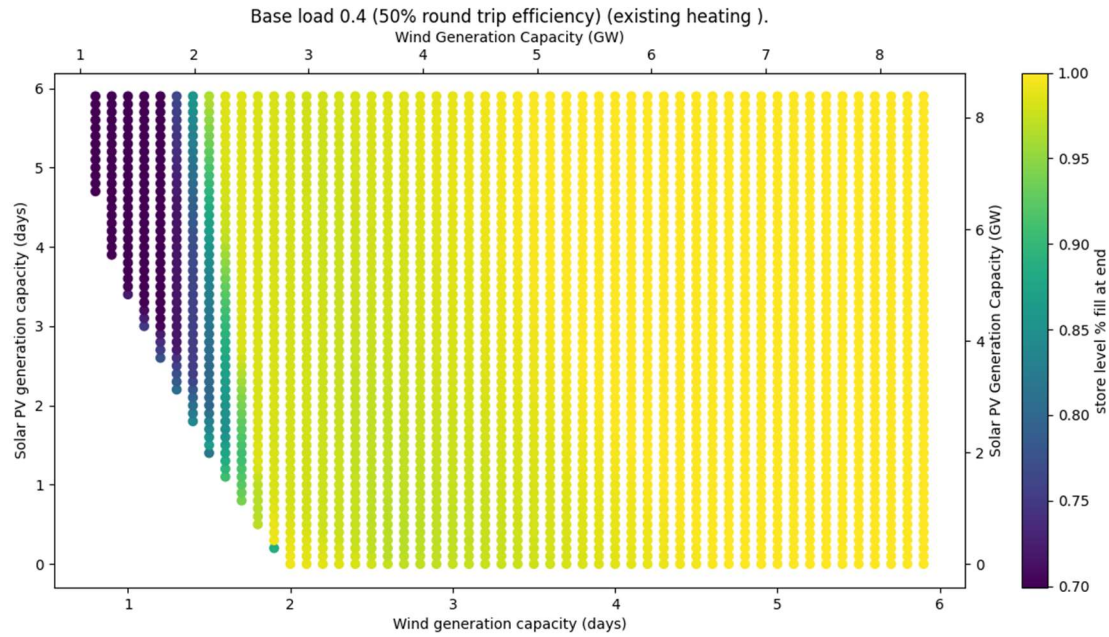


Figure 5-9 The fraction of initial energy remaining in the store after 40 years using the iterative model from this study.

This experiment has shown that the energy store is not empty enough with the maximum deficit storage model to cast doubt on its use as a validation method, but there are some configurations where it causes different results. The iterative model does not have this potential weakness.

5.4.4 Cost Model Validation

Table 5-11 Calculations to verify the cost model

Quantity	Symbol	Day units	Ordinary units
One day's energy		1.0 days	0.923297 TWh
Total Demand	E_d	1.0	3035 TWh
Energy generated over 9 years		1.15 relative to load	3490 TWh
Wind Fraction	W_f	84%	84%
Wind energy over 9 years	E_w	0.966 days	2931.9 TWh
PV energy over 9 years	E_p	0.184 days	558.5 TWh
Storage Capacity	C_m	46.57 days	43 TWh
One hour's energy		1/24 days	38.47 GWh
Maximum Charge rate	P_c	3.09 hours/hour	119 GW
Maximum discharge rate	P_d	1.586 hours/hour	61 GW
Cost of storage	K_e		£ 5.488 x 10 ¹⁰
Generation Cost	$K_p + K_w$		£ 1.85 x 10 ¹¹
Total Cost of Electricity	T_c		79.037 £/MWh

The study from which this cost model was taken [52] found that the cost optimal configuration for the UK was for a wind energy fraction of 84% with 15% energy generated over the load requiring energy storage of 43 TWh. The maximum charge rate was 119 GW and the maximum discharge rate was 61 GW. They found that the cost

was £80 / MWh. Table (5-11) shows calculations to verify the cost model defined by equations (32,33) using this configuration. These calculations result in a cost of £79 per MWh compared to the cost of £80 per MWh found by that study.

5.4.5 Validation of the model with today's energy system

The model defined in 5.2.1 was used to represent today's energy system. The 2018 UK annual electricity demand of 298 TWh required generation of average daily energy of 818.8 GWh which we equate to a unit of 1 day and use this as a measure of storage and normalised capacity. Table (5-12) shows estimated UK capacity and actual generation for 2018. Using the first two columns as a guide, the third column of that table defines the values used to model today's energy system in this chapter.

Table 5-12 Existing power generation capacities for 2018, those used to test out the model, and the energy generation shown by the model

Energy Source	Actual 2018 capacity (days)	Actual 2018 Generation (days)	Model input capacity (days)	Model generated energy (days)
Base Load Generation – nuclear or tidal (C_b)	0.3 [101]	0.2 [102]	0.2	0.2
Dispatchable Generation, eg gas (C_v)	2.0 [101]	0.60 [102]	2.0	0.81
Wind Generation (C_w)	0.63 [104]	0.19 [104]	0.63	0.24
Solar Generation (C_p)	0.38 [104]	0.04 [104]	0.38	0.04
Pumped Storage (C_m)	0.03 [101]	0.008 [102]		

With the inputs to the model defined as ($C_w = 0.63$, $C_p = 0.38$, $C_v = 2.0$, $C_b = 0.2$), a round-trip storage efficiency of 80%, and using hourly time series, the model was used to find the required energy storage. The experiment is summarised in table (5-13) using the format described in 5.3.1.

Table 5-13 Experiment with the model on today's energy system (see 5.3.1 for terminology)

Experiment Objective: Test the model with values comparable to today's energy system.						
Baseload: $C_b = 0.2$, Dispatchable: $C_v = 2.0$, Wind: $C_w = 0.63$ PV: $C_p = 0.38$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	80%	Baseline	Iterative	Ninja C	Ninja	1980-2019

The required storage was found to be 0.03 days which is the actual storage available in 2018. The final column of table (5-12) shows that the model used more dispatchable energy and wind energy than was actually used in 2018, and a similar amount of PV energy. This is a very simplified model, so it is not surprising that there are differences. Not all the generators are being modelled and actual usage is determined by the energy market, rather than the simplified model used here. However, the fact that the wind generation and storage are comparable with the values from the real system provides some validation.

Assuming that the storage is all pumped storage, the cost model from section 5.2.2 calculates the system cost as 97 £/MWh which is more expensive than the actual cost of electricity in 2019 of 65 £/MWh [52]. One possible explanation is that the model used more dispatchable (gas) generation than was actually used. Also the model does not include generation from biomass, hydro, coal or waste.

This experiment has shown how the simplified model compares to the real system. The energy use compares quite well; however, the modelled cost is higher. The objective here is not to cost the system but to assess the impact of changes such as heating electrification on that cost, and on the shares of renewables and storage.

5.5 Summary and Conclusions

A simplified power system model including 10 improvements over previous UK studies has been described. This includes a novel algorithm to find the minimum required energy storage ensuring that the energy store contains at least as much energy at the end of the analysis period than it started with. In contrast to previous work [41, 52] which applies different amounts of overgeneration, the algorithm from this study uses a series of regularly spaced generation capacities. It was found that the iterative algorithm for finding the required amount of storage used in this thesis gave results that matched those from the maximum deficit algorithm used by a previous study almost exactly, apart from at high PV generation. These discrepancies at high PV match those configurations where the energy store falls below 60% full in the max deficit model. The iterative algorithm used here ensures the store ends up with more energy than it started with so does not have this potential weakness.

Using generation capacities close to today's energy system, it was found using the model that enough energy was generated to satisfy the demand. The storage requirement was the same as the existing pumped hydro storage. However, the cost model calculates an electricity cost much higher than today's.

The model has been used to show that there is a wide range of possible combinations of wind, solar and energy storage that will meet the electricity demand with the heating technology of 2018. However, wind and solar generation capacities between 0 and 6 days capture those configurations likely to be important on both grounds of avoiding excessive energy generation and minimizing cost.

A future improvement to the model used by this study might be to find the optimum initial state of charge for the energy store which minimizes the required storage capacity. Comparing the findings of this algorithm with those used in other work would be useful.

6 The impact of the electrification of heating on shares of storage, wind and solar.

This chapter brings together the work on heating electricity with the energy storage model. In chapters 2-4 two 40-year electricity demand time series were produced, one for the existing heating technology and one for 41% of heating provided by heat pumps. In chapter 5 the model used to find the minimum energy storage for different wind and solar generation capacities was defined and tested. In this chapter that model is applied to the two electricity demand time series to investigate the impact of heating electrification. This will answer part of the main research question in this project which is how heating electrification will impact shares of wind, solar and energy storage. It will also answer the question: how can the results be assessed?

The chapter starts with some background and methods. The minimum energy storage required for different combinations of wind and solar generation is calculated. The results section discusses how to assess the impact of the electrification of heating on shares of wind, solar and storage. The chapter concludes with a summary of the findings on heating electrification.

6.1 Background

30% of primary energy demand in Europe is for the heat sector [5]. To reduce the burning of fossil fuels it is likely that in the future this heating will be provided by electric heat pumps which are the most efficient way of providing electric heating [21]. There are two previous UK studies reviewed in chapter 5 looking at different amounts of storage required for purely wind and solar PV systems under long term weather variation. One study uses 9 years' weather data [52] and one uses 30 years' [41]. However, both these studies use only the historic electricity demand and do not include the electrification of heat. One study was found that did consider varying amounts of wind, solar and storage, and also included weather dependent electrification of heating and transport [53]. The variation in wind and solar was limited to five different capacities, with no attempt to identify the ideal mix and it concentrated on a 3-year period between 2009 and 2011. However research has found that 10 years or more is required to capture the variation in renewable power generation caused by weather to fully test an energy model [11]. This chapter addresses that gap by studying the impact of heating electrification on wind, solar and storage using 40-years' weather data.

The simplified model of the power system used in this project contains a single energy store defined using one round-trip efficiency. However, the future power system is likely to be made up of different types of storage, to cover different requirements. A study on the economics of electrical storage [18] states that batteries are suitable for a period of a few hours, Compressed Air Energy Storage (CAES) and pumped hydro storage are suitable for 6-10 hours and power to gas such as hydrogen are suitable for long term storage. However previous studies into the amount of long term energy storage required in the UK have made the assumption of pumped storage (efficiency 80%) [41] and CAES (efficiency 70%) [52] finding requirements for 25 TWh and 43 TWh respectively. Seven plans for a net zero UK energy system from four different groups [19] use hydrogen generated from electrolysis of water for long-term storage. Another study [105] states that there is limited evidence that hydrogen is the most cost

effective option for long term inter seasonal storage and study power to methane (efficiency 39%) with CCS or Direct Air Capture to store the CO₂. It can be seen from these examples that there is some doubt as to what the future long term storage technology might be. As found in chapter 5, a large storage capacity will be required, but the potential availability of UK pumped storage is only about 0.5 TWh [61], so only a small proportion of it could be pumped hydro storage. In common with most plans of future UK net zero power systems [19] the assumption is made in this chapter that the storage will be mostly hydrogen. CAES will also be considered for comparison.

6.2 Methods

The two electricity demand time series generated in chapter 4 were compared using the model defined in chapter 5 to find the minimum energy storage. The model was run twice: one with the demand D_t in equation (27) using the existing heating technology and once with heating provided by 41% heat pumps. These two demand time series are:

- **Existing:** A 40-year electricity demand time series including the existing heating technology of 2018 based on 40 years of weather. From equation (22) chapter 4.
- **41% Heat Pumps:** A 40-year electricity demand time series including 13% of heating provided by hybrid heat pumps and 29% by ordinary heat pumps based on 40 years of weather. From equation (23) chapter 4.

The electricity generation part of equation (27) was defined to be zero dispatchable generation ($C_v = 0.0$), different combinations of wind generation (C_w) and solar generation (C_p) capacities, and a fixed baseload. A baseload capacity (C_b) of 0.4 days is assumed based on possible future UK nuclear and tidal power generation as in chapter 5.

In line with the discussion in the previous section, it is assumed that the round trip efficiency is 50% for hydrogen storage [61] (to specify $\eta = \sqrt{0.5}$ in equation (31)) . However, for comparison with other studies, a round-trip efficiency of 70% for CAES is also used.

The experimental parameters are summarised in table (6-1)

Table 6-1 Experiment to assess the impact of heating electrification on shares of wind and solar generation capacity (see 5.3.1 for terminology)

Experiment Objective: Assess the impact of heating electrification on storage and shares of wind and solar generation.							
Baseload: $C_b = 0.4$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$							
Electricity Demand	Frequency	$\eta\%$	Demand	Storage	Wind	PV	Years
Existing Heating technology	Hourly	50, 70	Baseline	Iterative	Ninja	Ninja	1980 - 2019
41% Heat pumps	Hourly	50, 70	Baseline	Iterative	Ninja	Ninja	1980 – 2019

6.3 Results

Figure (6-1) shows the electricity demand time series for the existing heating technology compared to 41% heat pumps based on 40 years of weather. It can be seen that with heat pumps there would be large increase in the winter electricity demand.

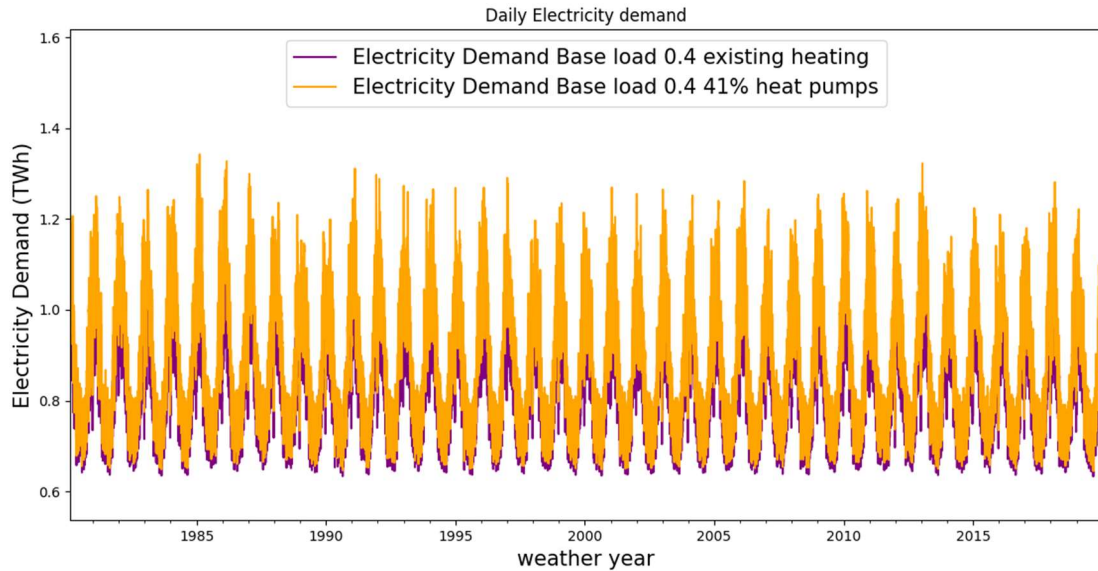


Figure 6-1 The impact of 41% of heating provided by heat pumps on the UK electricity demand

In the following sections the impact of this change to the electricity demand on capacities of wind generation, solar generation and energy storage will be investigated.

6.3.1 Minimum required storage for the existing heating technology and 41% heat pumps

Figure (6-2) shows for each combination of wind and solar PV capacities, the amount of energy storage required. A similar pattern can be seen for both with and without heat pumps. For large generation capacities, very little storage is needed.

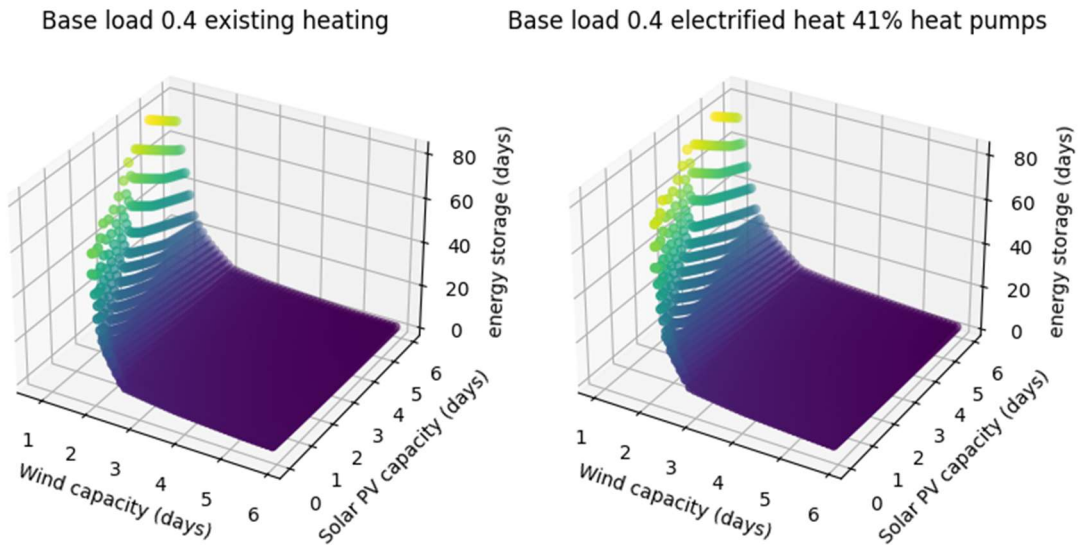


Figure 6-2 The impact of 41% of heating provided by heat pumps on capacities of wind, solar and storage.

It is difficult to tell the difference between the two images in figure (6-2). Therefore, to assess the change caused by heating electrification quantitatively, two quantities will be considered:

- the amount of energy storage
- the wind energy fraction: equation (34)

Figure (6-3) shows the difference between the storage requirements for the same configuration between the existing heating and 41% of heating provided by heat pumps. For each configuration the storage for 41% heat pumps has been subtracted from the storage for the existing heating technology, so that the result is always negative. As would be expected heating electrification always requires more storage for the same generation capacity because the demand is higher, apart from at very high generation where both tend to zero (indicated by yellow colours). For the lower generation configurations, the difference in storage is above 30 days, shown by purple. The bottom left corner is empty where there is not enough energy generated to satisfy the load for 41% of heating provided by heat pumps.

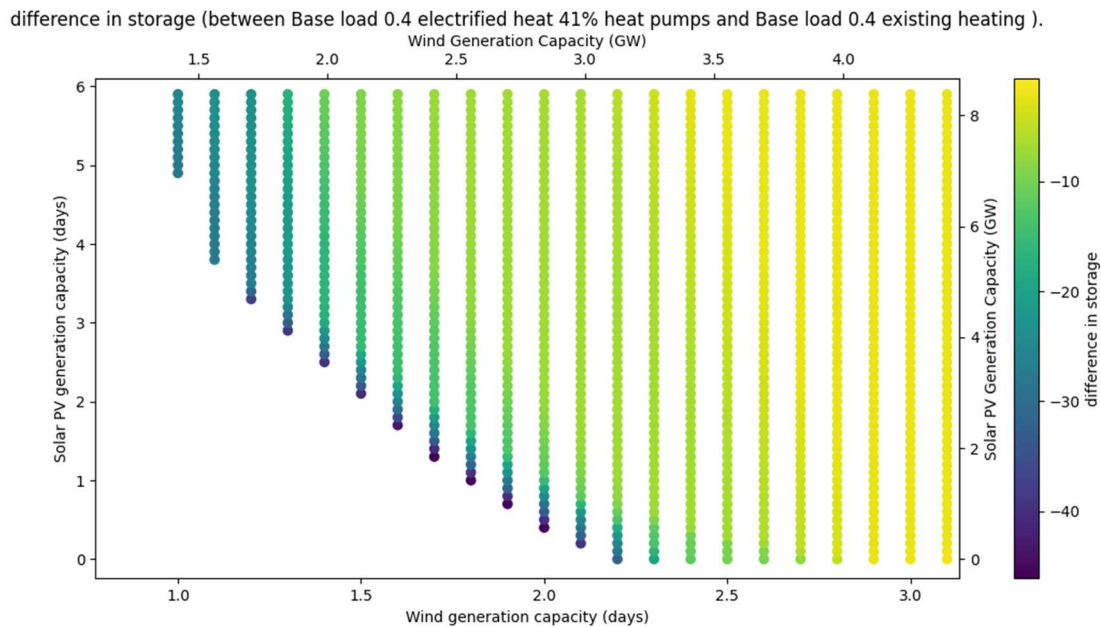


Figure 6-3 Energy storage (days) needed with 41% heat pumps subtracted from storage needed with the existing heating technology for different combinations of wind and solar generation capacity

The wind energy fraction will be considered in the next section.

6.3.2 Comparison of Experiments

This section describes how the results of the experiment with the electricity demand with the existing heating technology were compared with that with 41% heat pumps. To assess the impact of such a change to the system, a way is needed of comparing one set of 360 configurations with another. The 360 configurations arise from combinations of wind and solar PV capacities defined in table (6-1) and shown in figure (6-2). This same method will be used throughout the rest of the thesis to compare two experiments.

Some previous studies have compared cost [18], CO₂ emissions [61] or fuel used [61]. Some have minimized the amount of storage for configurations which generate less

than 50% excess energy [96]. Fragaki et. al. [41] which is explored further in chapter 7 chose an illustrative example with an intermediate amount of 30 days of storage. Research has found that looking for minimum excess energy generation (curtailment) results in the requirement for large storage [18] and not likely to be a low cost option. Using a cost metric has the disadvantage that future costs are unknown and that it is difficult to define. Using a particular amount of storage or excess energy generation have the disadvantage that the figure chosen is arbitrary. Trying to assess all the configurations at once, such as looking at the mean, might give too much weight to less important configurations. A combination of these measures from previous work was used allowing the results to be assessed from several different perspectives, and to see if any common trends become apparent.

For example, if there are two experiments, to compare experiment A which is the existing heating with experiment B which is 41% heat pumps, then there will be 360 configurations in each scenario. The following methods were used to choose a configuration from experiment A to compare with experiment B:

- Configurations with **equal for minimum storage**. Given a particular value of minimum value of storage, find configurations of wind and solar PV generation capacities that require that minimum storage, and join them with a contour line on a graph, for example figure (5-6).
- Configuration with **least storage for given excess energy**. Using the configuration with least storage from those generating less than a certain excess energy.
- Configuration with **minimum cost of electricity generation**. The wind and solar generation capacity that gives the least cost of electricity generation at today's prices (including storage cost).

These are expanded in the following sections using the comparison of the existing heating technology with 41% heat pumps to illustrate their use.

6.3.3 Configurations needing the same minimum storage

For a range of regularly spaced storage capacities: 10,20,30,40,50 days, the wind and solar PV generation capacities that require this minimum storage were found. For each wind capacity, the configurations with storage above and below the given storage requirement (for example, 30 days) were identified. Linear interpolation between these surrounding grid points was then used to find the values of wind and solar generation capacity. This set of storage capacities was chosen because above about 60 days there are not enough points to perform the linear interpolation. This set of points having equal storage can then be sorted by wind and solar capacity and plotted.

Figure (6-4) shows how the pattern of the 30, 40 and 50 days changes because of heating electrification. The 10-day and 20-day lines are not shown for clarity. As well as the wind and solar generation capacities, the following values were calculated by linear interpolation:

- Renewable energy generated (sum of wind and solar) expressed as a fraction of the load.
- Wind energy fraction expressed as a percentage of the renewable energy generated using equation (34).

- Cost of electricity generation.

For heating electrification, the lines for the same number of days of storage move to the right indicating a higher capacity of wind required for the same generation.

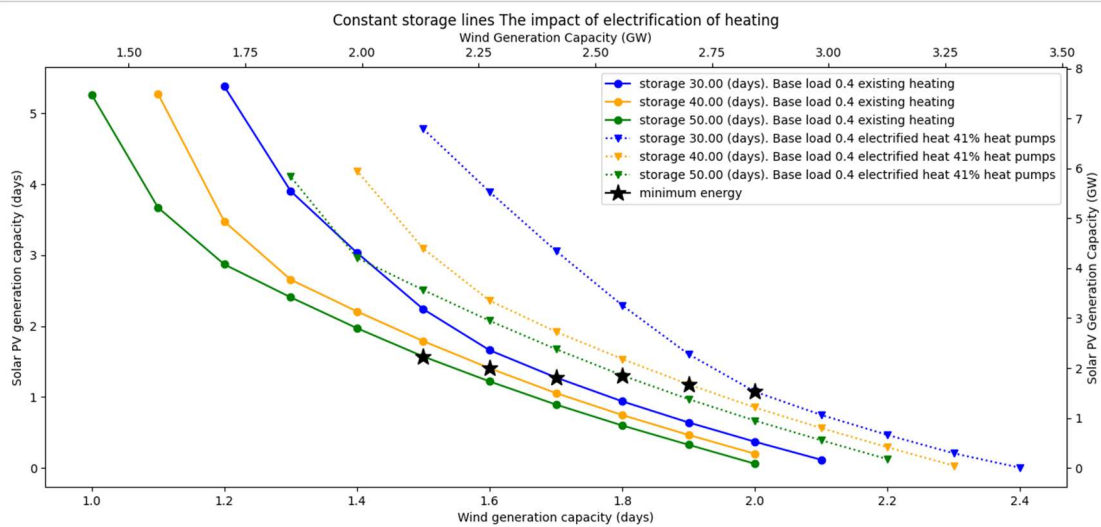


Figure 6-4 The impact of 41% heat pumps on energy storage with a 50% round-trip efficiency.

The black star in figure (6-4) indicates the location of the configuration requiring minimum energy generation which we look at because assuming equal costs for wind and solar this might be expected to be the cheapest and therefore optimum configuration of those with the same storage since they have similar levelized costs of energy [99].

Figure (6-5) shows the energy generated plotted against the wind energy fraction for the same lines of constant storage. The flatness of the lines near the minimum energy configurations shows that there is a wide range of wind energy fractions for similar energy, something that would be missed if we just searched for the minimum energy solution.

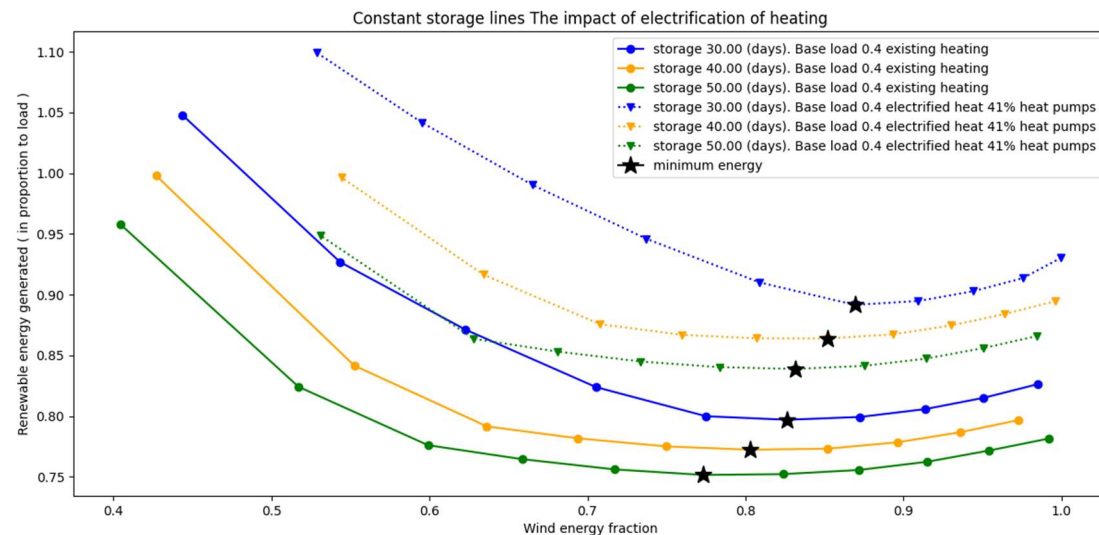


Figure 6-5 Wind energy fraction using the minimum energy generation configuration for different amounts of storage comparing the existing heating and 41% heat pumps.

Table (6-2) compares the minimum energy configurations requiring 30 days storage for the existing heating technology and for 41% heat pumps. This example of 30 days storage is used chosen as the half way point between 0 and 60, and also used as an

illustrative example from previous work. [41]. Because the minimum storage is the same (30 days) and with heating electrification, the electricity demand is higher, more renewable energy must be generated. The wind energy fraction for heating electrification is higher because more heating energy is required in winter when more wind energy is available.

Table 6-2 Comparison of existing heating and 41% heat pumps for 30 days minimum storage

Measure	Electricity Demand	
	Existing heating technology	41% heat pumps
Wind capacity (days)	1.7	2.0
PV capacity (days)	1.3	1.1
Wind Energy Fraction	83%	87%
Renewable energy generated in proportion to load	0.80	0.89

Figure (6-6) shows the wind energy fractions for different amounts of storage based on the same method as figure (6-5). For low amounts of storage, energy must be used close to when it is generated, so it makes sense that low storage equates to a high percentage of wind. This is because there is more wind energy available in winter at the same time as when demand is higher.

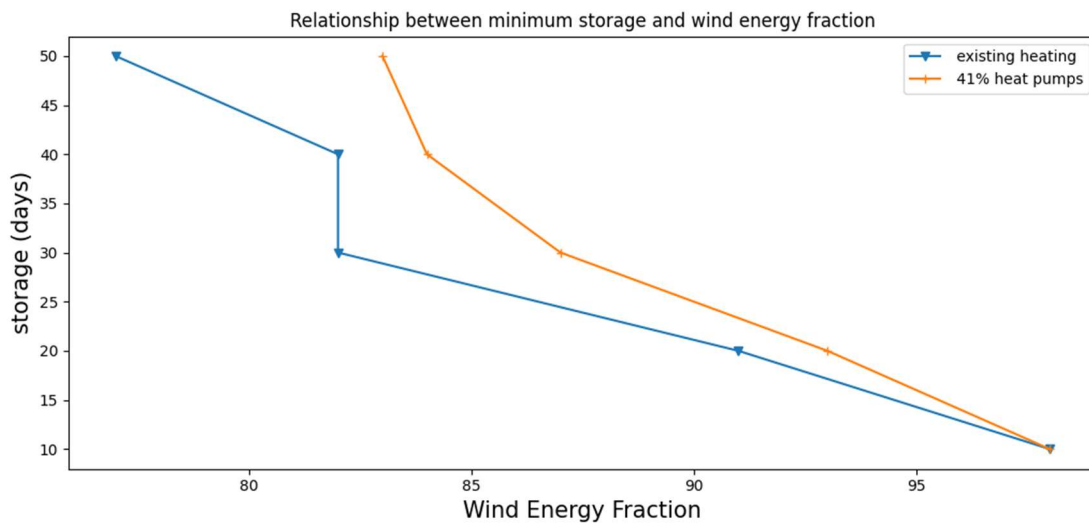


Figure 6-6 Relationship between minimum storage and wind energy fraction for existing heating and heat pumps

The difference in storage between the existing heating technology and 41% heat pumps is greater for higher storage (and hence the lower generation) capacities. Heating electrification increases the wind energy fraction by up to 10%, depending on the capacity of energy storage.

6.3.4 The least storage configuration for 50% excess energy generation

Previous research has shown that neither minimizing storage nor minimizing energy generation are likely to give an optimum solution to the question of how much storage, and generation capacity is required. Therefore, to calculate optimum wind energy fractions, a previous study [96] considered those configurations generating 50% excess

energy above the load and chose the one requiring the least storage. Other research has used 15% excess energy [52] which was the minimum cost configuration at today's prices. This method of choosing an excess energy is used as a comparison method here.

From those configurations that generate the given amount of excess energy over the load or less, the one that has the minimum storage is chosen from one experiment. Then linear interpolation on the configurations in the other experimental run is used to find a configuration with same wind and PV capacity.

Table (6-3) shows this 50% excess energy configuration for the existing heating technology and compares it with that for 41% heat pumps. It has 2.7 days wind capacity and 0.4 days PV capacity. The energy column indicating the total wind and solar generation shows 1.09 which when added to the baseload of 0.4 gives 1.49 which (with rounding) is 50% excess energy. With 41% of heating provided by heat pumps, 13 days of storage is required, compared to only 8 days with the existing heating technology.

Table 6-3 Comparison of the existing heating and 41% heat pumps for the configuration generating 50% excess energy that has the least storage.

Electricity Demand	Wind (days)	PV (days)	Wind Energy Fraction	Renewable Energy (days)	Storage (days)
Existing heating technology	2.7	0.4	96%	1.09	8
41% Heat Pumps	2.7	0.4	96%	1.09	13

Minimum storage from configurations generating less than 50% excess energy over the load is 5 days greater for 41% heat pumps than with the existing heating.

6.3.5 Minimum Cost of electricity generation

This section uses the cost of electricity based on today's costs for each configuration (of wind, solar and storage capacities) as a method of comparing the results using electricity demand with the existing heating technology with those for 41% of heating provided by heat pumps. The cost was calculated using equations (32) and (33) from section 5.2.2. Figure (6-7) shows the cost of electricity generation for each combination of wind and solar generation capacities using the electricity demand with the existing heating technology. The cheaper configurations are those with lower energy generation in the bottom left hand corner. To compensate for the lower generation these configurations would have higher energy storage. Where there is no coloured dot there was not enough energy available (either from generation or storage) to satisfy the load at each hour of the 40 years.

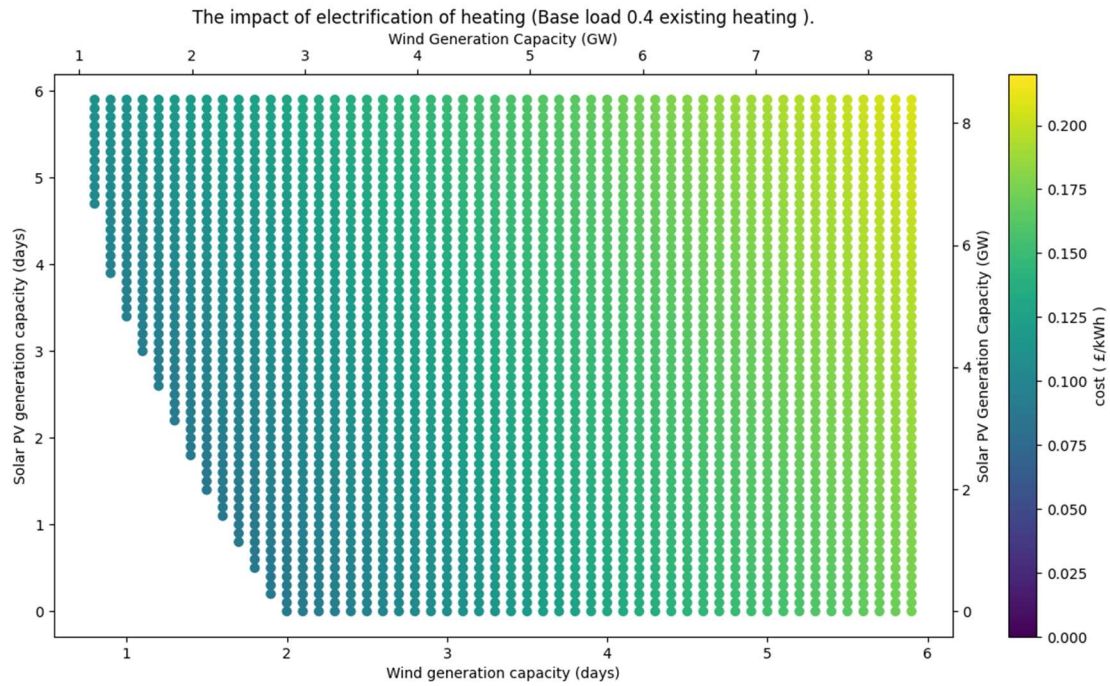


Figure 6-7 Cost of generating electricity at today's prices for 0,4 days base load and different wind and solar capacities for the existing heating

Figure (6-8) shows a similar pattern for the electricity demand including 41% of heating provided by heat pumps.

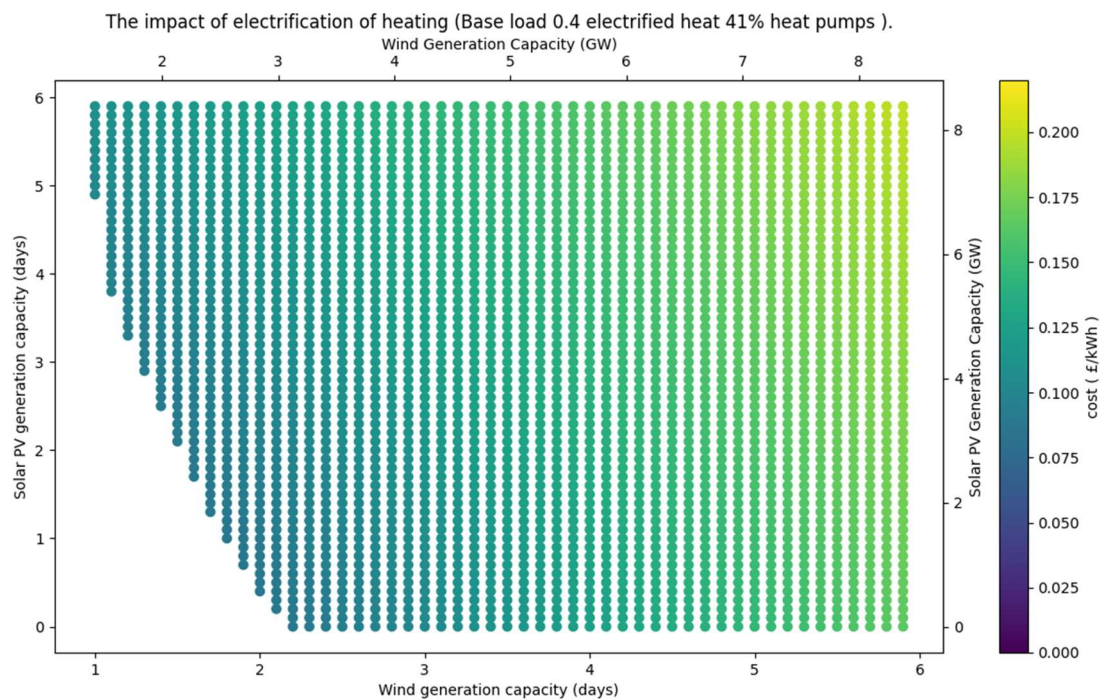


Figure 6-8 Cost of electricity generation at today's prices for base load 0.4 days and different capacities of wind and solar to satisfy the UK electricity demand but with 41% of heating provided by heat pumps

The reason that there are configurations with higher cost in figure (6-7) with the existing heating technology than in figure (6-8) with 41% heat pumps is that the cost is expressed in £/kWh. Although more electricity is generated for heating electrification, the cost per kWh can be cheaper, for example if the demand pattern changes so that less energy needs to be stored.

Table (6-4) shows the minimum cost configurations for the existing heating and for 41% heat pumps. At today's costs the minimum cost configuration for heating electrification has a wind energy fraction of 91%. Compared to the existing heating technology more energy has to be generated from wind and more storage is required. However, using the anticipated future costs of wind and solar show that these lower generation costs lead to both cases requiring lower wind generation and more storage. Because the future costs in table (5-3) anticipate solar being cheaper, the wind energy fraction declines.

The configuration having the minimum cost of electricity at today's prices of those needing 30 days of storage is quite close in cost to the minimum energy configuration shown in section 6.3.3. However, the wind energy fraction is 4% higher for the minimum cost, compared to the minimum energy. This is because wind is cheaper in the cost model used in table (5-3)

Table 6-4 Impact of heating electrification on the minimum cost configuration for hydrogen storage

Configuration	Measure	Electricity Demand	
		Existing heating technology	41% heat pumps
Configuration with minimum cost of electricity at today's prices	Wind capacity (days)	1.7	1.9
	PV capacity (days)	0.8	0.7
	Wind Energy Fraction	88%	91%
	Renewable energy generated in proportion to load	0.75	0.81
	Storage	59	72
	Cost of electricity at today's prices (£/kWh)	0.088	0.088
Configuration with minimum cost of electricity at future prices	Wind capacity (days)	1.5	1.7
	PV capacity (days)	1.4	1.3
	Wind Energy Fraction	79%	82%
	Renewable energy generated in proportion to load	0.73	0.80
	Storage	63	75
	Cost of electricity at today's prices £/kWh	0.079	0.078
Configuration requiring 30 days storage with minimum cost of electricity generation at today's prices	Wind capacity (days)	1.8	2.0
	PV capacity (days)	0.9	0.75
	Wind Energy Fraction	87%	91%
	Renewable energy generated in proportion to load	0.80	0.89
	Cost of electricity at today's prices £/kWh	0.091	0.097

Considering the minimum cost configuration for hydrogen storage, heating electrification increases the wind energy fraction by 3% and the amount of storage by 13 days (12 days for future costs).

Figure (6-9) shows lines of constant storage for the existing heating technology only with the minimum energy configuration marked by a black star. It can be seen that the minimum cost configuration marked by a black cross is close to it, but not the same.

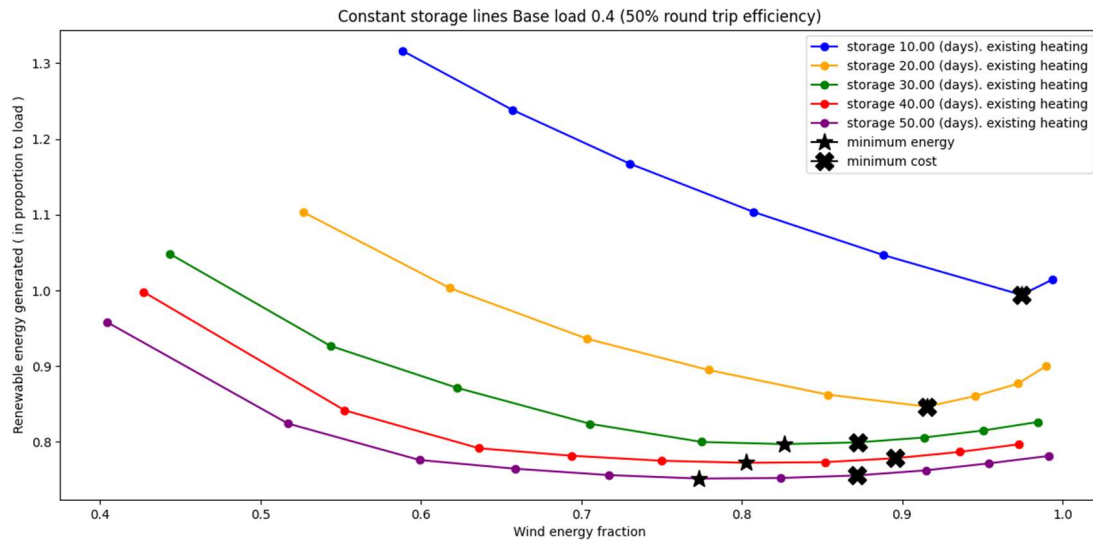


Figure 6-9 Minimum cost configuration at today's prices compared to minimum energy configuration for configurations with the same minimum storage capacity

6.3.6 Electrification of heat with CAES

So far, this section has been concentrating on a round-trip efficiency and cost for hydrogen storage. The analysis from sections 6.3.3 to 6.3.5 is now repeated, but for compressed air storage (CAES) instead. The experimental parameters are summarised in table (6-5).

Table 6-5 Experiment to assess heating electrification impact with CAES (see 5.3.1 for terminology)

Experiment Objective: Assess the impact of heating electrification on CAES capacity and shares of wind and solar generation.							
Baseload: $C_b = 0.4$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$							
Electricity Demand	Frequency	η	Demand	Storage	Wind	PV	Years
Existing Heating technology	Hourly	70%	Baseline	Iterative	Ninja	Ninja	1980 - 2019
41% Heat pumps	Hourly	70%	Baseline	Iterative	Ninja	Ninja	1980 - 2019

The results are shown in table (6-6). Coincidentally the minimum cost configuration for CAES with a round-trip efficiency of 70% has approximately the same cost as that for hydrogen storage with a round-trip efficiency of 50%. CAES has similar wind fractions, and lower amounts of storage. Similar to hydrogen storage, heating electrification increases wind energy fraction.

Table 6-6 The impact of 41% heat pumps on a system with 0.4 base load, wind, solar and compressed Air Storage

Configuration	Measure	Electricity Demand	
		Existing heating technology	41% heat pumps
Equal minimum storage (30 days min energy)	Wind energy fraction	84%	85%
	Renewable energy generated % of load	0.73	0.82
Least storage of those generating 50% excess energy above the load	Minimum storage (days)	7	9
	Wind capacity	2.7	2.7
	PV capacity	0.4	0.4
Minimum cost of electricity generation at today's prices	Wind energy fraction	87%	92%
	Renewable energy generated % of load	0.76	0.84
	storage (days)	23	25
	cost £/kWh	0.088	0.088

6.4 Summary and Conclusions

The configurations of wind generation capacity, solar generation capacity and energy storage from the model developed in chapter 5 have been used to investigate the impact of heating electrification. This compares the power system needed to meet the electricity demand with the existing heating technology to that with 41% heat pumps. Heating electrification always needs more storage for the same generation capacity. With 41% heat pumps, if the PV capacity is zero, then viable configurations range from 2.3 days (78 GW) wind with 47 days (38 TWh) of storage to 5.6 days (190 GW) wind with 6 days (5 TWh) of storage. The minimum cost configuration for hydrogen storage is the former, with a large storage capacity. For zero wind, 10 days (340 GW) PV capacity requires 127 days (104 TWh) storage with the existing heating and 159 days (130 TWh) after heating electrification. Whereas 80 days (2.7 TW) of PV generation capacity requires 2 days (1.6 TWh) storage with the existing heating and 3.5 days 2.8 TWh) with heating electrification. A PV only solution with a large amount of storage is possible, but the optimal solution will depend on the relative cost of wind and PV.

The overall patterns in the relationships between shares of wind, PV and storage are similar for both 41% heat pumps and the existing heating technology. However, the wind energy fraction is higher for heating electrification. This is logical because more heating energy is required in the winter when there is also more wind and less PV energy available. With 41% heat pumps and 30 days (25 TWh) storage, both the minimum energy and minimum cost configurations have a 4% higher wind energy fraction. The overall minimum cost configurations with both current and future costs have 3% higher wind energy fractions. For 41% of heating provided by heat pumps, the wind energy fraction of the minimum cost configuration is similar for both CAES

(92%) and hydrogen storage (91%). In contrast to previous work finding that CAES is cheaper than hydrogen storage, it was found that the minimum cost configuration for CAES had the same cost as that for hydrogen storage.

The configuration with the least storage of those generating 50% excess energy above the load is wind 2.7 days (92 GW) and PV 0.4 days (15 GW). With the existing heating it requires 8 days (6.5 TWh) of storage, but 13 days (10.6 TWh) storage with 41% heat pumps. The minimum cost configuration with 41% heat pumps requires 13 days (10.6 TWh) more hydrogen storage at today's prices and 12 days more at projected future prices.

For both the existing heating technology and 41% heat pumps, the amount of storage increases if less energy is generated and the wind energy fraction decreases. For lower amounts of storage, the difference in wind energy fractions between the existing heating technology and 41% heat pumps is greater.

One area for future research would be to define a cost model in terms of relative costs and investigate the implications on the optimal solution as the relative costs change.

A standard method of comparing two sets of results from the model has been developed and illustrated in this chapter using heating electrification as an example. The comparison method identifies configurations to compare using three methods: lines of constant storage, 50% excess energy generation and minimum cost. Two quantities are compared: the storage capacity and the wind energy fraction. This comparison method will be used throughout the rest of the thesis.

7 Sensitivity of storage model to inputs and previous studies

In this chapter results of two previous studies to find the required UK energy storage for a purely wind and solar system are examined to see how they would change had the methods from this thesis been used. The sensitivity of the model results to different inputs is investigated. The results of this sensitivity analysis are then used to identify what the main cause of the changes is in the results from two previous studies.

The background to the two studies was discussed in chapter 5, so this chapter starts with a discussion of the methods, followed by the sensitivity analysis. The results section shows how these two studies would have been different had this project's model been used. The sensitivity analysis to assess the impact of these different model inputs shows that wind generation time series have a high impact on the results, so there is a section investigating this further. The chapter concludes by summarising the findings.

7.1 Methods

The two UK studies previously discussed in chapter 5 will be examined in this chapter: Cardenas et al. [52] and Fragaki et. al. [41]. The latter study was reproduced in chapter 5 for validation purposes. This chapter will examine the following:

- Updating Fragaki with the methods from this study
- Updating Cardenas with the methods from this study
- Sensitivity analysis of the different inputs
- Extra study of wind generation time series pattern by scaling them so that they have the same capacity factor.

The Fragaki study was updated using chapter 5's methods but using a round trip efficiency of 85% for pumped storage. The objective is to see how this project's methods would change the results of that study.

Then the Cardenas study was updated using the methods from this study as specified in chapter 5, but for CAES at a round trip efficiency of 70%.

Differences in wind or PV generation time series could be due to either the mean capacity factor or a difference in the pattern of when the energy is generated compared to when it is needed. To assess this the generation time series with the lower mean capacity factor was scaled so it had the same capacity factor as the other time series using equation (35). In effect capacity is added to compensate for the lower capacity factor so that the same energy is generated.

$$GS_h = \frac{\sum GS_h}{\sum GL_h}(GL_h) \quad (35)$$

Where GS_h is the hourly (h) wind time series scaled to the higher capacity factor, GH_h is the wind time series with the higher capacity factor and GL_h is the wind time series with the lower capacity factor. The scaled time series then generates the same energy as the time series with the higher capacity factor, but at different times due to the pattern. Therefore, any difference seen is due to the difference in the temporal pattern.

7.2 Sensitivity to time period and frequency

In this section, the sensitivity of the results to the time period and frequency of data used is investigated.

7.2.1 Hourly or Daily time series

The objective of this section is to investigate the amount of energy storage needed for a system with an electricity demand like that of today, but with a high penetration of renewable generation. Also, the impact of using daily or hourly time series is investigated. It is normal practice for energy models of the type used in this study to be run at hourly resolution [25, 97]. One review paper on the amount of energy storage required [106] only considers other studies that have hourly resolution. However, other research has found that the temporal resolution required depends on the research question being answered [107] with models incorporating storage reducing the importance of high time resolution. One study of the storage and balancing needs of the European power system [96] found differences in optimal wind fraction and storage capacity between using hourly and daily time series. Therefore, the difference between using hourly and daily time series is investigated here.

The model defined in section 5.2 was used with a 50% round trip storage efficiency. The electricity supply consists of base load 0.4 days, and various capacities of wind and solar. The electricity demand represents the existing heating technology from 4.2.2. All other factors are the same apart from using hourly or daily time series. The inputs are summarised in table (7-1).

Table 7-1 Experiment to compare hourly and daily time series (see 5.3.1 for terminology)

Experiment Objective: Compare hourly or daily time series, generation wind, solar Baseload: $C_b = 0.4$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	50%	Baseline	Iterative	Ninja C	Ninja	1980-2019
Hourly	50%	Baseline	Iterative	Ninja C	Ninja	1980-2019

The following plot figure (7-1) shows constant storage lines for different capacities of wind and solar generation. Whilst the 30 day and 10-day contours match almost exactly, there is a significant difference for the 3-day contour. This suggests that using hourly time series (as opposed to daily) are less important for larger amounts of storage.

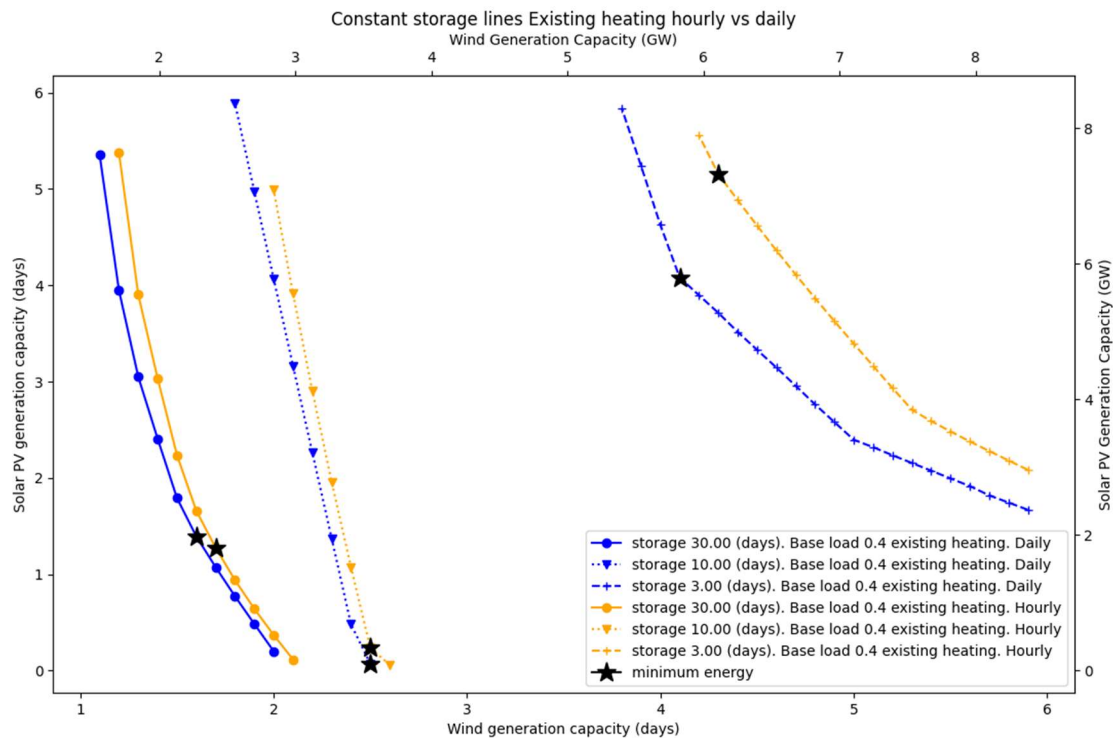


Figure 7-1 Lines of constant storage showing the difference between using daily or hourly time series

Table (7-2) compares hourly time series and daily time series according to the criteria defined in section 6.3. For the minimum energy configuration of those requiring 30 days storage, the hourly time series has a wind energy fraction 3% higher and generates 3% more energy above the load. For the configuration with wind capacity 2.7 days and PV capacity 0.4 days, the required energy storage is the same. The minimum cost configurations are quite different between daily and hourly time series. The cost is 85 £/MWh compared to 88 £/MWh. This is because most of the cost of hydrogen storage comes from the discharging or charging the store which is dependent on the charge rate.

Table 7-2 The difference between using daily or hourly time series using 3 comparison methods from 5.2.6

Comparison Configuration	Measure	Time Series Frequency	
		Daily	Hourly
30 days minimum storage (minimum energy)	Wind capacity (days)	1.6	1.7
	PV capacity (days)	1.4	1.3
	Wind energy fraction	80%	83%
	energy generated	0.77	0.80
Least storage for 50% excess energy generation	Wind capacity (days)	2.7	2.7
	PV capacity (days)	0.4	0.4
	Storage (days)	8	8
Minimum cost of electricity generation at today's prices	Wind capacity (days)	1.4	1.7
	PV capacity (days)	1.5	0.8
	Wind energy fraction	77%	88%
	energy generated	0.71	0.75
	storage (days)	65	59
	cost £/kWh	0.085	0.088

For daily time series the charge and discharge rates will be averaged over a longer time period and so their maximum values will be smaller. Using daily time series averages the charge rate across the whole day leading to lower calculated ramp rates. For daily, the wind energy fraction is 77% compared to hourly of 88%.

The conclusion is that using hourly time series is important for configurations with a small amount of storage or when calculating cost or wind energy fraction. For calculating the minimum required storage, daily time series are adequate.

7.2.2 Sensitivity to using a subset of the data

The objective of this section is to investigate if the results of the study would be different if only part of the data were used. The same experiment was run on four distinct decades of the 40 years of data. The input parameters used are shown in table (7-3).

Table 7-3 Experiment to compare the impact of using different decades of data (see 5.3.1 for terminology)

Experiment Objective: Compare different decades of weather.						
Baseload: $C_b = 0.2$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	50%	Baseline	Iterative	Ninja C	Ninja	1980-1989
Daily	50%	Baseline	Iterative	Ninja C	Ninja	1990-1999
Daily	50%	Baseline	Iterative	Ninja C	Ninja	2000-2009
Daily	50%	Baseline	Iterative	Ninja C	Ninja	2010-2019

Each plot below shows constant storage lines for 4 distinct decades of data. The first plot shows the 50 days storage lines, the second 30 days and the third 10 days storage.

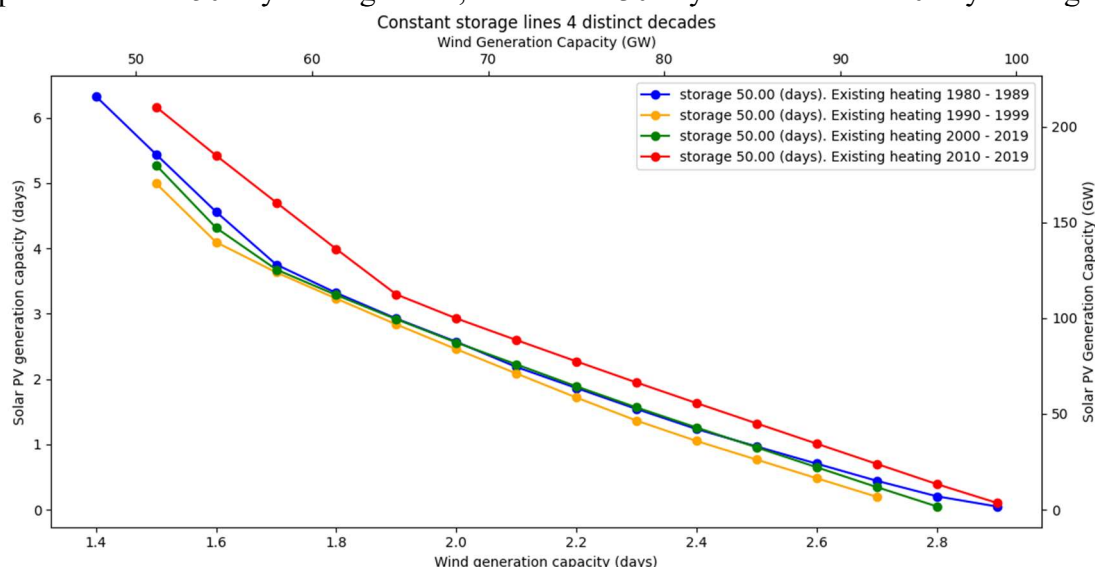


Figure 7-2 Comparison of 50 days storage lines for 4 distinct decades

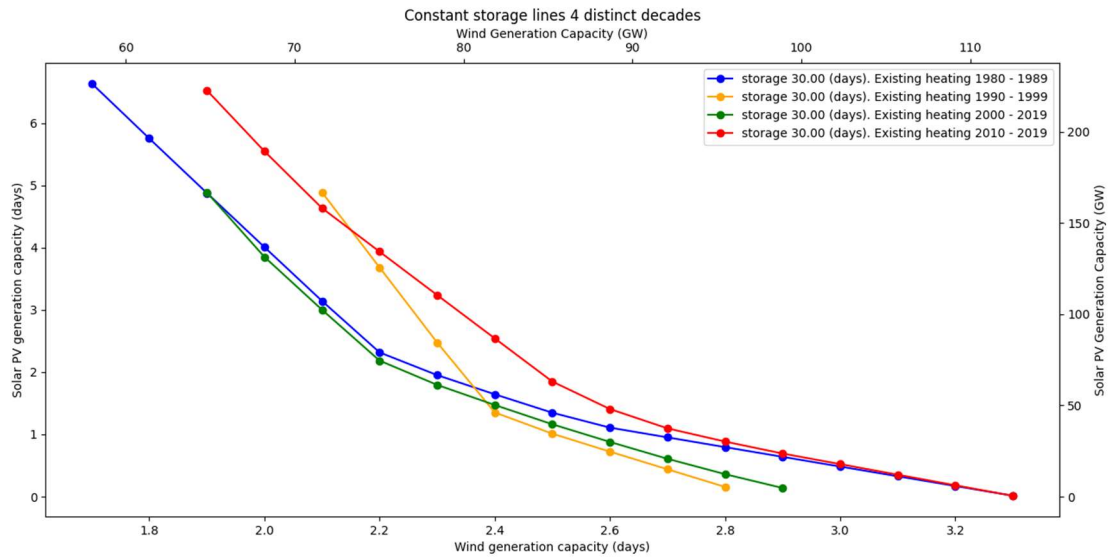


Figure 7-3 Comparison of 30 days storage lines for 4 distinct decades

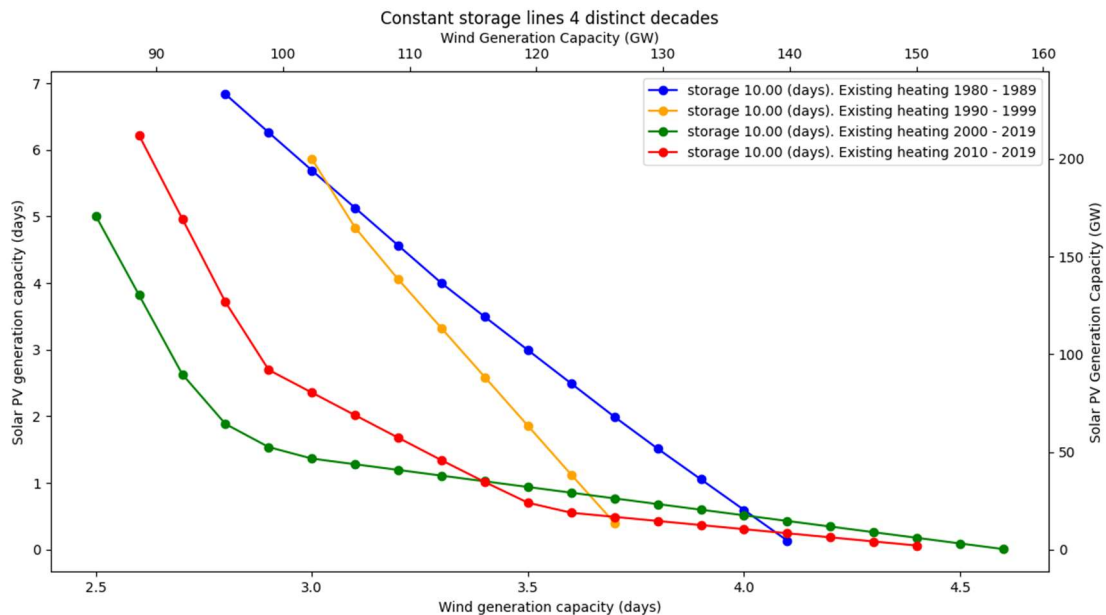


Figure 7-4 Comparison of 10 days storage lines for 4 distinct decades

It can be seen that for smaller storage capacities there is a bigger variation amongst the results for the different decades. For example, for configurations with PV capacity 5.0 days, the configurations requiring 30 days of storage range from wind 1.9 to wind 2.1. However, with 10 days of storage, the wind capacity ranges from 2.6 days to 3.2 days. This experiment suggests that the time period doesn't make much difference to the results apart from for small capacities of storage. The bigger difference at small storage capacities is probably due to variations becoming smoothed out a large amounts of storage because there is more energy available to cope with short term variation.

7.2.3 Comparing 4 years with an extreme cold year to 40

Some studies choose a single year or a short period of years which includes a cold year with the assumption that this would adequately provide a suitable range of conditions to test the model. However, high heating requirements may not coincide with low

generation. A study quantifying the sensitivity of the power system to climate variability [85] states that even 36 years is a relatively short period for quantifying climate extremes. They study the impact of randomly sampling different number of years and different years on a model to minimize the long-term economic cost of a particular wind power scenario. Looking at 1000 different samples of years they find a difference of 50% with single years down to 15% with 10 years. In this experiment the 4 years 2009-2012 which includes a particularly cold year of 2010 is compared to using the full 40 years of data.

Table 7-4 Experiment to compare 40 years data with 4 years that includes a cold spell (see 5.3.1 for terminology)

Experiment Objective: Compare 40 years with a cold spell.						
Baseload: $C_b = 0.2$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	50%	Baseline	Iterative	Ninja C	Ninja	2009-2012
Hourly	50%	Baseline	Iterative	Ninja C	Ninja	1980-2019

The plot below shows that for 10 days of storage there are significant differences in the results. For larger amounts of storage between 20 and 50 days, the differences are small.

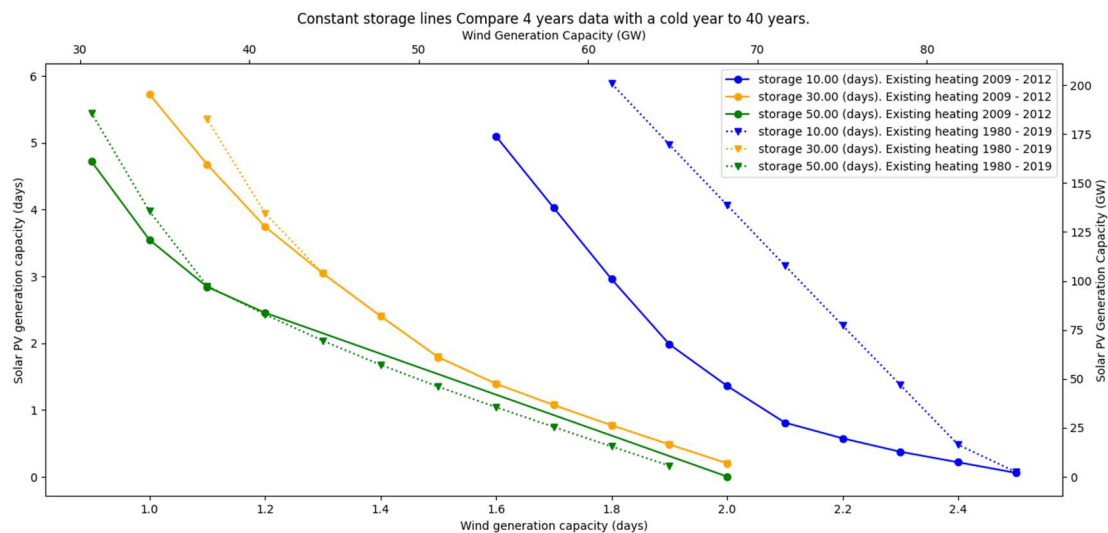


Figure 7-5 Lines of constant storage using 4 years with a cold spell compared to using 40 years

The wind energy fraction for the minimum cost configuration and its cost for hydrogen storage is the same for both experiments. However, for the 50% excess generation configuration needing the minimum storage, which is wind 2.4 days and PV 2.1 days, the 40-year case needs 4.5 days (80%) more storage. This example shows that the using only a few years with a cold spell can yield inaccurate results.

7.3 Sensitivity to model inputs Fragaki et. al.

Different model inputs are used in this project to those of two previous UK studies. In the following sections the impact that these different inputs have will be examined individually. They are grouped together by the two studies because of the data used by the two studies being available in different time periods. This also has the advantage that it will be possible to comment on why the inputs used by this study give different

results. The impact of the different time period itself to the 1980-2019 period of this study is also investigated. This section considers the inputs to Fragaki et. al.:

- Time period of 1984-2013, compared to 1980-2019 used in this thesis
- Electricity demand time series (scaled by adding a constant)
- Solar PV Generation data
- Wind power generation data (offshore and onshore)

7.3.1 Sensitivity to time period 1980-2019 compared to 1984-2013

The Fragaki et. al. study uses the period 1984 – 2013, whereas this study uses 1980 – 2019. The objective of this section is to look at the impact of keeping all other aspects the same, but to use different time periods. The experimental parameters are summarised in table (7-5)

Table 7-5 Experiment to compare the different time periods of the two studies (see 5.3.1 for terminology)

Experiment Objective: Compare the effect of using different time periods.						
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	85%	Baseline	Iterative	Ninja C	Ninja	1984-2013
Daily	85%	Baseline	Iterative	Ninja C	Ninja	1980-2019

Figure (7-6) shows the same constant lines of storage for 85% efficiency shown in figure (5-4) with the addition of a 50 days line (to replace the 60 day line that the previous study had). The solid lines for the period 1984 – 2013 are compared to dotted lines for the period 1980 – 2019. It can be seen that the impact of the time period alone causes the lines to move to the left indicating lower wind generation requirements for the same storage for the longer time period. The points with minimum energy generated for constant storage are shown with a black star. For 30 days storage using the shorter time period causes the wind energy fraction to rise from 80% to 81% and the amount of energy generated to rise from 1.14 times the load to 1.19 times the load.

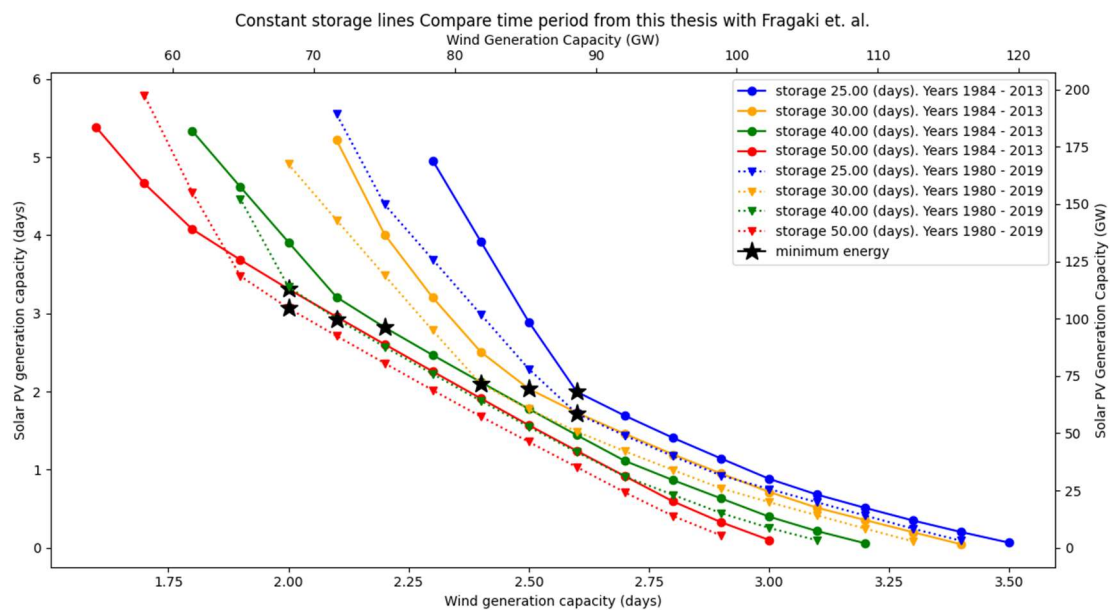


Figure 7-6 Lines of constant energy storage modelled using the time period of 1984-2013 compared with those modelled using 1980-2019.

7.3.2 Sensitivity to electricity demand time series created by different processes

The objective of this section is to investigate the impact of using electricity demand time series created using the baseline method of chapter 4 compared to a scaled historic electricity demand. The historic electricity demand was scaled by subtracting a constant amount from each day of the year so that every year generates the same amount of energy, to remove the effect of socio-economic and technological changes over the years. This has the disadvantage of also removing differences due to the amount of heating electricity in the time series due to the temperature of different years. Since the aim of the current work is to compare the impact of heating electrification it is important to address this issue. That is why the baseline method in this study was developed. It uses a baseline electricity demand created by removing heating electricity from a recent year and then adding in the heating electricity for each year based on the weather. The experimental parameters are summarised in the table (7-6). The years 1984-2013 were used due to the data being available for that year.

Table 7-6 Experiment to assess the impact of electricity demand time series created in different ways (see 5.3.1 for terminology)

Experiment Objective: Assess impact of scaling historic demand.						
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	85%	Baseline	Iterative	Ninja C	Ninja	1984-2013
Daily	85%	Historic Add	Iterative	Ninja C	Ninja	1984-2013

Figure (7-7) shows that the same storage line is quite close in both time series although moved slightly to the right implying more wind generation capacity required for the same amount of storage for the scaled historic time series. The configuration with minimum energy generation shown with a black star for the 30 days storage line occurs at a wind energy fraction of 85% for the baseline method compared to 80% for the scaled historic demand. The baseline demand requires energy generated of 1.14 times the load compared to 1.13 for the scaled historic demand.

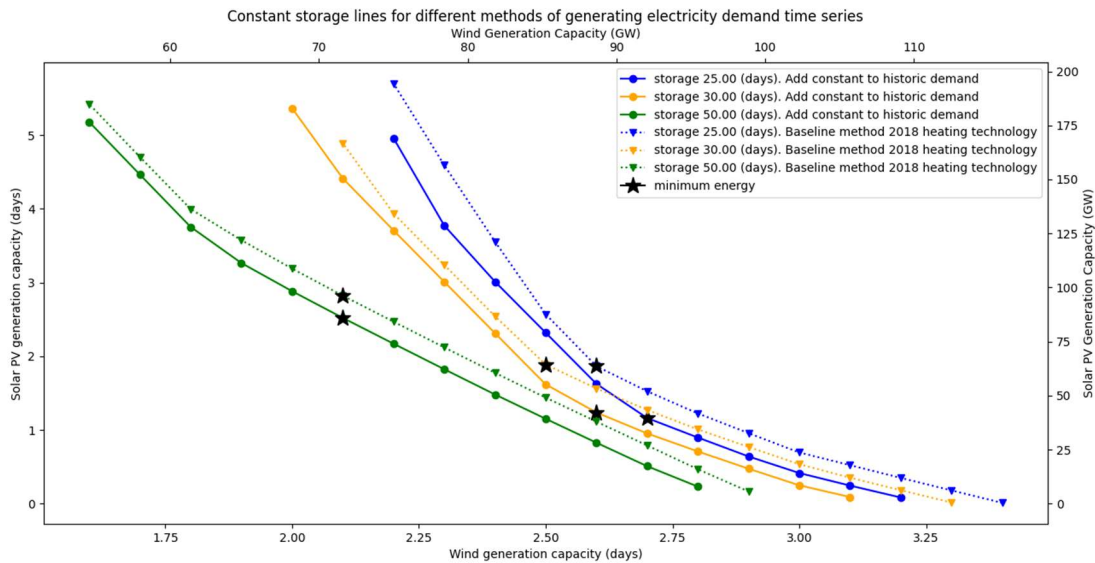


Figure 7-7 Constant storage lines using electricity demand time series created in two different ways.

It is difficult to assess the exact reasons for these differences because modifying the historic time series to have the same demand each year will have lowered the demand for cool years, whilst raising the demand for warmer years, yet some of this change was due to socioeconomic variation. The advantage of using the baseline method is we know the variation is all due to weather.

The impact on energy generated for fixed storage size of using an electricity time series generated using the baseline method, rather than the scaled historic time series is small. The impact on the wind energy fraction is more significant.

7.3.3 Sensitivity to solar PV Power generation data

The objective of this section is to investigate the impact of using different PV generation data. The PV generation time series used in Fragaki et. al. was generated by modelling south facing PV panels at optimal angles at 4 MIDAS weather stations without including temperature affects. It was a daily time series from 1984 to 2013. It was converted to time series of capacity factors. The mean capacity factor is 0.116 over the 30-year period.

In contrast, Renewables Ninja, models a panel at each MERRA2 reanalysis weather grid point taking into account temperature effects. No population weighting is done. However, the density of PV installations is likely to be influenced by the climate of the area as well as its population. The hourly time series was converted to daily. The mean capacity factor is 0.1085 over the same 30-year period.

Figure (7-8) shows part of these two solar PV generation time series. The Ninja generation appears to have fewer extreme values. Possibly because it is based on a wider range of geographic locations (each weather grid point), and also perhaps because reanalysis weather data tends to have fewer extreme values. How well either of these capture the actual pattern of solar installations in the UK is difficult to know because domestic embedded solar is only metered quarterly. However, they compare well with each other with nRMSE 0.31 and R^2 0.932.

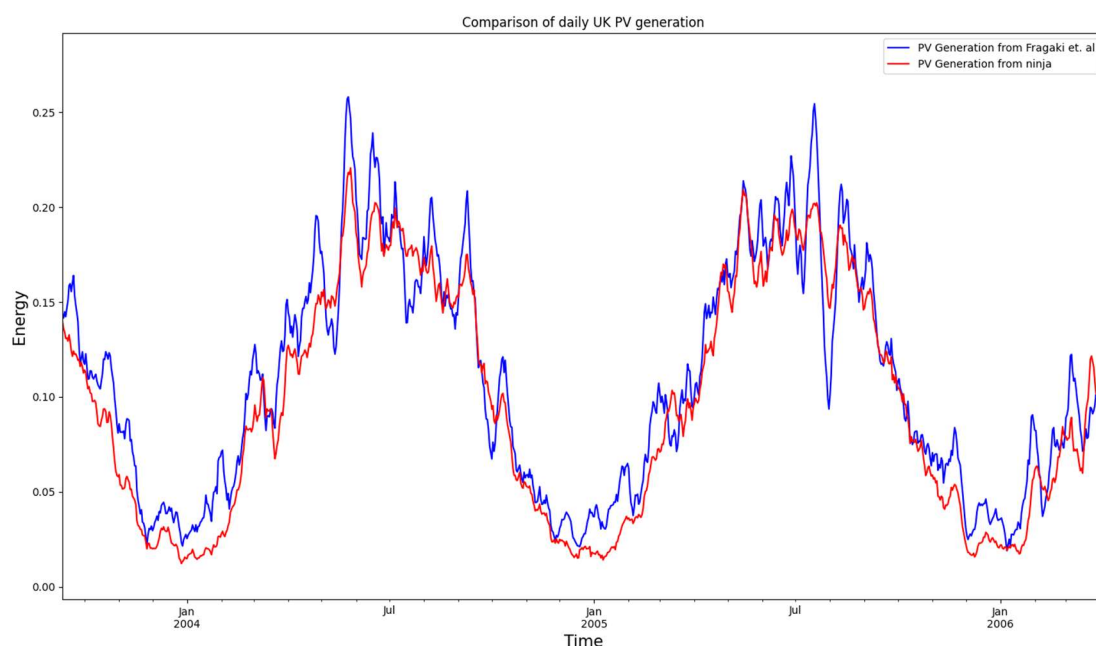


Figure 7-8 - UK PV generation using MIDAS stations compared to a PV panel at each weather grid point from Renewables Ninja - Zoomed in (10 day rolling average)

Another PV time series was generated by scaling the Fragaki time series to have the same capacity factor as the Ninja time series using equation (35). This PV series would generate the same energy as the Ninja PV series but at different times. The objective is to see how much of the difference is down to capacity factors and how much to the pattern of generation.

An investigation was done to see what impact using these different PV generation time series had on the amount of energy storage required. Whilst using different PV time series, these three experiments all use Ninja combined wind generation, and a storage efficiency of 85%. The experimental parameters are summarised in table (7-7).

Table 7-7 Experiment to compare the impact of using different PV generation time series (see 5.3.1 for terminology)

Experiment Objective: Compare PV generation time series.						
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	85%	Baseline	Iterative	Ninja C	Ninja	84-2013
Daily	85%	Baseline	Iterative	Ninja C	Fragaki	84-2013
Daily	85%	Baseline	Iterative	Ninja C	Fragaki S	84-2013

Figure (7-9) shows lines join configurations needing 30, and 50 days of storage in different colours. There are three sets of lines for each colour representing the Ninja PV series, the Fragaki PV series and the Fragaki PV series scaled to the Ninja PV capacity factor. Only the 30-day and 50-day contours are shown as the others overlap. The Renewables Ninja configurations require more wind energy for the same storage compared to the Fragaki generation. The storage lines for the Fragaki generation scaled to the same capacity factor as the Ninja time series are very close to the unscaled line which suggests that most of the difference between these two generation models is due to the pattern, rather than the capacity factors. It can be seen that as would be expected the difference becomes greater at larger proportions of PV. At high PV, the Renewables Ninja time series need more wind capacity to compensate for the lower PV generation. This could be because the Fragaki time series model more PV panels in the south where the weather is sunnier, whereas Renewables Ninja model a PV panel at each weather grid point.

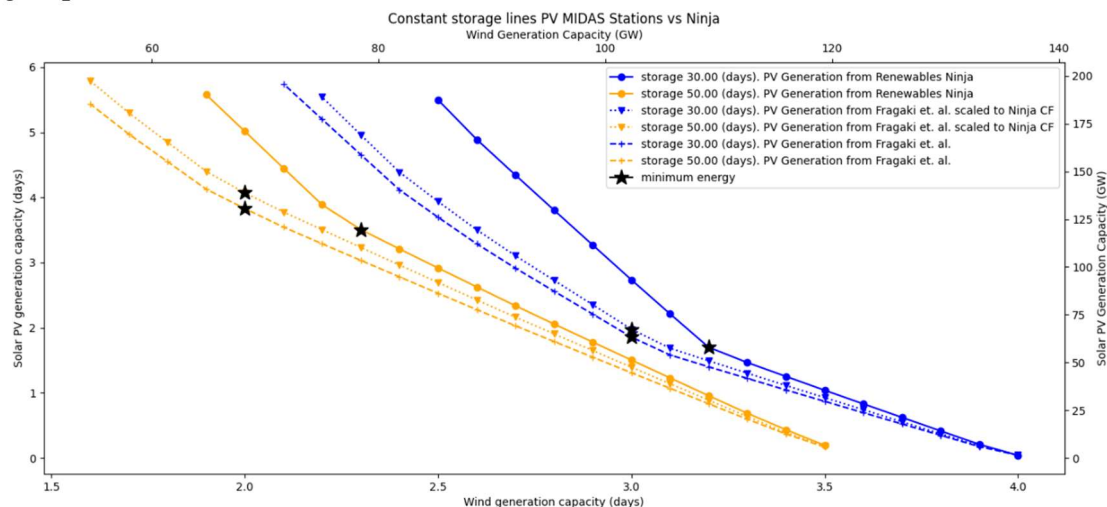


Figure 7-9 - Comparison of constant storage lines modelled using PV generation from MIDAS weather stations with those modelled using PV generation data from Renewables Ninja with one PV panel at each weather grid point

The black star in figure (7-9) shows the minimum energy configuration of those requiring the same amount of storage. For 30 days storage it was 85% wind for the ninja PV series whereas for the Fragaki series it is 83% wind. The scaled Fragaki series has the same wind energy fraction, so this difference is due to the generation pattern and not the difference in capacity factor. The Ninja PV series required energy generation of 1.14 above the load compared to 1.17.

Neither of these PV capacity factor time series is the actual PV generation. It is not known which is more accurate, but they do not differ that much. The difference seems to be mainly caused by the generation pattern, rather than capacity factors.

7.3.4 Sensitivity to wind power generation data

The objective of this section is to assess the impact of using different wind generation data. In contrast to using the hourly generation data from Renewables Ninja used in this study, Fragaki et. al. used a typical wind turbine power curve to generate daily wind power generation time series at the locations of 6 UK land-based weather stations using observations from MIDAS. First the Renewables Ninja generation data for the same years 1984 – 2013 was converted from hourly to daily and the mean capacity factors compared. Table (7-8) shows that whilst the Ninja Current onshore wind has a capacity factor only slightly higher than the Fragaki one, that offshore wind is much higher. It also shows how capacity factors are expected to evolve into near the future.

Table 7-8- Wind Generation Capacity Factors

Capacity Factors	Renewables Ninja			Fragaki et. al.
	Current	Near Future	Long term Future	
Onshore Wind	0.2924	0.3379	(Not available)	0.28
Offshore Wind	0.3835	0.3927	(Not available)	N/A
Combined	0.3277	0.3878	0.3961	0.28

First the difference between the wind generation in the Fragaki study (onshore) and this thesis (Ninja onshore and offshore combined) is investigated. Then this will be broken down in subsequent sections to compare differences between:

- Onshore from Renewables Ninja and onshore from 6 MIDAS weather stations.
- Ninja onshore and offshore

The experimental parameters for the comparison between Ninja combined (onshore and offshore) compared to 6 MIDAS weather stations (onshore only) are summarised in table (7-9) below.

Table 7-9 Experiment to assess the impact of wind generation from 6 MIDAS weather stations compared to Renewables Ninja (see 5.3.1 for terminology)

Experiment Objective: Assess the impact of Wind generation data source.						
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	85%	Baseline	Iterative	Fragaki	Ninja	1984-2013
Daily	85%	Baseline	Iterative	Ninja On	Ninja	1984-2013

Figure (7-10) shows lines requiring the same amount of storage. The impact of the higher wind capacity factor of the Ninja data is seen in a move of the contours to the left. Not so much wind capacity is needed to balance the system for the same amount of storage.

The black star shows the configuration with the minimum energy generation. For the 30-day storage line this configuration has 83% wind for Renewables Ninja, whereas it has 87% for MIDAS weather stations. The energy generated for Ninja is 1.14 times the load compared to 1.35 for the same amount of storage.

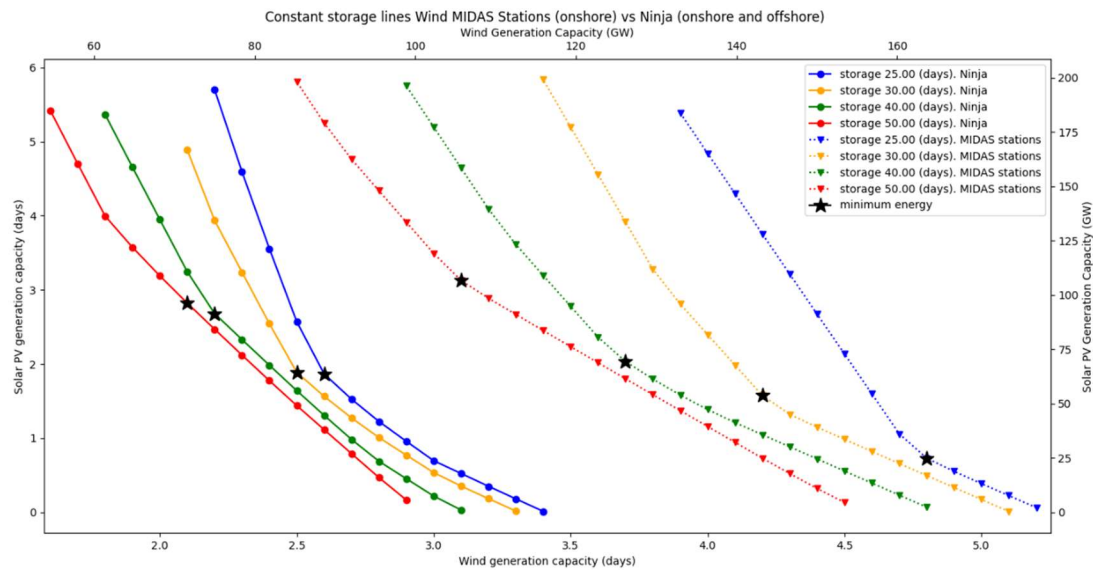


Figure 7-10 Constant storage lines modelled using 6 turbines at MIDAS onshore weather stations compared with those modelled using Renewables Ninja wind generation data (onshore and offshore)

7.3.5 Onshore wind generation from MIDAS stations compared with Renewables Ninja

To assess how much of the difference with the Renewables Ninja time series is due to offshore wind and how much is due to using 6 MIDAS weather stations, the two are investigated separately. This section looks at onshore wind only comparing Renewables Ninja with MIDAS weather stations. The experimental parameters are summarised in table (7-10)

Table 7-10 Experiment to compare the difference between using onshore wind from MIDAS stations with onshore wind from Renewables Ninja (see 5.3.1 for terminology)

Experiment Objective: Compare onshore wind generation from 6 MIDAS stations v Renewables Ninja onshore.						
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	85%	Baseline	Iterative	Fragaki	Ninja	1984-2013
Daily	85%	Baseline	Iterative	Ninja On	Ninja	1984-2013

Figure (7-11) shows the difference between these two on lines of constant storage. The 50-day contour is not shown because it overlaps the others. For the Ninja data the

contours move to the left indicating more wind capacity is needed to balance the system for the same amount of storage. The difference is not as large as that for combined onshore and offshore seen in the previous section. The black star shows the configuration with the minimum energy generation. For the 30-day storage line this configuration has 85% wind for Renewables Ninja, whereas it has 87% for MIDAS weather stations.

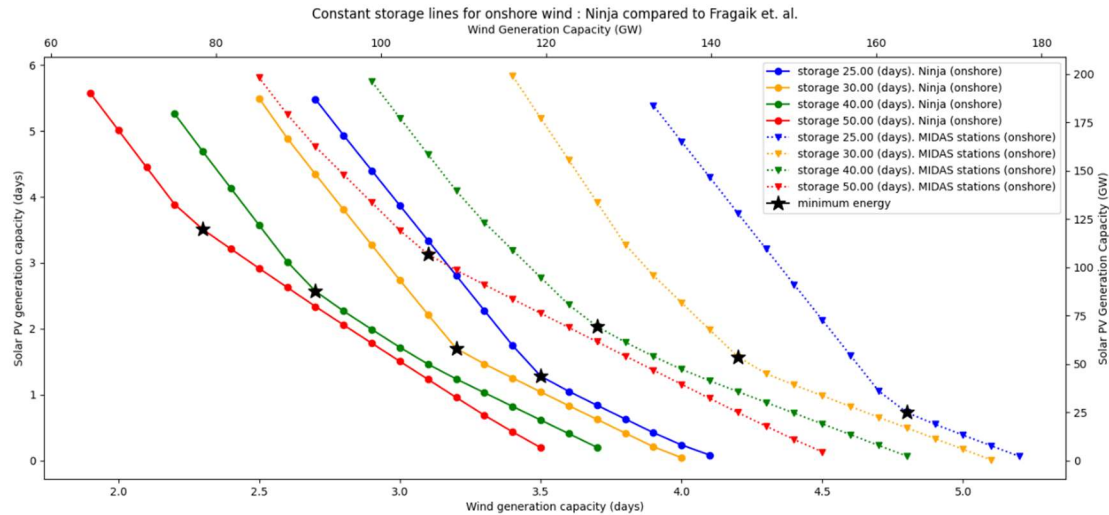


Figure 7-11 Lines of constant storage modelled using onshore wind generation from Renewables Ninja compared with those modelled using MIDAS weather stations.

The figure below compares the wind generation from Fragaiki et. al. with that from Renewables Ninja. It appears to be showing fewer low values for the Ninja time series.

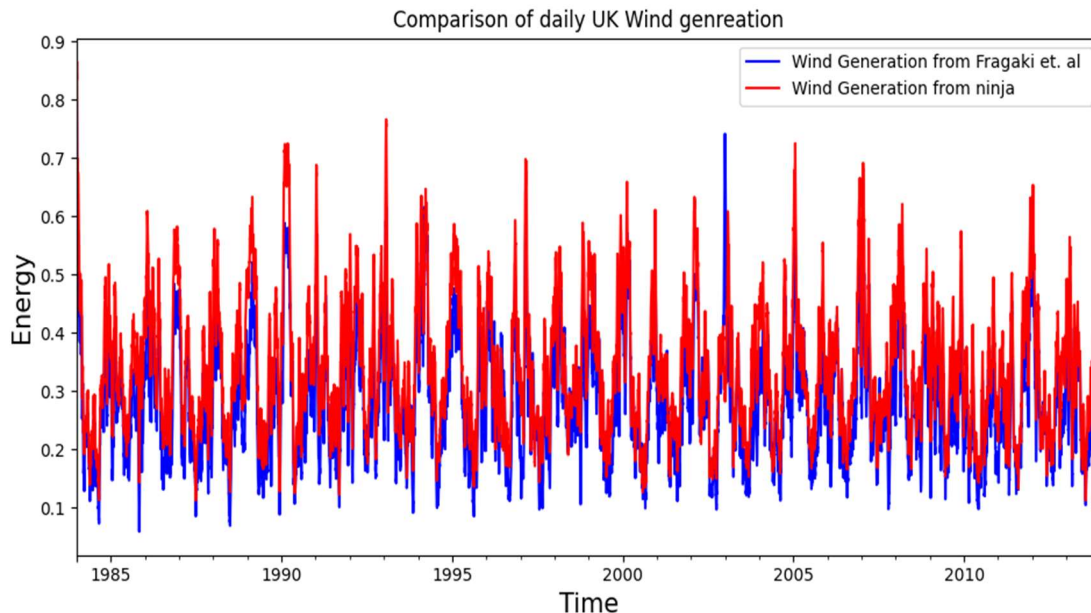


Figure 7-12 Wind generation from Renewables Ninja compared to Fragaiki et. al. 20 day rolling average.

The generation from Renewables Ninja has fewer time points with low wind generation and no days when it is zero, perhaps because it is derived from a far larger number of geographical locations and turbine types. This would be expected to result in lower storage requirements. The ninja time series incorporate all the current and near future wind farms, so would be expected to reflect the actual wind generation more accurately.

They have been bias corrected to account for the fact that reanalysis weather data smooths out terrain details and so does not model local wind conditions well.

7.3.6 Onshore wind compared to offshore wind

The objective of this section is to compare the difference between using onshore and offshore wind. All other aspects are kept constant. Three Ninja wind generation time series are compared: onshore, offshore, and onshore scaled to the offshore capacity factor. The experimental parameters are summarised in table (7-11).

Table 7-11 Experiment to compare onshore and offshore wind (see 5.3.1 for terminology)

Experiment Objective: Compare onshore and offshore wind.						
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	85%	Baseline	Iterative	Ninja Off	Ninja	84-2013
Daily	85%	Baseline	Iterative	Ninja On	Ninja	84-2013
Daily	85%	Baseline	Iterative	Ninja S	Ninja	84-2013

Figure (7-13) shows constant lines of 10 days and 50 days storage. The 20, 30 and 40 lines are not shown because the storage contours overlap. There is a much larger separation between the 10-day storage contours than the 50-day storage contours indicating a large difference in wind generation between the three cases. The position of the middle of the three lines in each set representing onshore scaled to the capacity factor of offshore, shows that approximately one third of the difference appears to be due to the pattern of generation and the rest due to the capacity factor.

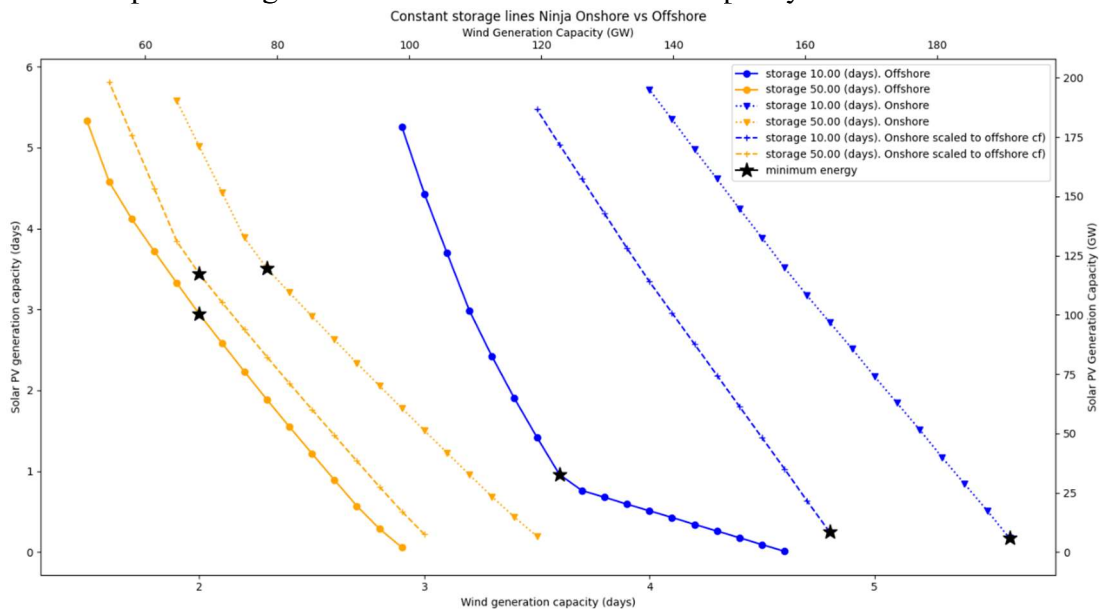


Figure 7-13 Lines of 10 days and 50 days energy storage modelled with offshore wind compared to those modelled using onshore wind.

Figure (7-14) shows the 30-days of storage line, but with the energy generated plotted against the wind energy fraction. The green and orange lines overlap because they have the same pattern of energy generation. The minimum energy point is shown using a black star. The wind energy fraction for offshore is 78%, for onshore it is 85% and for

onshore scaled to the offshore capacity factor it is 87%. This suggests that most of the difference in wind energy fraction is due to the difference between the patterns of offshore and onshore wind, rather than the capacity factor. Plotting energy against fraction makes it easier to see where the minimum occurs, and how distinct it is compared to other configurations with the same amount of storage.

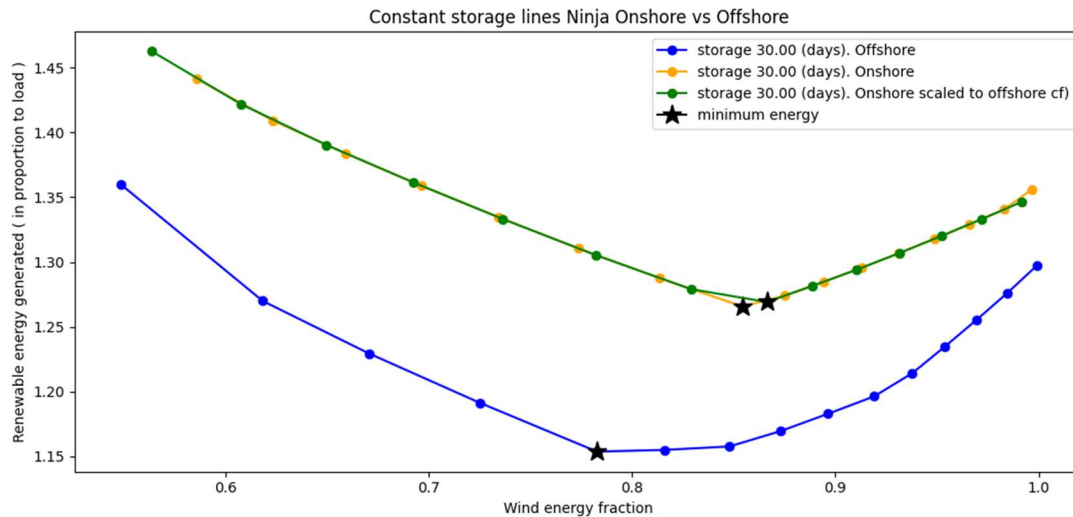


Figure 7-14 Comparison of wind energy fraction found using 30 day storage lines modelled with the onshore wind generation from Renewables Ninja compared with those from Fragaki et. al.

That difference in the wind generation pattern has resulted in energy generation of 1.27 in proportion to the load compared to 1.15 for the same amount of energy storage. The correlations between the different wind series are discussed in 9.6.

7.3.7 Summary of impact of the model differences

The previous sections have examined the sensitivity of the results to different modelling inputs. This section compares all these various inputs. They are:

- the time period of the data: 1980-2019 or 1984-2013
- electricity demand time series created by a different process
- PV generation data
- wind generation data (MIDAS stations and onshore v offshore)

Figure (7-15) shows the 30-day storage contour for the model and data from this study (light green) compared to all the other differences listed above. The difference made by the method used to find the required storage (from the validation in 5.4.2) is also shown. It can be seen that the largest impact is caused by the wind generation data (red). The same wind generation data scaled to the Ninja capacity factor (purple line) shows that most of this difference is due to the capacity factor and not the different patterns of generation. However, the difference caused by the pattern is still significant.

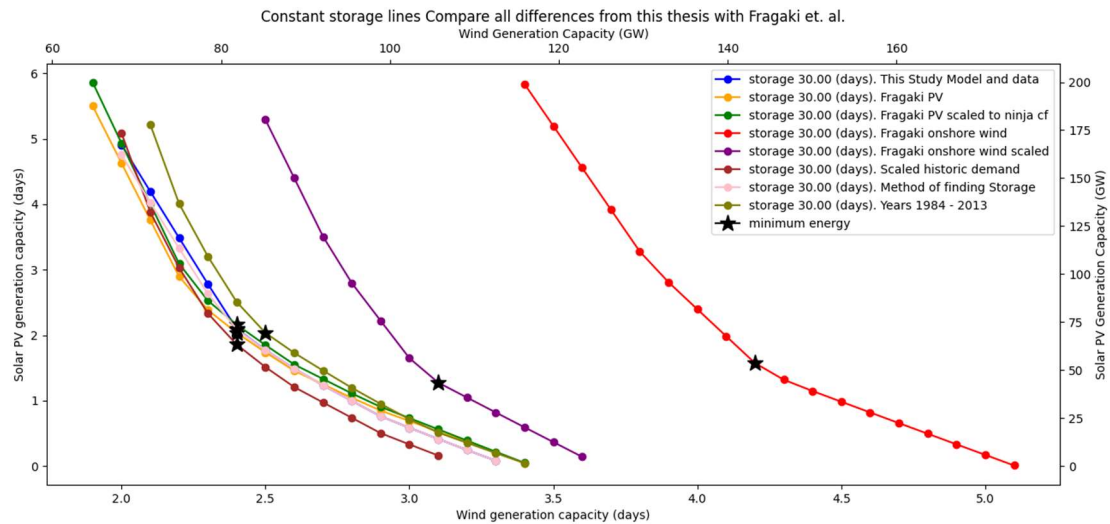


Figure 7-15 30-day storage lines generated using the model and data in this study compared to those modelled using all the individual modelling differences between this study and Fragaki et. al.

Figure (7-16) shows the same contour lines but with energy generated plotted against the wind energy fraction. This shows that using the different wind generation time series leads to larger energy generation for the same amount of storage and higher wind energy fractions. The flatter lines, for example using the scaled historic demand show less distinct optimum wind energy fractions.

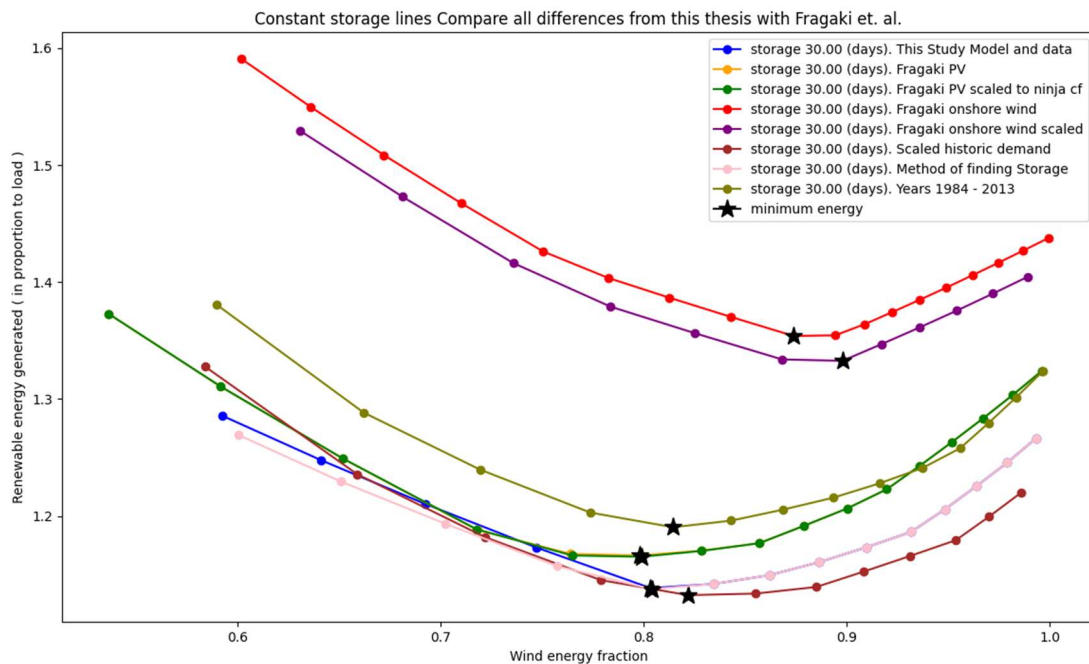


Figure 7-16 Wind energy fractions found using minimum energy points for 30 days storage compared for all modelling differences.

Table (7-12) shows the impacts of these differences in modelling. The differences in model inputs are listed along the top and they are compared according to the criteria defined in section 6.3 listed down the left-hand side. These criteria define which configurations from the range of wind and solar capacities shown in figure (7-15) are compared.

Table 7-12 Sensitivity of the wind/solar/storage mix to different modelling inputs

Criteria for choosing Configuration	Measure	Result from This Thesis	Modelling Input Difference from thesis			
			Time Period	Electrical Demand	PV MIDAS	Wind MIDAS
Equal Minimum Storage (30 days min energy)	wind energy fraction	80%	81%	82%	80%	87%
	energy generated % of load	1.14	1.19	1.13	1.17	1.35
Least Storage for excess energy 50%	Storage (days)	10	11	11	13	47
	Wind	3.7	3.7	3.7	3.7	3.7
	PV	0.8	0.8	0.8	0.8	0.8
Minimum cost of electricity generation at today's prices	Wind energy fraction	95%	96%	97%	96%	86%
	energy generated % of load	1.41	1.53	1.4	1.49	1.92
	storage (days)	11	11	12	11	12
	cost £/kWh	0.149	0.157	0.158	0.157	0.194

The first comparison method in table (7-12) is to examine those configurations needing a minimum storage of 30 days and find the configuration that generates the minimum amount of energy during the period of the experiment. This configuration is marked by a black star in figures (7-15, 7-16). The most significant differences are shown for using MIDAS wind generation where the wind energy fraction is 87% and energy generation of 1.35 times the load.

The second comparison method in table (7-12) is to compare a particular capacity of 3.7 days wind and generation 0.8 days solar PV generation. This was chosen as the configuration in the model for this study with the minimum storage requirement of those which generate 50% excess energy above the load. The largest difference to the amount of storage required for this configuration (10 days) is caused by using different wind generation data (47 days). No study has been found that remarks on the large difference in energy storage modelled from difference methods of modelling renewable generation.

The third comparison method in table (7-12) is to find the configuration that has the lowest cost of electricity generation. The cost is calculated using the capacities of wind generation, solar generation and pumped hydro storage at today's prices as defined in section 5.2.2. The minimum cost configurations all have storage of 11 or 12 days. However, using the MIDAS weather stations wind generation series requires much higher energy generation and a lower wind energy fraction.

The differences found illustrate the significant impact to the model of using wind generation time series created in a different way.

7.4 Sensitivity to model inputs from Cardenas et. al.

Another previous study to find the minimum energy storage required for the UK was done by Cardenas et. al. [52]. Cardenas et. al. also found the minimum energy storage required for a purely wind and PV system, using the historic electricity time series. However, they used different power generation data, scaled the electricity demand in a different way, and used a different algorithm to find the minimum energy storage. This section looks at the impact of these modelling differences. There are four main differences between the Cardenas model and that used in this study:

- Each day of the historic electricity demand was multiplied by a different factor for each year so that all the years had the same annual demand of 335 TWh. Whereas in this study the baseline method is used.
- National grid wind generation was used instead of Renewables Ninja
- The time period was 2011 – 2019 instead of 1980 – 2019.
- A different algorithm was used to calculate the required energy storage.

The storage algorithm has not been reproduced but, the first three changes were all investigated individually to see what impact they had.

The experiments are summarised in table (7-13) using the terms defined in section 5.3.1. The time period 2011 – 2019 was used as that was when the electricity demand data and wind capacities for scaling the national grid wind generation data were available.

Table 7-13 Experiments to compare the impact of different model inputs of wind generation and electricity demand on the results of Cardenas et al. (see 5.3.1 for terminology)

Experiment Objective: Investigate the impacts of modelling differences between Cardenas et. al. and this project's model.							
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$							
Experiment	Frequency	η	Demand	Storage	Wind	PV	Years
This thesis	Hourly	70%	Baseline	Iterative	Ninja C	Ninja	1980-2019
Time period	Hourly	70%	Baseline	Iterative	Ninja C	Ninja	2011-2019
Demand	Hourly	70%	Historic Mult	Iterative	Ninja C	Ninja	2011-2019
Wind	Hourly	70%	Baseline	Iterative	NGrid	Ninja	2011-2019

Figure (7-17) shows the impact of the different modelling methods on the 30-day storage line for the methods used in this study (blue), compared to different methods used by Cardenas. It can be seen that the different wind generation data (green) makes the largest difference. The time period of the data (yellow) and the method of scaling the historic demand (red) only make a small difference. The configuration on the 30-day storage line which generates the least energy is shown by a black star.

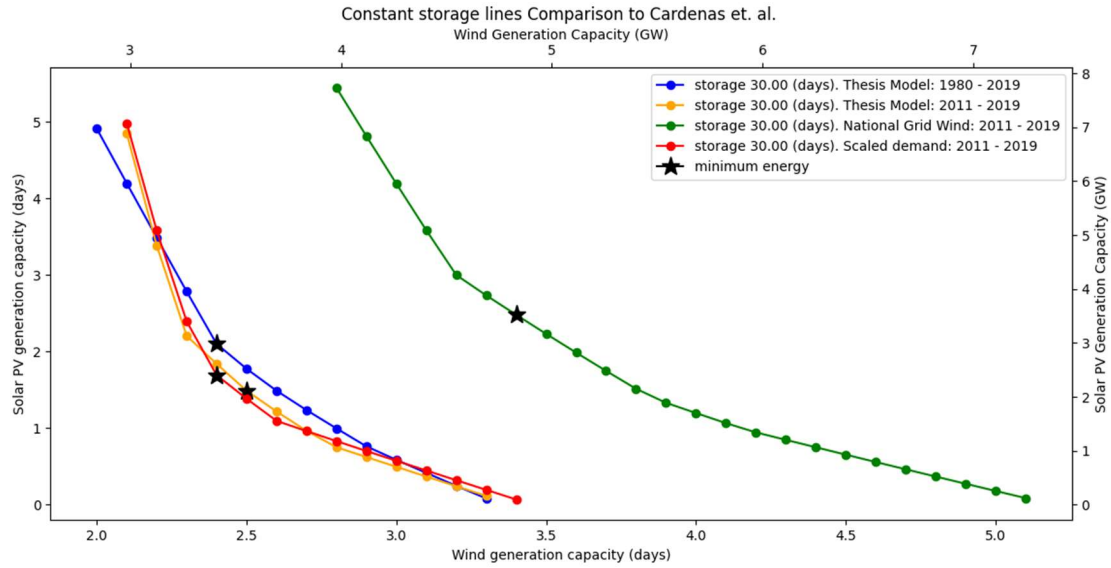


Figure 7-17 Lines of 30 days energy storage showing the impact of different modelling methods

Figure (7-18) shows the same lines, but with energy generated plotted against wind energy fraction. It can be seen that the national grid wind generation data (green line) is flat indicating no distinct minimum energy and hence optimal wind energy fraction for 30 days storage. The time period of data and the scaling method of Cardenas both cause an increase in wind energy fraction. These first two results are summarised as the first two rows of table (7-14). Of the configurations requiring 30 days of storage, the one with the minimum energy generation is shown.

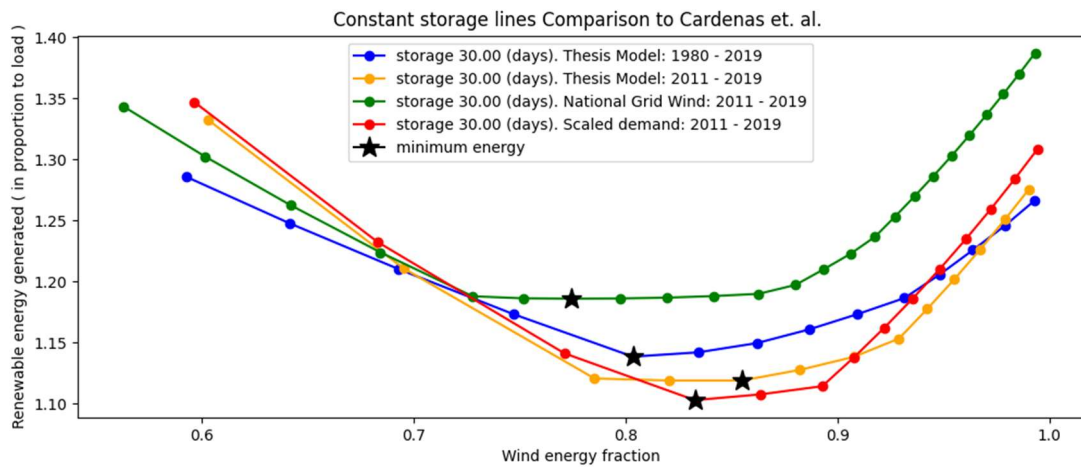


Figure 7-18 Impact of different methods used by Cardenas on the 30-day storage line wind energy fraction

The second comparison method in table (7-14) is to compare a particular capacity of 3.7 days wind and generation 0.8 days solar PV generation. This was chosen as the configuration in the model for this study with the minimum storage requirement of those which generate 50% excess energy above the load. The largest difference to the amount of storage required for this configuration (10 days) is caused by using different wind generation data (43 days).

Table 7-14 The impact on the results of the modelling methods used by Cardenas

Comparison		Modelling Difference			
Configuration	Measure	This Thesis	Time Period	Electricity Demand	National Grid wind
Equal Minimum Storage (30 days min energy)	wind energy fraction	81%	85%	83%	77%
	energy generated	1.19	1.12	1.1	1.19
Least Storage Configuration for excess energy of 50%	storage (days)	11	12	10	38
	wind capacity (days)	3.7	3.7	3.7	3.7
	PV capacity (days)	0.6	0.6	0.6	0.6
Minimum cost of electricity generation at today's prices with CAES	wind energy fraction	82%	88%	85%	82%
	energy generated	1.15	1.14	1.12	1.23
	storage (days)	29	24	25	17
	cost £/kWh	0.072	0.070	0.070	0.074

The third comparison method in table (7-14) is to find the configuration that has the lowest cost of electricity generation. The cost is calculated using the capacities of wind generation, solar generation and CAES at today's prices as defined in section 5.2.2. The minimum cost configuration also shows that using the national grid wind generation series instead of Renewables Ninja has the largest impact on the results, requiring more energy generation and a lower storage.

7.5 Wind patterns and storage

Both comparisons with previous studies show that different wind generation data cause a large difference in the results. This is investigated further in this section using the example of the Renewables Ninja onshore wind generation compared to their offshore wind generation data. Not only is the capacity factor for offshore wind higher than onshore, but the patterns are also different. At daily resolution offshore wind compares to onshore wind with $nRMSE=0.31$ and $R^2=0.94$.

Looking in detail at the 30 days storage line figure (7-19) below shows the effect of scaling the onshore wind to the same capacity factor as offshore. It can be seen that there is still a difference in that offshore needs a lower capacity for the same storage. Approximately two thirds of the reduction in wind generation needed for the same storage is explained by the difference in capacity factors. The remainder must be due to the generation pattern (how peaks of generation coincide with high periods of demand).

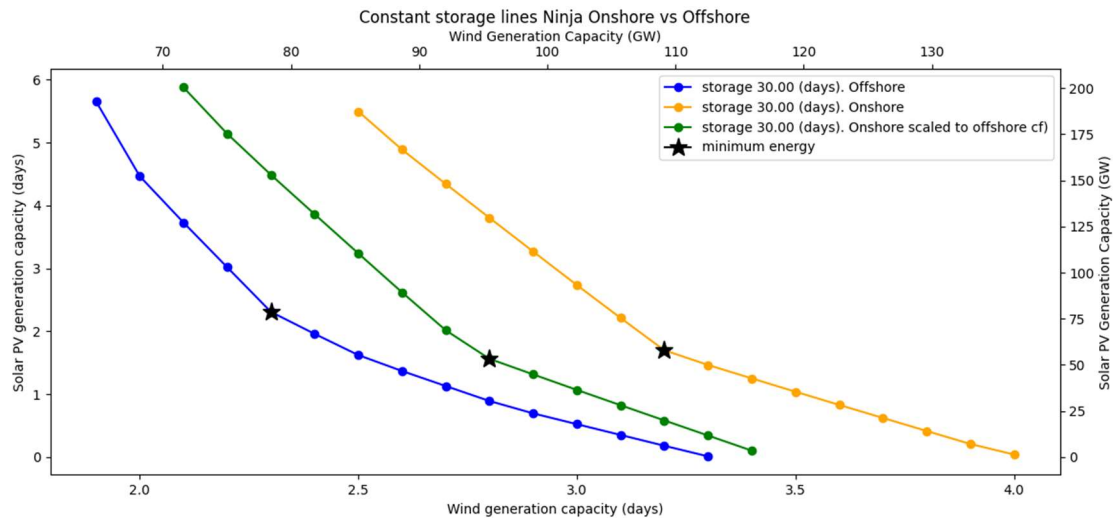


Figure 7-19 - Comparison of 30 day storage lines modelled using onshore wind, offshore wind and onshore wind scaled to the mean offshore capacity factor.

As well as the importance of how much energy is generated it is also important when it is generated. The pattern seems to be significant for 30 days storage, but what about other amounts of storage? The following table (7-15) shows how the wind fraction of the minimum energy configuration varies for different amounts of storage. In general, more solar is required for offshore wind, although for 15 days of storage it is the other way round. This suggests some sensitivity to the times when the store becomes full for different amounts of storage relative to the times when either PV or wind is generating more energy. Offshore wind requires less energy to be generated (between 10% and 39% of the mean daily load per day)

Table 7-15 Impact of wind pattern on wind fraction and energy generated.

Storage (days)	Wind energy fraction		Energy Generated		
	Onshore scaled to offshore	Offshore	Onshore scaled to offshore	Offshore	Difference
5	78	78	2.82	2.82	0.0
10	99	93	1.88	1.49	0.39
15	90	92	1.46	1.3	0.16
20	94	86	1.36	1.21	0.15
25	89	83	1.3	1.16	0.14
30	87	78	1.25	1.13	0.12

To investigate the findings from the previous section further, a wind only configuration was examined in more detail. Rather than looking at a whole set of wind and PV configurations, a wind capacity of 6.0 days and a PV capacity of 0.0 days was examined. This configuration is approximately that requiring 10 days storage i.e. the configurations showing a larger difference in section 7.3.6.

Table 7-16 Experiment to assess the impact of wind pattern without PV (see 5.3.1 for terminology)

Experiment Objective: Assess the impact of wind generation pattern without PV. Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ PV: $C_p = 0.0$ Wind: $C_w = 6.0$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	50%	Baseline	Iterative	Ninja Off	0	1984-2013
Daily	50%	Baseline	Iterative	Ninja On	0	1984-2013
Daily	50%	Baseline	Iterative	Ninja S	0	1984-2013

The figure (7-20) below shows how the state of charge of the store varies over a period of 30 years. The store stays full for a long time apart from for a few extreme events.

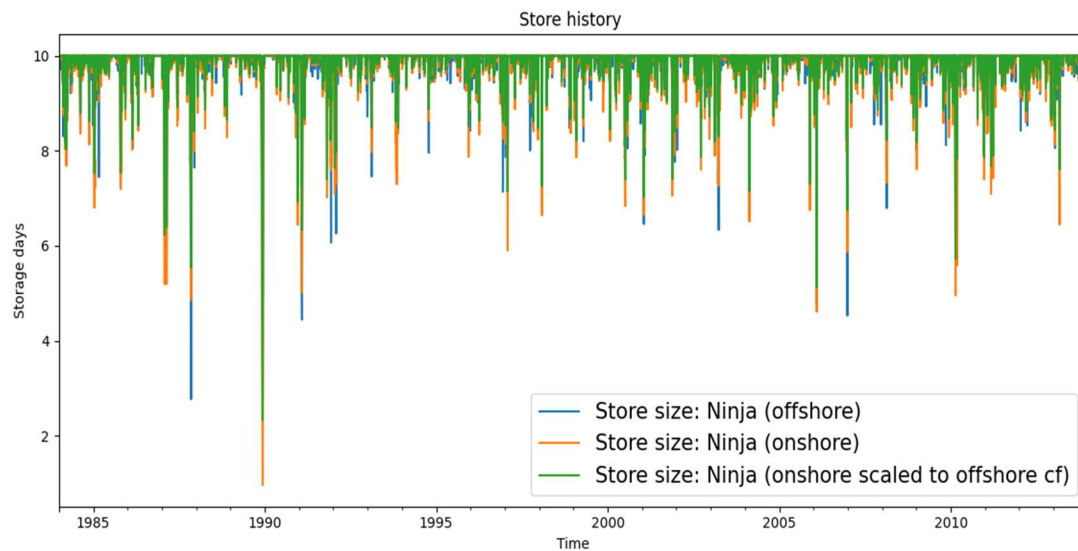


Figure 7-20 State of charge: Comparison of wind generation offshore, onshore, and onshore scaled to offshore capacity factor.

Figure (7-21) below shows a zoomed in view of figure (7-20) at the start of the period. The store quickly fills up at the start of the period due to high wind generation. It can be seen that because of the different patterns of onshore and offshore wind that at some times the store is emptier with onshore wind and at others it is emptier with offshore wind.

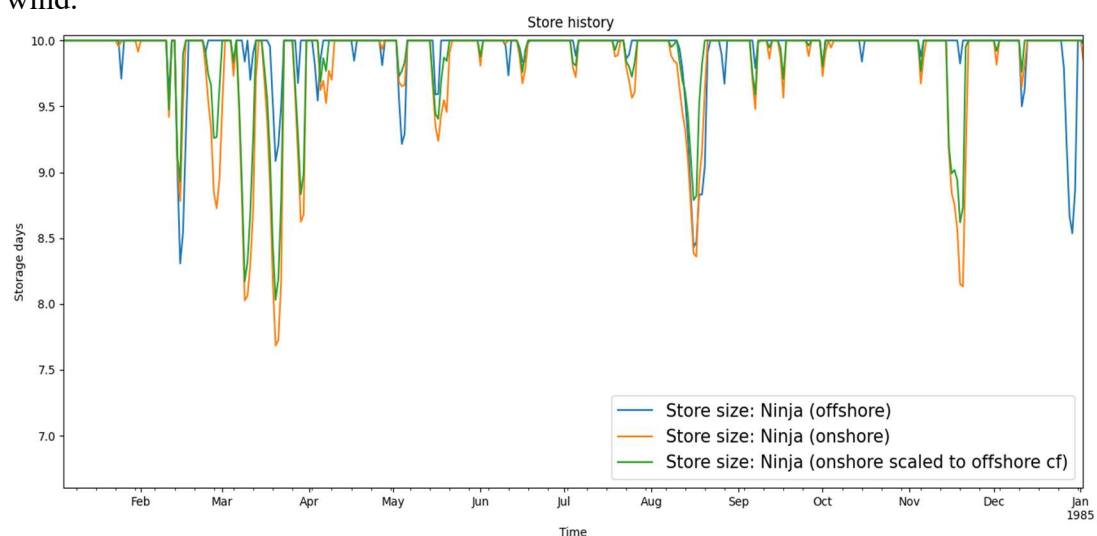


Figure 7-21 State of charge: Comparison of wind generation offshore, onshore, and onshore scaled to offshore capacity factor.

Investigating the point when the store is most empty will determine how much storage is needed. It can be seen from the figure (7-22) below that in this case with onshore wind the store is more depleted (lowest point of orange line in January 1990). The low points in the store occur at different times for the different wind generation patterns, and their lowest points lead to different minimum storage requirements.

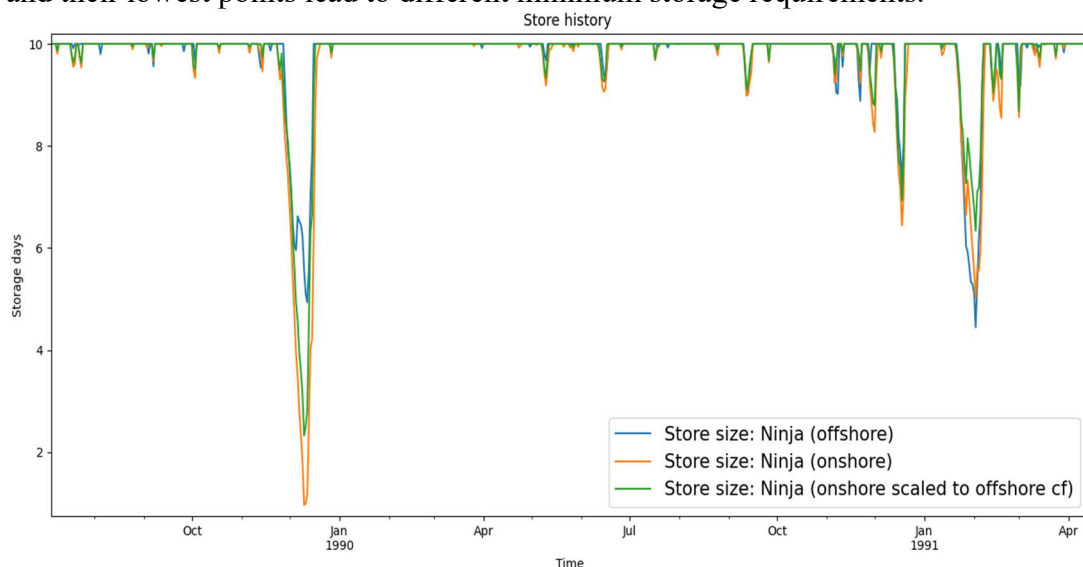


Figure 7-22 Lowest state of charge: Comparison of wind generation offshore, onshore, and onshore scaled to offshore capacity factor.

The following figure (7-23) shows the variation in the amount of wind generation and energy storage for a purely wind configuration at 85% round trip efficiency. For large amounts of storage, the onshore wind scaled to the same capacity factor as offshore wind requires more wind capacity, however for smaller amounts of energy storage, the scaled onshore wind requires less wind capacity. The difference in the pattern of offshore wind causes the wind capacity requirement to climb more steeply as storage capacity declines. Low storage and high generation favour a pattern where energy is generated close to when it is required. For higher storage the generation pattern needs to be able to charge the store at the right time. A comparison between the pattern of supply and demand is shown in 9.6.

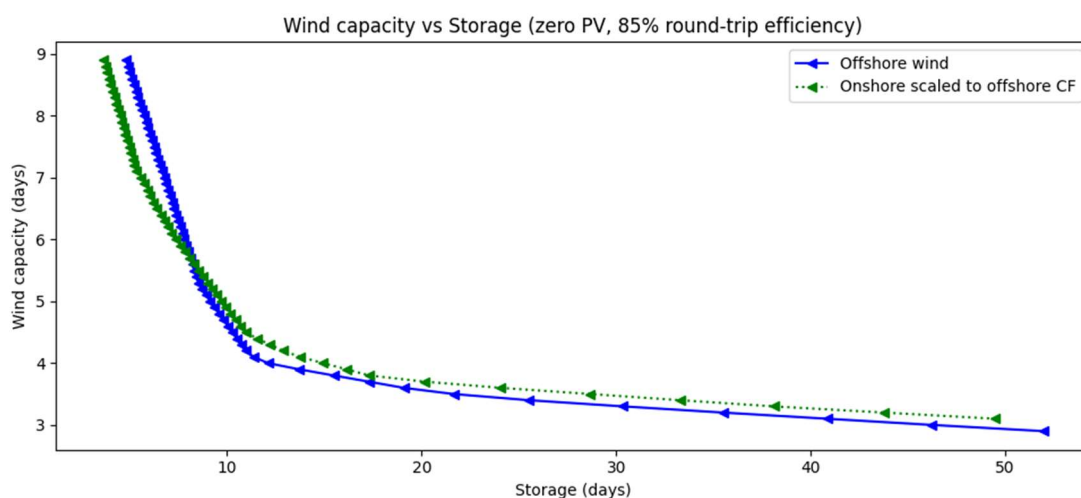


Figure 7-23 Wind capacity vs storage for offshore wind and onshore wind scaled to the same mean capacity factor as offshore wind.

The most extreme differences caused by the pattern shown in figure (7-23) is illustrated by table (7-17).

Table 7-17 Most extreme differences in storage requirements between onshore and offshore wind

Wind generation capacity (days)	Storage (days)		
	Offshore	Onshore	Difference
7.2	6.5	5.2	+1.3
3.1	40.8	49.5	-8.6

This section has shown that different wind generation patterns can cause significant differences in the amount of energy storage required. In other words, the impact of when the energy is *generated* compared to when it is *needed*. However, the significance of this effect depends on the particular configuration being studied.

A further implication from the impact of the pattern of the generation curve is that the more closely the locations of actual wind farms are modelled the more accurate the pattern would be expected to be, but this has not been tested. Perhaps there might even be a consideration as to where it would be best to site wind generation? In fact this was one of the conclusions of a Europe wide study which experimented with varying the siting of wind turbines between countries [12] although they only considered maximizing the amount of generation and reducing the interannual variation rather than the demand net of renewables or energy storage. They note the difference between turbines at different sites but do not specifically make a distinction between onshore and offshore. Other studies find that offshore wind has smoother generation patterns and higher capacity factors than onshore [18], although no study mentioning the impact of the different pattern of onshore and offshore generation on storage has been found.

Also, it should be noted that the Renewables Ninja offshore and onshore wind are bias corrected separately [33], so it could be a feature of the way the data was generated, although the methods have been extensively validated. Another factor is that more onshore wind is located in sparsely populated areas or on high ground which leads to a different geographical distribution from offshore which is located around the coasts of the country. See figure (7-24) for the locations of UK wind farms.

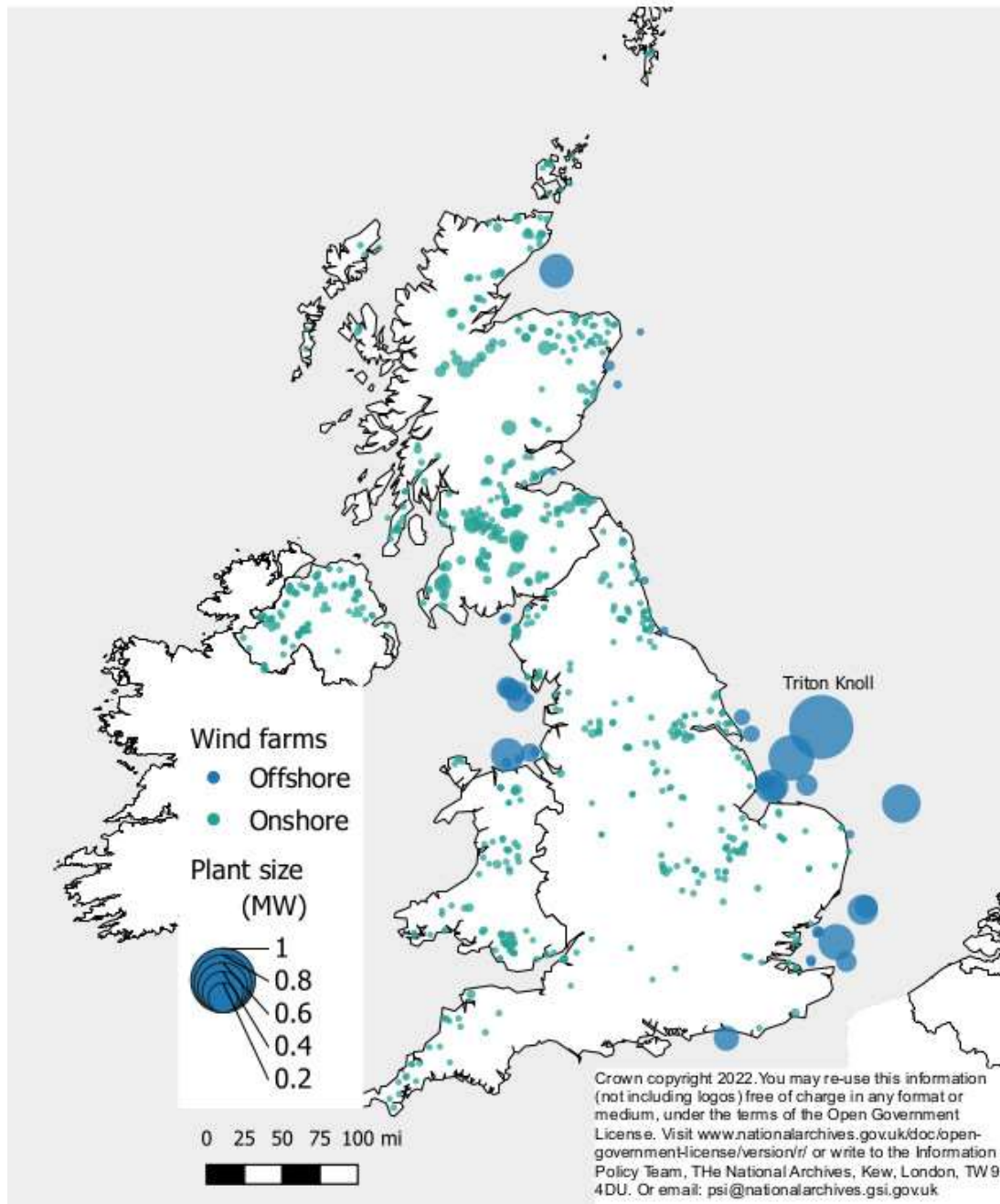


Figure 7-24 Locations of UK wind farms

Since the differences between onshore and offshore are similar in magnitude to the differences between different wind time series due to difference turbine locations it seems likely that differences in the pattern of onshore wind compared to offshore is due to the geographical location of the turbines rather than any difference between onshore and offshore generation. Even if there were a difference favouring offshore wind, the potential for offshore wind is much greater, so a future net zero energy system must have more offshore wind anyway. The existing onshore capacity is approximately 0.3 days with a future potential of 1.5 days. The existing capacity of offshore is 0.3 days with a potential 23 days [19] in the future. Also, offshore wind is expected to get cheaper and therefore this may not appear a very significant finding as the UK would likely go for more offshore wind anyway. Another factor to note is that this could just be a result of geography unique to the UK or wind patterns which could alter with

climate change. Wind patterns are due to a complex interaction of many factors, so there is a danger in searching for patterns which are not there. But the impact pattern has in general, means that not correctly modelling the location of actual turbines gives significantly inaccurate results regarding the required energy storage for configurations with smaller amounts of energy storage. Some locations might have wind generation patterns such that power is generated at times when it is needed more, but there could be a trade off as they might have lower wind speeds and so generate less power and require more turbines.

One possible area of future work might be to analyse the patterns in store state of charge shown in fig (7-20) and fig (7-21) using Fourier series to see if there are any underlying cycles (such as yearly).

Because of the potential significant differences, comparisons between energy models using different wind generation time series should be treated with caution.

7.6 Results

This section presents the results of repeating the analysis from two previous studies but using the model inputs from this project from chapter 5 instead. The results of the comparison with these two studies use the same comparison criteria and format of chapter 6.

7.6.1 Update to 30-30 rule: running all UK on wind and photovoltaics

A previous study [41] found that the UK could be powered fully on various combinations of wind and solar for 30 years. Round trip storage efficiencies of 75% and 85% were used to represent pumped hydro storage. The differences in the modelling methods between that study and those used in this thesis are shown in the Fragaki column in table (5-1). They found that generating 30 days more energy than the current supply combined with 30 days storage was sufficient. This result was confirmed by reproducing the study in section 5.4.1.

The purpose of this section is to find out what this study would have shown differently had the improved methods of this thesis been used. This includes the electricity demand time series generated using the baseline method from chapter 4. Electricity generation data is from Renewables Ninja and the energy store starts 70% full and ends up more than 70% full. The parameters are summarised in table (7-18).

Table 7-18 Experiment to update the results of Fragaki et. al. with methods from this project (see 5.3.1 for terminology)

Experiment Objective: Assess how the modelling methods from this study change the result of the previous study						
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	75%,85%	Baseline	Iterative	Ninja C	Ninja	80-2019

Figure (7-25) shows the results of this experiment. The curves occur in different places compared to Fragaki et. al figures (5-4,5-5). The proportion of wind needed is much

less. There is no 60-day storage contour because there are no configurations where 60 days is the minimum storage requirement.

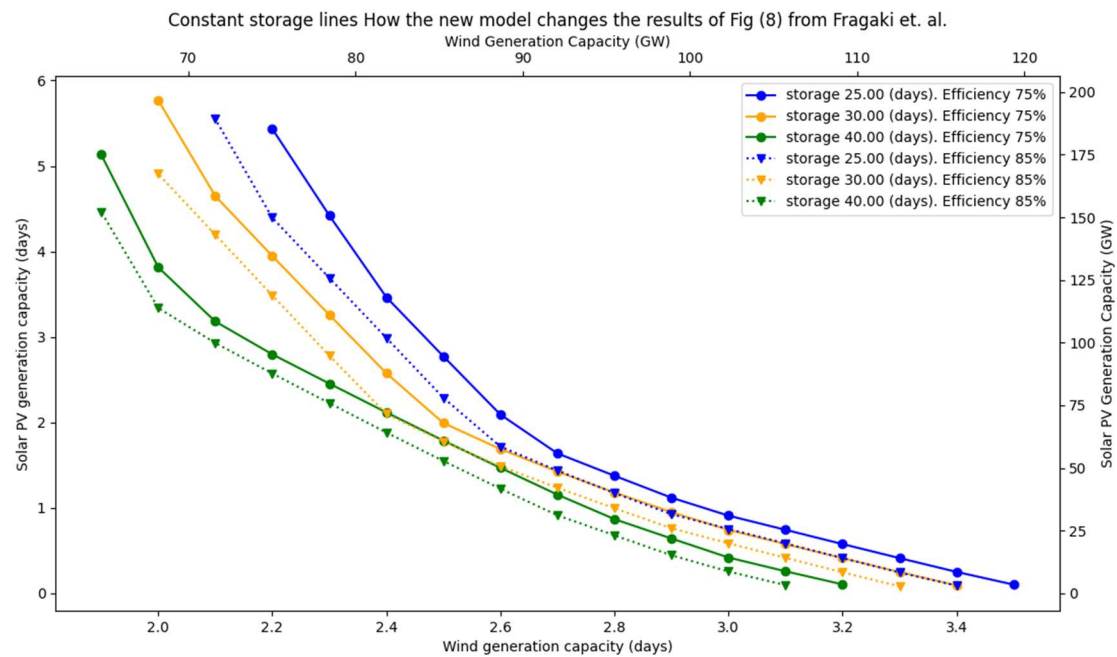


Figure 7-25 Results using the modelling methods of this thesis but presented in the same way as figure (8) from Fragaki et. al.

In figure (7-25) one day of energy is the mean daily energy of a year. The “Historic Add” method used there scales each year of the historic electricity demand time series to the same annual energy, so it is the same for each year. However, the baseline method used in this project includes the heating electricity and therefore there is a different total energy each year and so the size of a day of storage would change. Therefore, in figure (7-26) below both are scaled to the historic 2018 electricity demand and so days of storage in this graph are not compatible with figure (5-4). The different values of “1 day” are summarised in table (7-19).

Table 7-19 Units of days for energy and power in Fragaki et. al. and this study

Measure	Fragaki et. al.	Historic 2018 (this study)
Mean Daily energy and size of 1 day's storage.	835.616 GWh	818.386
Generation Capacity of 1 day	34.8 GW	34 GW

We now concentrate on the 85% round-trip efficiency configuration and investigate the impact of these differences in modelling methods in more detail.

Figure (7-26) below shows the lines of 30 days constant storage using the modelling methods of this thesis (orange line) on the same plot as the 30-day storage line for the Fragaki et. al. model (blue line) from figure (5-5). The configuration which generates the least energy is marked by a black star. The increase in wind capacity needed for the same storage is apparent.

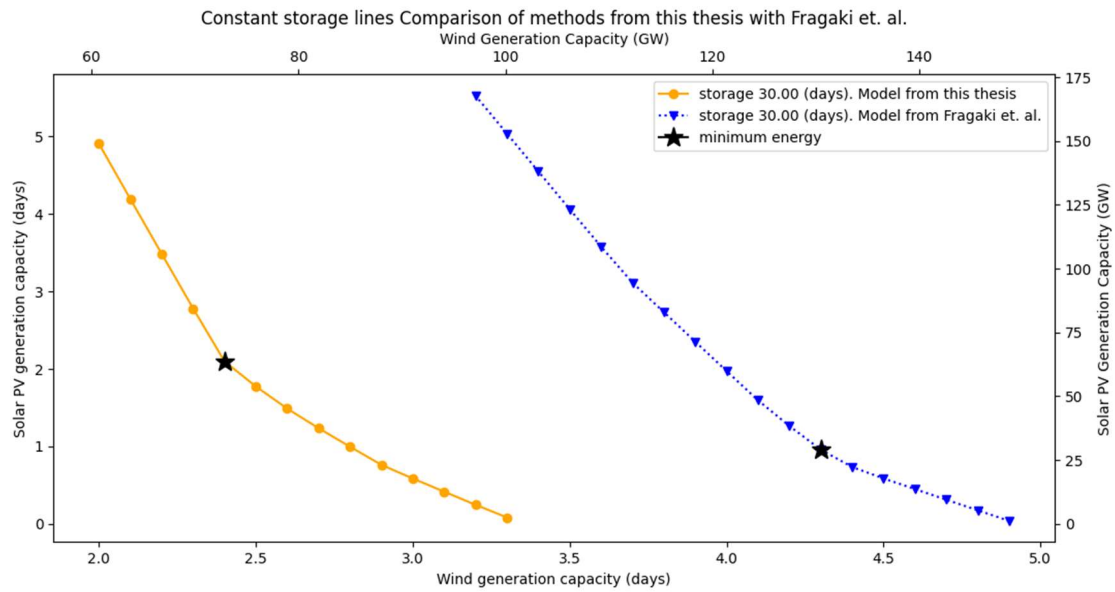


Figure 7-26 Comparison of 30 days storage line using the methods from this thesis with those of Fragaki et. al.

Figure (7-27) shows the same lines but with energy generated plotted against the wind energy fraction. For the methods from this thesis 80% of the energy is generated by wind and the amount of energy generated is 14% above the load. In contrast using the Fragaki model 32% more energy is generated and 92% of it comes from wind.

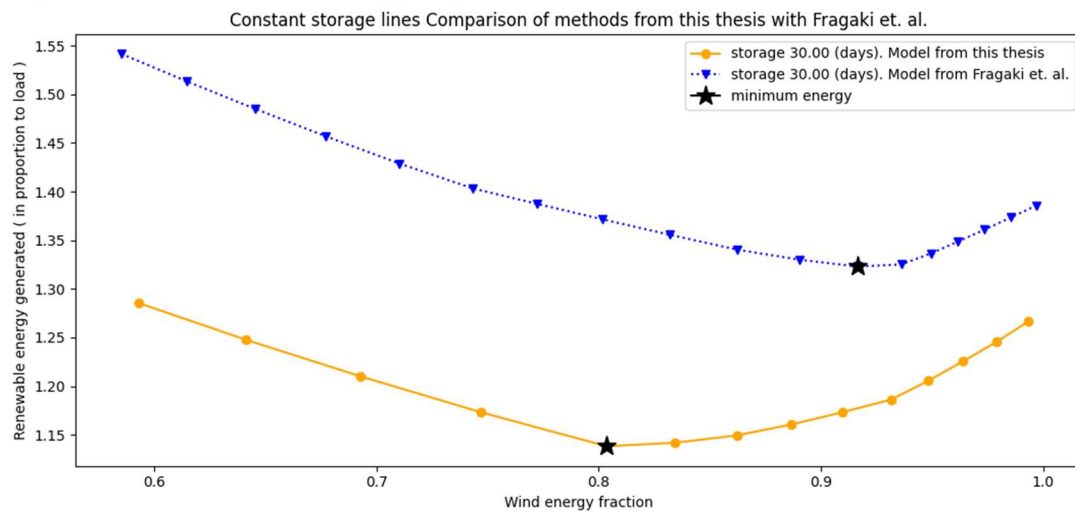


Figure 7-27 - Minimum energy configuration from those requiring a minimum of for 30 days of energy storage

The above result is summarised as “30-days minimum energy” in table (7-20). This table also shows a comparison of the two studies using the other comparison methods defined in section 6.3.2.

The “30-days minimum cost” configuration in table (7-20) shows that for those configurations that need a minimum storage of 30 days, the one with lowest cost of electricity generation has the same wind energy fraction and energy as the “30-day storage minimum energy” configuration. In contrast to the illustrative configuration from the original study which found that generating 30 days more energy than the current supply combined with 30 days storage was sufficient, this study has found that only 15 days more energy is needed.

Table 7-20 Comparison of this project's methods to Fragaki et. al. for 85% round trip storage efficiency

Configuration	Measure	Model Inputs	
		This thesis	Fragaki et. al.
Equal Minimum Storage: 30-days minimum energy	Wind energy fraction	80%	92%
	Energy (proportion of load)	1.14	1.32
Equal Minimum Storage: 30-days storage minimum cost	Wind energy fraction	80%	92%
	Energy (proportion of load)	1.14	1.32
Least Storage Configuration for excess energy generation: 50%	Wind capacity (days)	3.7	3.7
	PV capacity (days)	0.8	0.8
	Wind energy fraction	94%	92%
	Storage capacity (days)	10	82
Minimum cost of electricity generation at today's prices.	Cost (£/kWh)	0.149	0.203
	Wind capacity (days)	3.5	5.9
	PV capacity (days)	0.7	1.2
	Energy (proportion of load)	1.41	1.8
	Wind energy fraction	95%	92%
	Storage capacity (days)	11	14

Of all the configurations from the model used in this study that generate 50% excess energy above that required by the load, the one that has the least storage has a wind capacity of 3.7 days and a PV capacity of 0.8 days. This is shown as the “Least storage configuration for excess energy generation” table (7-20). It requires 10 days storage. However, using the methods from the Fragaki model requires 82 days storage. The wind energy fraction of 92% compares to 94% from this thesis.

Table (7-20) also shows the configuration from each study's model that generates electricity at the lowest cost using today's prices assuming that the storage is pumped hydro storage. The model used in this thesis requires 3 days less storage capacity, has a 3% higher wind energy fraction and lower cost.

7.6.2 Update to cost optimal storage for CAES

Another previous study was to find the cost optimal configuration for CAES at today's prices. This used the modelling methods shown in the Cardenas column of table (5-1). This section uses the inputs and methods from this project to find the same thing, but using the model inputs from this study.

Table 7-21 Experiment to compare hydrogen storage with CAES (see 5.3.1 for terminology)

Experiment Objective: Compare results of Cardenas et. al. with this projects model using hydrogen storage.							
Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$							
Experiment	Frequency	η %	Demand	Storage	Wind	PV	Years
1	Hourly	70	Baseline	Iterative	Ninja C	Ninja	1980 - 2019

The result is shown in table (7-22) compared to that found by this study. It shows the amount of energy generated in proportion to the load, the wind energy fraction, and the storage capacity for the configuration with the lowest total cost of energy. It is compared to the cost optimal solution found by the algorithm from this study. Note that the conversion from days to TWh is based on the mean daily energy from Cardenas of 0.917808 TWh per day for comparison purposes. Only 11 TWh of storage was needed, compared to the 43 TWh found by Cardenas. The generation capacities were 3.7 days wind and 1.8 days PV. Because the storage was lower, more energy needed to be generated (1.21 days compared to 1.15).

Table 7-22 Cost optimal configuration found here compared to that found by Cardenas et. al.

Study	Wind fraction	Energy (proportion of load)	Storage (days)	Storage (TWh)	Charge rate (GW)	Discharge rate (GW)	Cost £/kWh
Cardenas et. al [52]	84%	1.15	46	43	119	61	0.080
This project	84%	1.21	18	11	119	94	0.073

The most significant input difference in the sensitivity analysis was shown to be the National Grid wind data. This could be one cause of the difference. However, the algorithm to find the required storage has not been reproduced and so could be a cause of the difference. It is possible that the Cardenas algorithm did not consider the cost optimal solution found here.

7.7 Summary and Conclusions

The sensitivity of the storage model to different inputs was investigated.

It was found that using hourly time series is important for configurations with a small amount of storage or when calculating cost or wind energy fraction. For calculating the

minimum required storage, daily time series are adequate. Experiments suggest that for large amounts of storage, using a few years data including a cold spell is adequate and that it does not matter which decade of data is used. However, for small capacities of storage, these choices in the data make a much larger difference to the results. Differences were also seen for small storage capacities when using different decades from the 40-year time series, but for larger amounts of storage the results were not much different.

A sensitivity analysis to using different model inputs used by Fragaki et. al. showed that they only made a small difference to the results, apart from the wind generation data from Renewables Ninja which made a large difference. The experiments in this section have shown that the main cause in the difference in results is that the Renewables Ninja wind generation data has a higher capacity factor, particularly for offshore wind which was not modelled in that study. Because the Renewables Ninja wind generation data is based on the actual locations and turbine types of wind farms and has been extensively validated, it seems reasonable that this new result is more accurate than the previous study. The difference for PV is much less marked than with wind generation, which is expected considering the lower variability in the pattern [12] and the lower correlation with the demand profile in table (9-4). However, with PV the difference in pattern was more significant than the difference in capacity factor. The overall pattern of the results using the modelling methods from this thesis is similar to the previous study.

A similar sensitivity analysis on the inputs to Cardenas et. al. also showed that wind generation data caused the most significant difference in the results. Not only does the National Grid wind time series vary with the weather, but the actual wind turbines in it will have evolved over time. Despite scaling it to maintain a constant generation capacity this will have caused a change to the pattern of generation.

Both comparisons with previous studies show that different wind generation data patterns cause significant differences in the results. It was found that different patterns in wind generation as well as capacity factors can have a large impact on the amount of storage required, a result that has not been mentioned in the literature before. In other words, the impact of when the energy is *generated* compared to when it is *needed*. However, the significance of this effect depends on the particular configuration being studied. For example, with 30 days storage, offshore wind requires less energy to be generated (between 10% and 39% of the mean daily load per day). With a wind capacity of 3.1 days, onshore requires 8.6 days more storage, but with a wind capacity of 7.2, offshore requires 1.2 days more storage. Although previous work has considered how different siting of wind turbines might result in higher capacity factors, no previous study has been found that notes the impact that a different *pattern* of generation can have. The differences between using onshore wind in the model compared to offshore wind are more significant at lower amounts of storage. The debate between offshore and onshore wind tends to consider cost, capacity factors and political reasons such as public opposition. The generation pattern has been identified here as a significant fourth factor to consider. Because of the potential significant differences, comparisons between energy models using different wind generation time series should be treated with caution.

The results from two previous studies to find the amount of energy storage required by the UK for different proportions and of wind and solar have been recreated but using the modelling methods of this thesis.

The 80% wind energy fraction for 30 days storage found here compares to 90% using the methods from Fragaki et al. The cost calculation in this study illustrates that the optimum solution might be for lower amounts of storage in the region of 10 days and consequently higher energy generation, than the illustrative example of 30 days storage used in Fragaki et. al. Using the methods from this thesis it was found that for 30 days storage only 15 days additional generation would be required compared to the 30 days found by Fragaki et. al.

The wind energy fraction found here of 84% was the same as that found by Cardenas. However, using the model from this thesis the cost optimal configuration for CAES at today's prices is 11 TWh of storage generating an excess generation of 21% above the load, compared to the 43 TWh and 15% excess generation found by Cardenas.

Future work on this project could be to try and reproduce the actual algorithm used by Cardenas to find the required energy storage capacity and then investigate the impact of their different assumptions.

Another point of interest is that although the storage algorithms for both studies work in terms of energy generation, Fragaki et. al. plot their results in terms of generation capacities, whereas Cardenas plot their results in terms of energy. Both studies quote results in terms of generation capacities which are dependent on the mean capacity factors of the wind and solar generation time series used, and thus not comparable. The algorithm used in this thesis works in capacities, and results are plotted in both capacity and energy. For comparison purposes, it might be desirable for all studies to use energy. However, it is understandable that policy makers want results in terms of generation capacity and cost.

8 Demand Case Studies

Chapter 6 looked at the change in wind, solar and storage due to the electrification of heating. In this chapter other future changes to electricity demand are considered as shown in figure (8-1). The alternative heating possibility of using hydrogen boilers is discussed. But first the impact of electric vehicle charging is investigated which will contribute to the answer to the main research question of the thesis: the impact of transport electrification on the mix of wind, solar and storage.

Model Case Studies

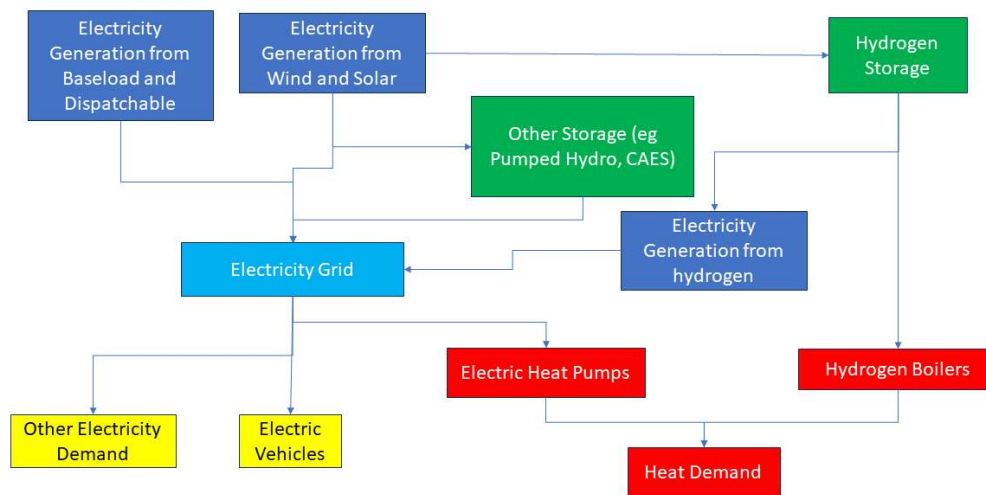


Figure 8-1 Flow of energy from supply to demand in the model used in this thesis

8.1 The Impact of Electric Vehicles

Chapter 6 showed what the impact of heating electrification would be on shares of wind generation, solar generation, and storage. In this section the impact of electric vehicles (EVs) is considered. An EV charging time series is created and combined with the electricity demand time series with the existing heating technology from chapter 4. This is used with the storage model from chapter 5 to study the impact of EVs alone on shares of wind generation, solar generation, and energy storage.

The section starts with some background and a description of the methods. The results section presents the impact of EVs on the electricity demand, generation, and energy storage. This is followed by the conclusions.

8.1.1 Background

Previous studies incorporating EVs into generated electricity demand time series tend to focus on the impact on peak demand. For example, in a study of a 100% renewable UK electricity system [34] hourly fluctuations of EV charging are modelled, but the same energy is used each day. Energy Plan [108] allows the user to supply an hourly profile, but no seasonal variation. The DESSTINEE model [6] includes seasonal factors, but does not link EV electricity usage directly to the weather. However the Customer-Lead Network Revolution trial [109] found that domestic EV energy use is seasonal. Petrol sales [110] however show no such seasonal trend. It therefore seems

that this seasonal difference is due to the performance of the vehicles, rather than consumer behaviour. A Chinese study of electric taxis [10] found that energy consumption increases when the temperature is lower than 10°C and when the temperature is higher than 28°C. This chapter models EV charging electricity time series by including weather dependency using the findings from that study to address this gap.

8.1.2 Methods

First an hourly 40-year electricity demand time series was created for EV charging. Then this was added to the electricity demand with the existing heating technology generated in chapter 4.

To generate the EV time series an annual EV energy of 95.83 TWh is used. This is based on the assumption that most road transport is electrified apart from a small number of heavy vehicles including buses that run on 31 TWh of hydrogen [24]. It does not include rail transport. This annual demand is split into days equally and then modified using the finding from a study of Chinese taxis [10] that electricity consumption normally at 14.4 kWh per 100 km, increases when the temperature is lower than 10°C by 2.4 kWh per 100 km for each 5°C below 10°C and also that when the temperature is higher than 28°C that electricity consumption increases by 2.3 kWh per 100 km for each 5°C. The mean day time temperature for Great Britain between the hours of 8am and 8pm was used on the assumption that most driving occurs during the day. To convert the daily series to hourly it is assumed that 60% of charging occurs at night between 1am to 3am and 40% during the day 2pm and 6pm. The EV electricity is added to the generated electricity demand with the existing heating technology from chapter 4 assuming that the electricity used by electric vehicles in 2018 was negligible and therefore can be ignored. The hourly electricity demand including EVs is given by equation (36)

$$U_h = \left(\frac{A}{N} + I_d \right) e_i + R_h \quad (36)$$

Where U_h is the hourly electricity demand with the existing heating technology but including electricity due to vehicle charging, A is the annual electric vehicle energy of 95.83 TWh for 2050, N is the number of days in the year, e_i is the hourly charging profile for hour i set to 0.2 for $i=1,2,3$ 0.1 for $h=14,15,16,17$, R_h is the generated electricity demand including the existing heating technology from 4.2.2 and I_d is the increase in daily electricity due to extreme temperatures given by equation (37)

$$I_d = \begin{cases} r \left(\frac{2.4}{100} \right) \left(\frac{10 - T}{5} \right), & T < 10.0 \\ (0), & 10.0 \leq T < 28 \\ r \left(\frac{2.3}{100} \right) \left(\frac{T - 28}{5} \right), & T \geq 28. \end{cases} \quad (37)$$

Where I_d is the daily additional electricity due to extremes of temperature, T is the UK population weighted daily temperature in °C, and r is the daily range of electric vehicles in km. The range, r is calculated using equation (38)

$$r = \frac{A}{365.25} \frac{100}{14.4} \quad (38)$$

Where A is the annual EV energy of 95.83 TWh from above and 14.4 is the electricity consumption in kWh per 100 km from above.

8.1.3 Results

Figure (8-2) shows the electricity for EV charging (red) compared to the historic 2018 electricity demand (blue) to which it will be added. The daily EV electricity demand is modelled as constant apart from those days that have exceptionally high or low temperatures. The seasonal impact is noticeable, but less pronounced than for electrification of heating seen in chapter 4.

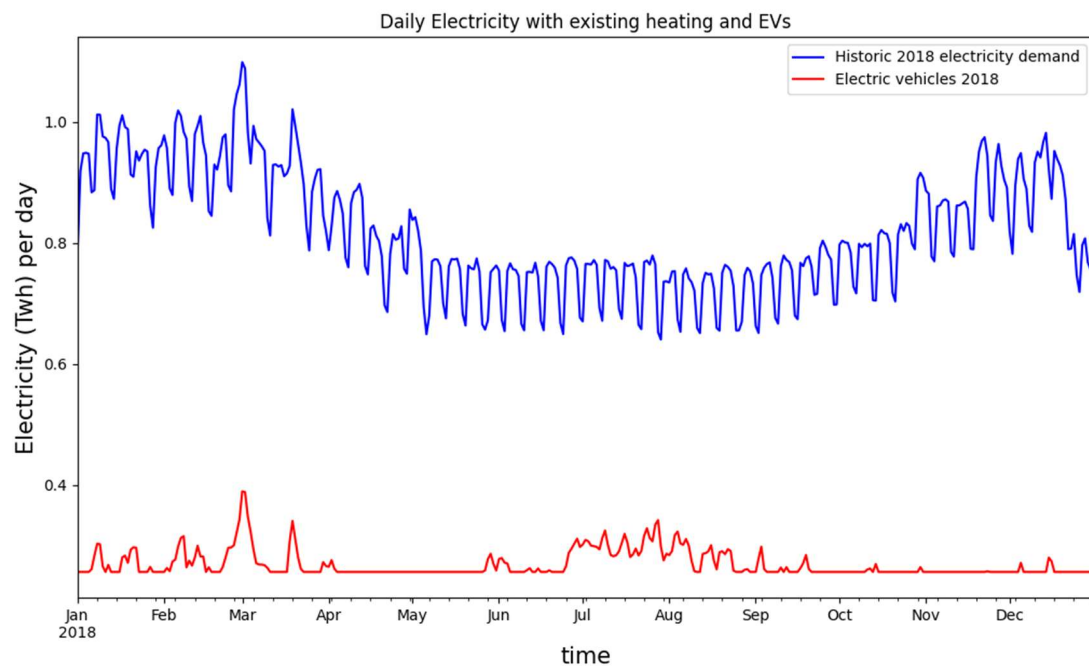


Figure 8-2 EV charging electricity demand time series for 2018 compared to the historic electricity demand with the existing heating technology.

Figure (8-3) shows the electricity time series for 10 arbitrary years including the heating electricity for the existing heating technology based on weather in orange. In purple is the result of adding the weather dependent EV electricity time series to this. The electricity demand is much higher, but the seasonal pattern appears quite similar.

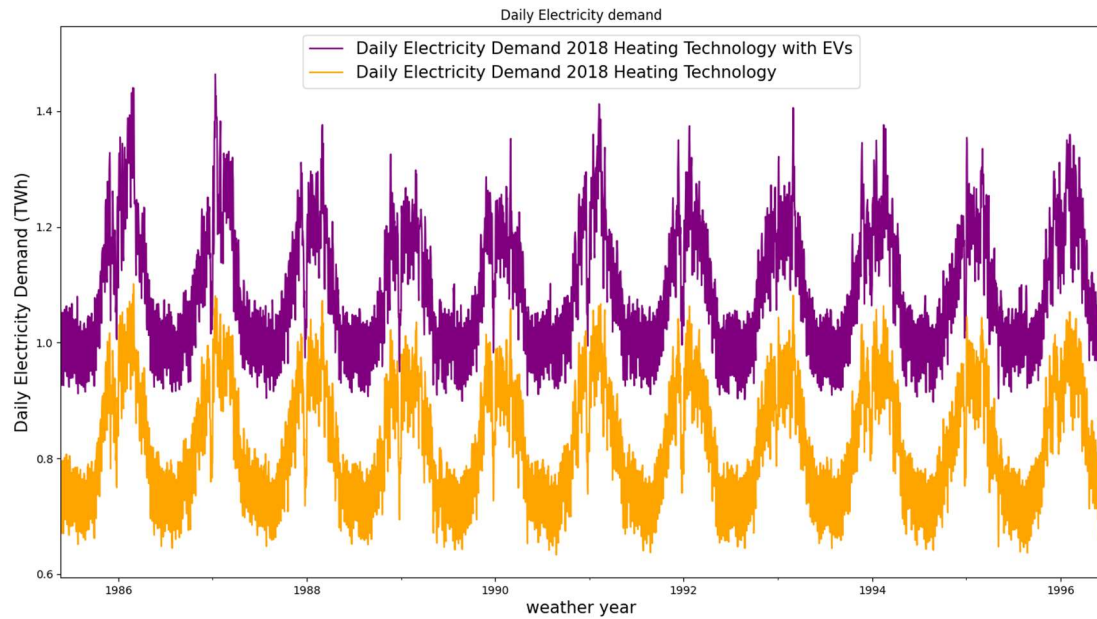


Figure 8-3 The impact of electrification of transport for 10 years historic weather on a time series incorporating the existing heating technology of 2018

Figure (8-4) shows the variation in yearly demand. Without EVs it varies between 367 TWh and 377 TWh. Whereas with EVs it varies between 483 TWh and 497 TWh, only a 1% increase in variability.

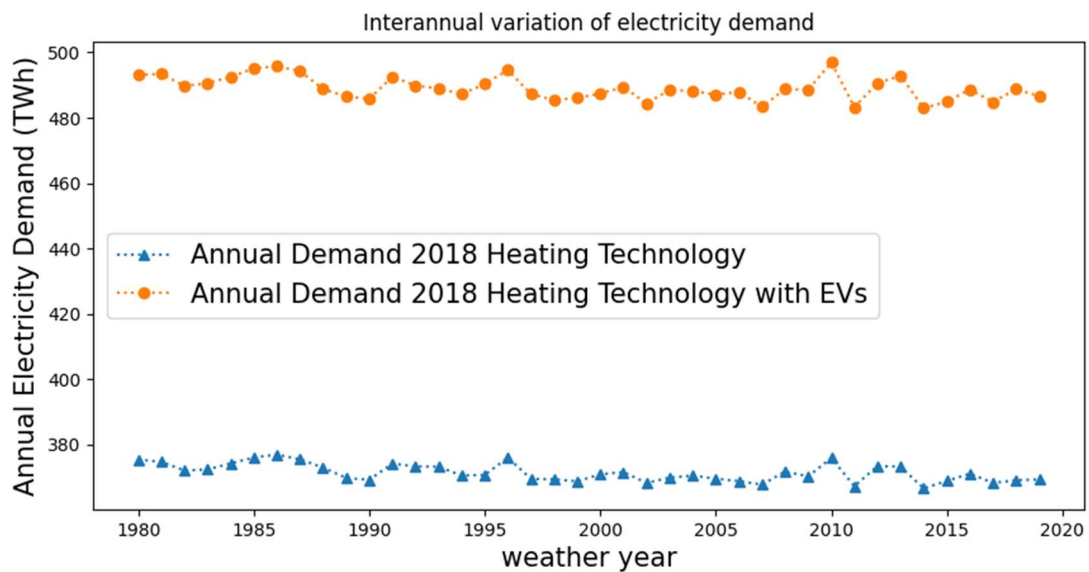


Figure 8-4 Interannual variation in electricity demand including EVs

The EV charging time series that has been generated shows that electrification of transport increases the annual electricity demand from 371 TWh to 489 TWh. The seasonal impact is less significant than for that of heating electrification: with electricity demand varying over a range of 10 TWh between years without EVs and 14 TWh with EV's included.

An experiment was done to assess the impact on shares of wind generation, solar generation and energy storage using the model from chapter 5. The results are compared with those for the existing heating technology from chapter 6.

Table 8-1 Experiment to assess the impact of EVs on shares of wind generation, solar generation and hydrogen storage (see 5.3.1 for terminology)

Experiment Objective: Assess the impact of transport electrification on shares of wind and solar generation, and hydrogen energy storage. Baseload: $C_b = 0.4$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$							
Electricity Demand	Frequency	η	Demand	Storage	Wind	PV	Years
Existing Heating technology	Hourly	50%	Baseline	Iterative	Ninja	Ninja	1980 - 2019
Existing heating technology with EVs	Hourly	50%	Baseline	Iterative	Ninja	Ninja	1980 – 2019
41% heat pumps, no EVs	Hourly	50%	Baseline	Iterative	Ninja	Ninja	1980 - 2019

Figure (8-5) below shows lines joining configurations with 30 days storage with and without the impact of EVs, the black star showing the minimum energy configuration. It can be seen that the green line representing most transport being EVs requires much more energy to be generated for the same storage, compared to the orange line representing 41% heat pumps or the blue line representing the existing heating.

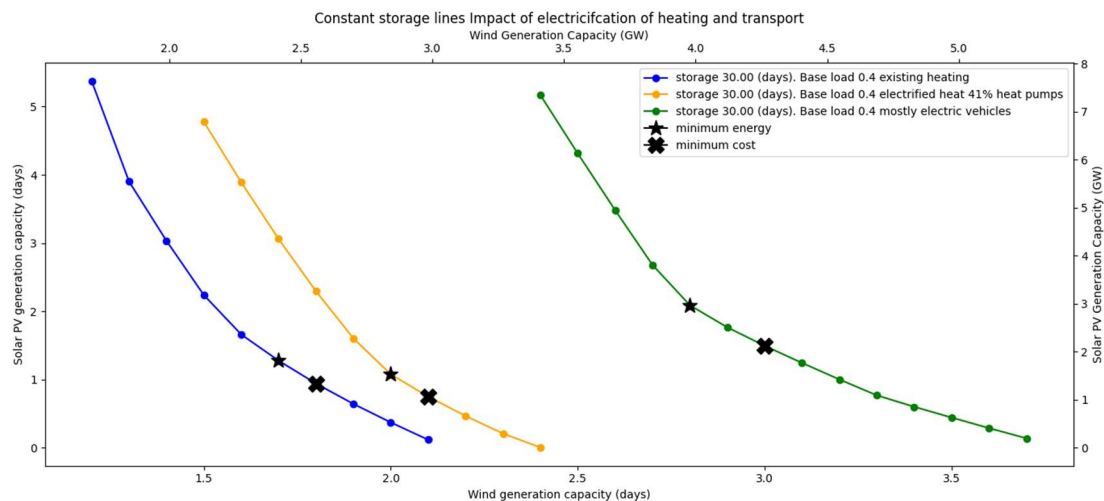


Figure 8-5 The impact of electrification of most transport on lines of constant storage

Table (8-2) compares these three cases of no EVs, and mostly EVs with the impact of 41% of heating provided by heat pumps. For 30 days storage heat pumps increase wind energy fraction from 83% to 87%, but EVs leave it unchanged. This is probably because the EV charging demand is spread more evenly throughout the year, and only changes due to extremes of weather which are unusual in the UK climate.

Table 8-2 Impact of EVs using the comparison methods defined in section 6.3.2

Comparison		Electricity Demand		
Configuration	Measure	No EVs, existing heating	Mostly EVs, existing heating	No EVs, 41% heat pumps
Equal minimum storage 30 days minimum energy	wind energy fraction	83%	83%	87%
	energy generated	0.8	1.31	0.89
Least storage of those generating 80% excess energy above the load	storage (days)	6	21	8
	Wind capacity	3.2	3.2	3.2
	Solar PV capacity	1.4	1.4	1.4
Minimum cost of electricity generation at assuming hydrogen storage today's prices	wind energy fraction	88%	72%	91%
	energy generated	0.75	0.8	0.81
	storage (days)	59	44	72
	cost £/kWh	0.088	0.091	0.088

In chapter 6 on the impact of heating electrification, configurations requiring 50% excess energy generated over the load were considered as a comparison point. However, for EVs it was found that this wasn't enough energy. So, table (8-2) shows configurations needing 80% energy above the 2018 electricity demand. Both heat pumps and EVs require more storage. However, EVs require a lot more storage.

Table (8-2) shows that the minimum cost configuration for EVs has a lower wind energy fraction, which makes sense because the EV load will be spread more evenly throughout the year.

8.1.4 Conclusions

Weather dependent EV charging electricity demand time series have been incorporated into electricity demand time series with the heating technology of 2018 and 40 years weather. This allows us to study the impact of transport electrification alone. The model has shown that electrification of transport increases the annual electricity demand from 371 TWh to 489 TWh. The seasonal and interannual impact is less significant than for that of heating electrification: with electricity demand varying over a range of 10 TWh between years without EVs and 14 TWh with EV's included. Previous work including EVs into generated electricity demand time series do not take the weather into account.

The minimum cost configuration for EVs occurs with a 72% wind as opposed to 88% without EVs and uses 15 fewer days of storage but generates more energy. This contrasts with heating where the proportion of wind increases. This could be because most of the cost of hydrogen storage is due to charging and discharging. Heat pumps have a big impact on peak demand and so could lead to high charge rates, whereas EVs are being modelled as charging partly overnight. The minimum energy point on the 30 days storage contour also occurs at higher proportion of PV with electric vehicles. This is likely to be due to heat pumps requiring more energy in the winter, but EV charging is spread more evenly across the year.

No other studies have been found that quantify the impact of electric vehicles on the proportions of wind, solar and energy storage.

8.2 Hydrogen Boilers or Heat Pumps

8.2.1 Introduction

The scenario used as basis for chapter 6 assumes 41% of heating provided by heat pumps, but what about the remainder? If it is not heat pumps, then how do we reach net zero? This section looks at the proposal to provide that heating using hydrogen boilers. The hydrogen would be delivered to buildings via the existing gas network.

The remainder of the section is structured as follows. The background section discusses previous work on hydrogen boilers. The methods section describes a simple way of expanding the model to include heating with hydrogen boilers. This is followed by a presentation of the results and conclusions.

8.2.2 Background

National Grid's future energy scenarios 2019 [24] Net Zero scenario assumes that the heating not provided by heat pumps is provided by boilers fuelled by hydrogen. This hydrogen would be piped through the existing gas network. This domestic use of hydrogen in the UK was only in a trial phase in 2019. The industry led Leeds City Gate Project [22] proposed that the hydrogen could be produced from steam methane reforming of natural gas (called grey hydrogen). The report states that both the medium pressure and low-pressure gas distribution networks have been modelled using network analysis software and that the gas networks "have the capacity to be 100% hydrogen with relatively minor upgrades". A new transmission system to connect hydrogen production into the gas network at a cost of £230 million would be required. Appliances need converting and there are already hydrogen ready gas boilers on the market. Whilst the approach seems to be practical, since this process emits CO₂, it would be difficult to achieve a net zero energy system. It has to be combined with CCS to capture the emissions, which is described as blue hydrogen. A previous study on blue hydrogen [23] found that boilers using hydrogen from natural gas with CCS cannot achieve net zero. The alternative is to use hydrogen produced by electrolysis of water which is termed green hydrogen. This is what is assumed here. It should be noted that in a review of the evidence [111] (conducted after the work described below was completed), it was found that none of the 32 independent studies identified hydrogen as a viable solution for decarbonizing space and water heating in buildings.

The only previous UK energy model study found that included hydrogen boilers [53] compared them with the alternatives of district heating and electric heat pumps. They used an optimisation model ESTIMO which includes the impacts of climate change, building heat and cooling, transport, synthetic fuels and energy storage. They modelled the UK as one node and Europe as three nodes, enabling interconnectors and market simulation. However, they only used the years 2009-2011 identifying 2010 as a stress year due to extreme cold weather, which was shown in chapter 5 to give different results from using 40 years. District heating is also considered, so that excess heat from generating electricity from stored hydrogen can be used in conjunction with thermal

storage. They found that systems with consumer or district heat pumps require about four times less electricity per unit of heat than hydrogen boilers. They only modelled five different wind and PV generation capacities.

No previous study was found that includes hydrogen boilers into an energy model under long term weather variation. This section addresses that gap.

8.2.3 Methods

To incorporate heating from hydrogen boilers, a small change is made to the model from chapter 5. The energy store used by the model is considered to be hydrogen with a 50% round-trip efficiency as used in chapter 6 for modelling heating electrification with heat pumps. The hydrogen is created by excess wind and solar PV electricity using electrolysis from water and is therefore green hydrogen. As well as using this hydrogen as an energy storage mechanism, the hydrogen could also be piped through the gas network to run a heating boiler. In contrast to the heating electrification scenario from chapter 6 which accounts for 41% of heating with heat pumps, this one accounts for all heating. The process is illustrated in figure (8-1)

First a hydrogen demand time series is created from the heat demand using equation (39)

$$Z_t = \eta_H P_H \sum_{g=0}^{NG} H_{sh,h,g} + H_{wh,h,g} \quad (39)$$

Where Z_t is the hourly hydrogen demand, η_H is the hydrogen boiler efficiency (0.8), NG is the number of weather grid points and $H_{sh,h,g}$ and $H_{wh,h,g}$ are heat demand time series from section 3.2.1 equations (13,14) for hour h and grid point g . P_H is the proportion of heating provided by hydrogen boilers and is calculated on the assumption that it is all heating not provided by heat pumps.

$$P_H = 1 - P_E - P_M \quad (40)$$

Where P_E and P_M are the proportions of ordinary heat pumps and hybrid heat pumps respectively from section 3.2.5 equation (20).

Then the energy storage model is modified, so that this hydrogen is removed from the energy store on each hourly cycle. The hydrogen is removed from the energy store following equation (30) in section 5.2.1 by using equation (41)

$$S_t = S_t - Z_t \quad (41)$$

Where S_t is the energy store from equation (31).

A similar analysis to that from chapter 6 was performed, except that as well as having an electricity demand, there is also a hydrogen demand.

Three heating scenarios were compared:

- All electric heat pumps, no hydrogen boilers
- Half electric heat pumps, half hydrogen boilers
- All hydrogen boilers

The cost calculation was modified so that instead of calculating the system cost per unit of electricity demand, it was calculated per unit of energy, based on the total energy over the 40-year period as per table (8-3). This is because some of the heating demand is not provided by electricity. This gives a new value of E_d to be used in equation (32).

Table 8-3 Total energy demand over the 40-year period combining baseline electricity with heat demand.

Baseline electricity demand (with no heating)	18426 TWh
Heat demand	12580 TWh
Total energy (E_d)	31006 TWh

Because so much more electricity is needed to generate the hydrogen, a much greater range of generation capacities must be considered. Consequently, a larger difference between capacities (0.5 days as opposed to 0.1 days) was used. The experimental parameters are summarised in table (8-4).

Table 8-4 Experiment to assess the impact of heating with hydrogen boilers on electricity generation and storage (see 5.3.1 for terminology)

Experiment Objective: Assess the difference between heating with electric heat pumps and heating with hydrogen boilers and their impact on hydrogen storage capacity and shares of wind and solar generation. Baseload: $C_b = 0.4$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 29.5$ Solar $0.0 \leq C_p \leq 29.5$							
Electricity Demand	Frequency	η	Demand	Storage	Wind	PV	Years
All hydrogen boilers	Hourly	50%	Baseline	Iterative	Ninja	Ninja	1980 - 2019
Half hydrogen boilers and half heat pumps	Hourly	50%	Baseline	Iterative	Ninja	Ninja	1980 - 2019
All heat pumps	Hourly	50%	Baseline	Iterative	Ninja	Ninja	1980 - 2019

8.2.4 Results

Figure (8-6) shows the three electricity demands for four arbitrary years. For all hydrogen boilers, the electricity demand for heating is zero and so this plot shows the baseline electricity demand without any heating (see chapter 4). Of course, a lot more electricity is generated than is shown here because it is used to create hydrogen for heating and storage. However, the amount of electricity that must be generated to fill the energy store with hydrogen also depends on how much is used to satisfy electricity demand net of renewables, which depends on the particular combination of wind and PV capacities.

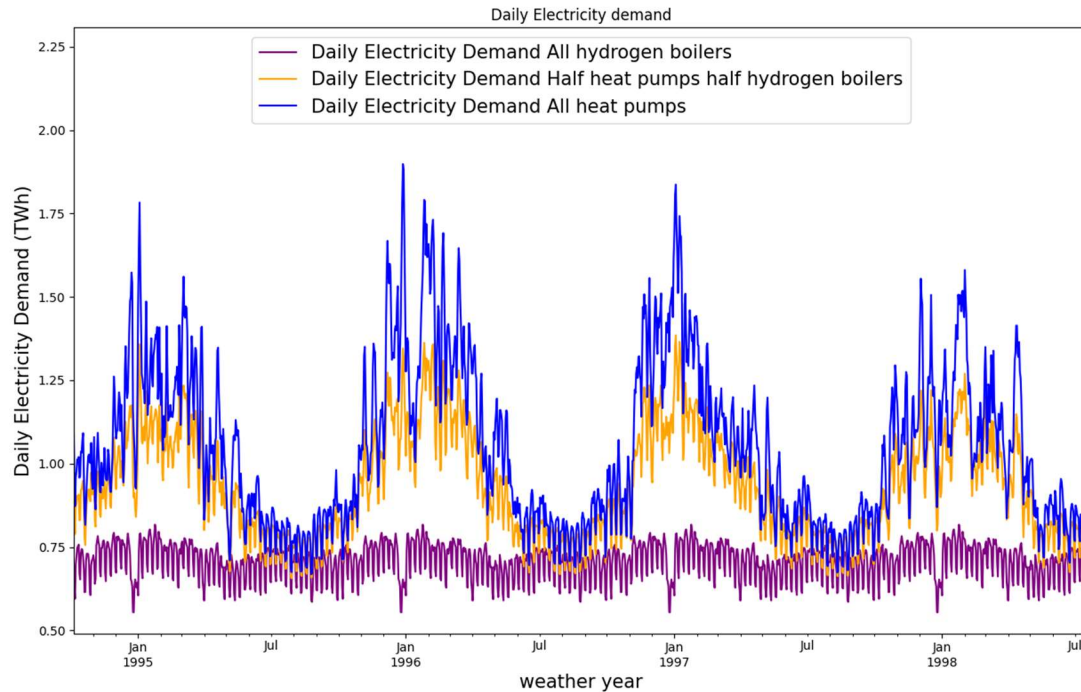


Figure 8-6 Electricity demand comparing heat pumps and hydrogen boilers

Figure (8-7) shows the hydrogen demand for gas boiler heating. For the “all heat pumps” scenario there is no hydrogen. More hydrogen than this is created because some of it is used as a storage medium to satisfy the electricity demand net of renewable generation which depends on the particular configuration of generation capacities.

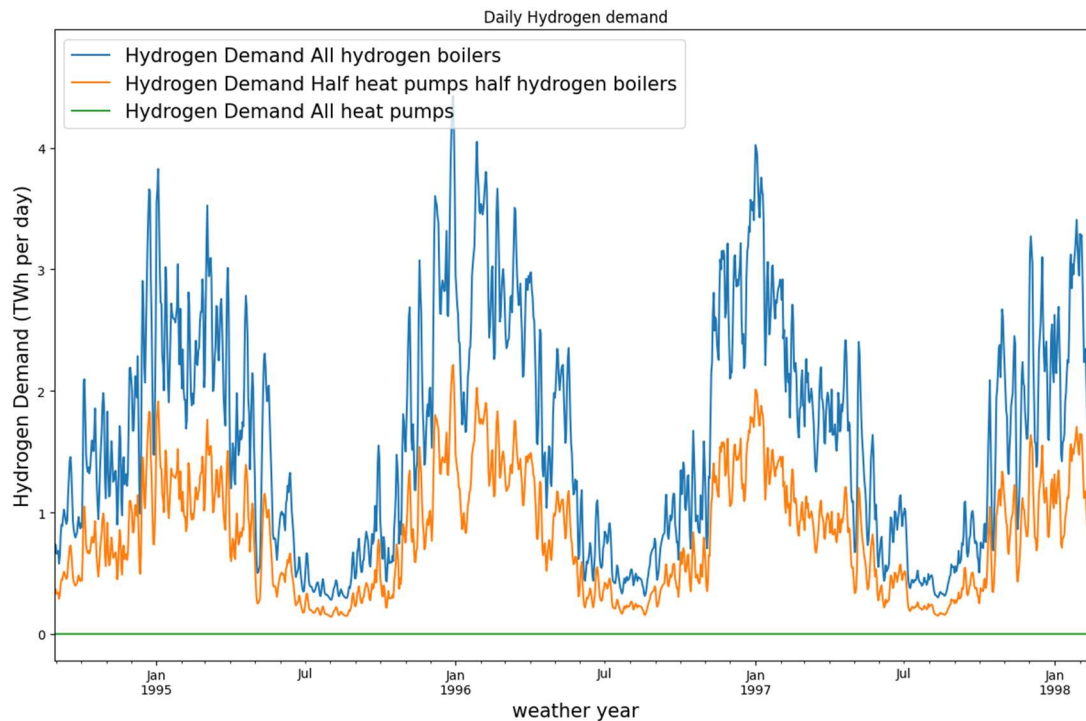


Figure 8-7 Hydrogen demand for heat pumps and hydrogen boilers

The 30 days of storage used to compare scenarios for heating electrification is not enough for hydrogen boilers because the hydrogen is being used to run the boilers as well as for an energy store. Therefore, in this chapter configurations requiring a

minimum of 40 days storage are examined. Figure (8-8) shows lines representing configurations which all require a minimum of 40 days storage. It can be seen that the wind generation capacity needed is much greater for hydrogen boilers than heat pumps.

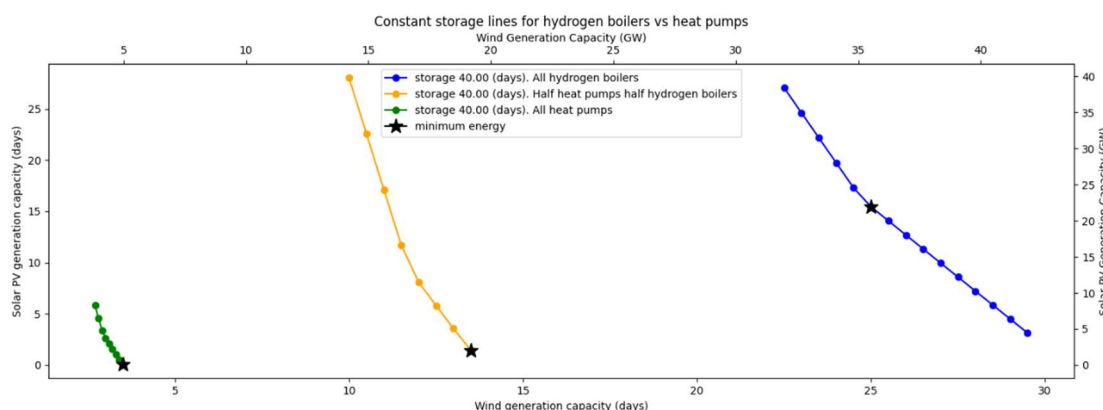


Figure 8-8 Comparison of heat pumps or hydrogen boilers for configurations needing 40 days hydrogen storage

Table (8-5) compares the three experiments of all hydrogen boilers, all heat pumps, and half of each. It shows the minimum cost configurations and the configurations needing 40 days of storage. Note that the cost includes the storage and generation for the electricity to generate the hydrogen. There is no comparison of the cost of installing heat pumps with the cost of converting the gas network and appliances to use hydrogen, so the comparison is only made on the basis of the electricity system. It can be seen that using all hydrogen boilers has over four times the electricity cost. The minimum cost configurations have very high wind fractions (92% - 100%). The minimum energy configuration with 40 days of storage for all boilers occurs at 85% wind fraction, for half heat pumps and half boilers it occurs at a wind fraction of 97% and for all heat pumps at a wind fraction of 99%. However, it can be seen from figure (8-9) below that there is little difference between the minimum energy point and the energy of other points so there is not a very distinct ideal wind energy fraction in this case. This could be because with a large amount of storage, the advantages of generating energy at the time it is needed are less. Providing all heating with hydrogen boilers requires seven times as much renewable electricity generation as all heat pumps.

Table 8-5 Comparison of hydrogen boilers and heat pumps

Comparison		Heating		
Configuration	Measure	All Heat pumps	Half heat pumps half hydrogen boilers	All hydrogen boilers
Equal minimum storage 40 days min energy	wind energy fraction	99%	97%	85%
	energy generated (days)	1.36	5.39	11.36
Minimum cost of electricity generation assuming hydrogen storage at today's prices	wind energy fraction	92%	100%	99%
	energy generated (days)	1.18	4.0	8.0
	storage (days)	76	77	80
	cost £/kWh	0.046	0.114	0.281

Unlike other chapters, no 50% excess generation case is shown. This is because the all boilers case has no viable 50% excess generation configurations – it needs 750% excess. However, that all heat pumps case does not have any configurations that need that amount of energy generation, so it is not a very meaningful comparison point.

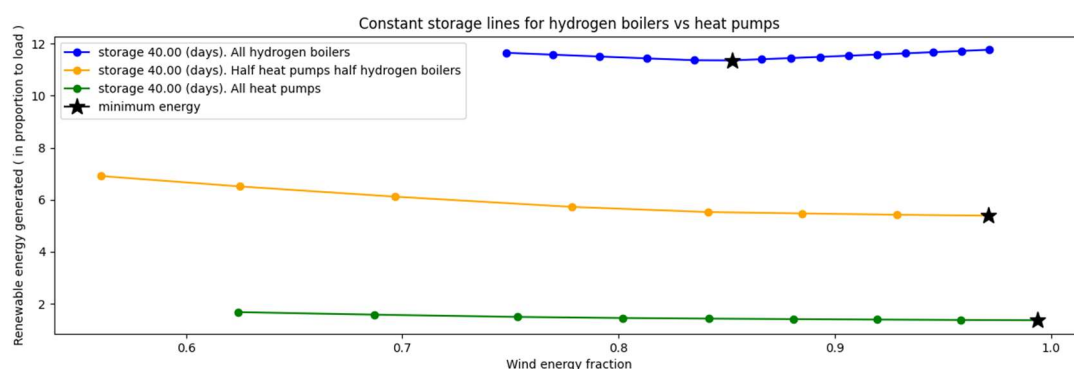


Figure 8-9 Comparison of heat pumps and hydrogen boilers wind energy fraction for 40 days storage

It is not surprising that using hydrogen boilers requires a lot more wind for the same amount of storage considering that electric heat pumps produce more heating for the same amount of energy. Table (8-6) shows estimates of annual energy based on conversion efficiencies between hydrogen and electricity. For hydrogen boilers, assuming 95% efficiency for transmission through pipes (using the existing gas network), and 85% conversion efficiency to heat gives 54% overall. For heat pumps, assuming an efficiency of 45% converting hydrogen to electricity and heat pump COP of 3.0 gives overall 86%. The 2018 annual electricity demand was 298 TWh and the heat demand was 448 TWh which equates to 521 TWh at 86% for heat pumps and 830 TWh at 54% for hydrogen boilers.

Table 8-6 Annual electricity and hydrogen demand for heat pumps or hydrogen boilers

Heating Supply	Annual Electricity	Annual Hydrogen for boilers	Total Energy
All hydrogen boilers	337 TWh	703 TWh	1040 TWh
Half Heat pumps half boilers	411 TWh	351 TWh	962 TWh
All heat pumps	486 TWh	0	486 TWh

A previous study using only 3 years data, comparing hydrogen with heat pumps [53] found that architectures based on district heating and electric heat pumps need about four times less electricity per unit of heat and have a whole system cost 33% lower than those providing 70% of heating using hydrogen boilers.

8.2.5 Summary and Conclusions

The energy storage model has been updated so that if the energy storage is hydrogen, then the hydrogen can also be used to supply heating using hydrogen boilers. It was found that for hydrogen boilers there is no obvious optimum wind energy fraction. Heat pumps use about 7 times less electricity and an energy cost less than 25%. Heat pumps use about 10 times less electricity and have an electricity cost less than 20%. However, this model does not take account of the cost of upgrading boilers and the gas network to use hydrogen and installing heat pumps for all heating to be provided by heat pumps.

No previous work that quantifies the impact of hydrogen boilers on wind energy fraction has been found. However, the one study doing a similar comparison, all be it with only 3 years weather, also found that hydrogen boilers were much more expensive.

9 Generation Case Studies

This chapter contains several case studies related to changes in the energy supply, rather than the demand. These are:

- the transition away from an energy system with a high capacity of dispatchable generation like that of today to a system based on base load, wind and solar.
- The relationship between wind and solar generation and storage
- Baseload
- Lost energy
- How long the energy store stays full for.

Two sections look at the time series of generation and demand from a more mathematical perspective, rather than an energy model. The first section looks at the correlation between demand and supply. The second section looks at two mathematical methods of finding the optimum wind energy fraction and then compares them with the other wind fractions found in the thesis.

9.1 The transition away from dispatchable generation

How will storage requirements change as the UK power system moves away from a large amount of gas power generation to a large fraction of wind and solar? In this section the dispatchable generation capacity is gradually reduced to model the transition away from fossil fuels towards wind and solar.

Table (5-12) in section 5.4.5 shows values for the generation capacities needed for this model to approximate the energy system of 2018. A base load of 0.2 days was used since that was the actual generation for 2018 and the theoretical capacity 0.3 would probably not have been available due to maintenance and outages. The amount of storage was set to 0.03 days which is approximately the amount of storage available in 2018. To balance supply and demand using the existing wind and solar capacities it was found that a dispatchable generation capacity of 1.2 days was required. Starting at that point, the dispatchable generation capacity was gradually reduced. The experimental inputs are summarised in table (9-1).

Table 9-1 Experiment to assess the impact of reducing dispatchable generation (see 5.3.1 for terminology)

Experiment Objective: Find out how storage requirements and wind fraction change as dispatchable generation is gradually reduced. Baseload: $C_b = 0.2$, Dispatchable: $1.2 \geq C_p \geq 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$						
Frequency	η	Demand	Storage	Wind	PV	Years
Daily	80%	Baseline	Iterative	Ninja C	Ninja	1980-2019

Figure (9-1) shows contours of constant storage of 0.03 days. The y-axis shows the amount of energy generated (the sum of dispatchable, wind and solar). The x axis shows the wind energy fraction: the proportion of the energy that came from wind. The dispatchable generation is reduced from its current value of 1.2 (where no storage is

needed) down to 0.7. It is clear that if the dispatchable portion of the energy supply is reduced (representing a reduction in coal and gas power stations), then the amount of wind and solar must increase markedly, but what about their relative proportions? The black star shows the minimum energy point on the contour. In contrast to figure (6-5) where the same style of plot was used to illustrate ideal proportions of wind and solar for the same storage for a system with no dispatchable generation, there is no obvious pattern here.

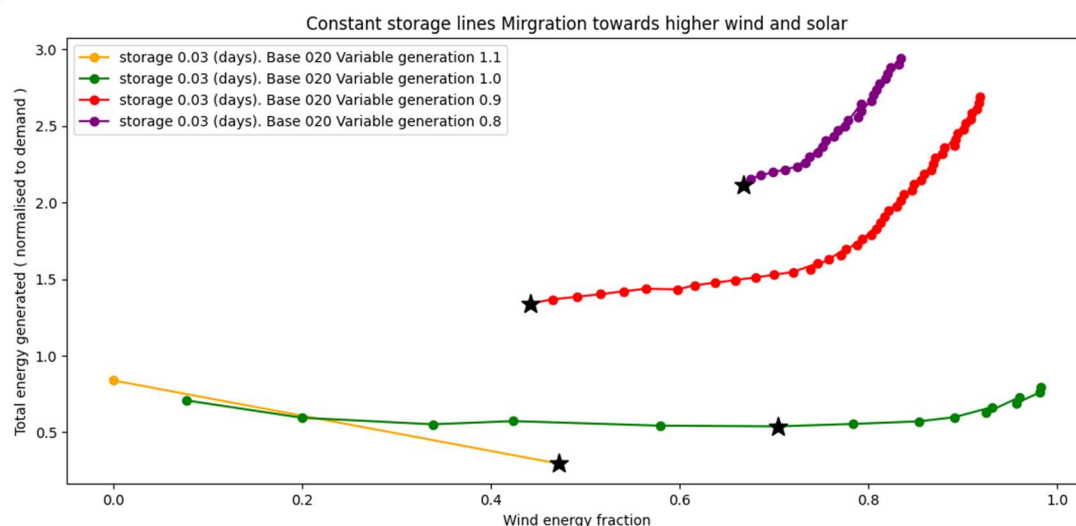


Figure 9-1 Wind energy fraction for configurations needing 0.03 days storage for different amounts of dispatchable generation

Table (9-2) shows the wind energy fraction with storage of 0.03 days (as we have currently) compared to 0.6 days. Neither shows a consistent pattern in wind energy fraction. It is noteworthy that these configurations have large amounts of PV, in contrast to the high wind configurations with no dispatchable generation in the previous section. These two configurations have a small amount of storage, and a large capacity of dispatchable generation which can be supplied at any time of year. Therefore, the dominating factor in determining the optimal wind solar mix becomes how much energy is curtailed, rather than generating energy close to when it is need as has been seen in previous sections. The amount of curtailed energy is determined by how long the generation exceeds the demand.

Table 9-2 Wind energy fraction with decline in dispatchable generation for fixed storage of 0.03 days and 0.6

Dispatchable Generation Capacity (days)	Wind Energy Fraction for 0.03 days storage	Wind Energy Fraction for 0.6 days generation
1.1	48%	47%
1.0	58%	23%
0.9	44%	96%
0.8	55%	46%
0.7	75%	72%

Figure (9-2) shows how storage requirements based on 50% excess energy generation increase as dispatchable generation is reduced. The 50% excess energy point defined in section 5.4.2 is the configuration with minimum storage requirement from those wind and PV capacities where the sum of the baseload, wind and solar energy generated is less than 1.5 times the load. For some experimental runs it is not possible to identify

the configuration with the minimum storage of those configurations generating 50% excess or less because there are many with a storage of 0.01 which is the threshold for minimum storage (see methods section 5.2), ie there is no storage requirement. The 50% excess energy configuration used in the plot below is 1.7 wind and 5.7 solar. It is the first configuration where there is some storage required. It can be seen from figure (9-2) that storage is needed after about 20% renewables. Other research, not specific to the UK has found that above 30% renewable penetration, storage is usually required [112].

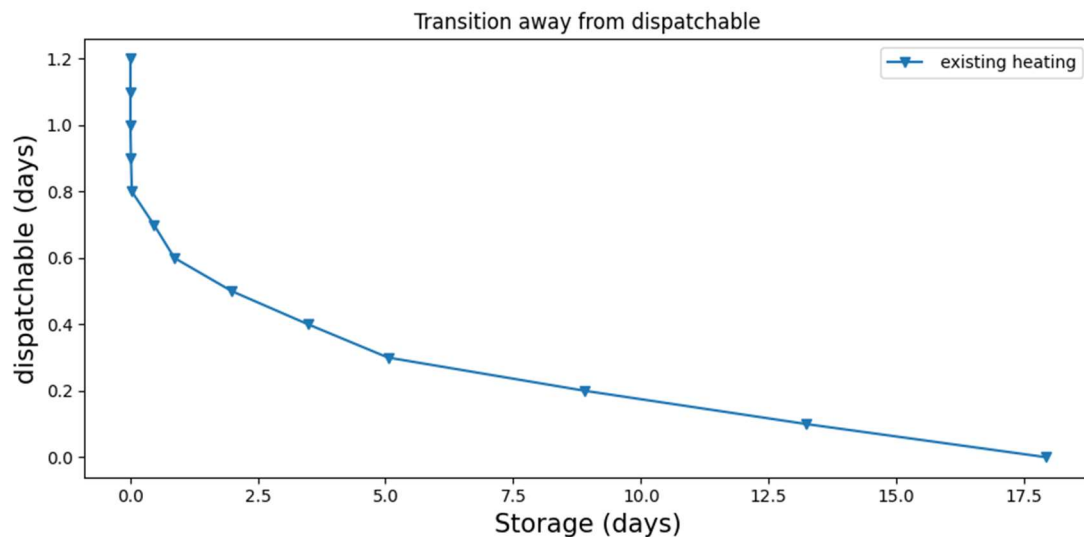


Figure 9-2 Increase of storage needed with transition away from dispatchable generation to renewables

9.2 The relationship between storage capacity and Wind and Solar

In this section, rather than considering configuration with the same amount of storage as was done in section 6.3.3, constant amounts of wind and solar capacity are considered. Figure (9-3) shows lines of constant wind capacity. This shows that the point at which storage requirements climb steeply occurs at a higher PV value for 41% heat pumps than it does for the existing heating technology. Passed this inflection point, adding move PV generation only reduces storage by a small amount.

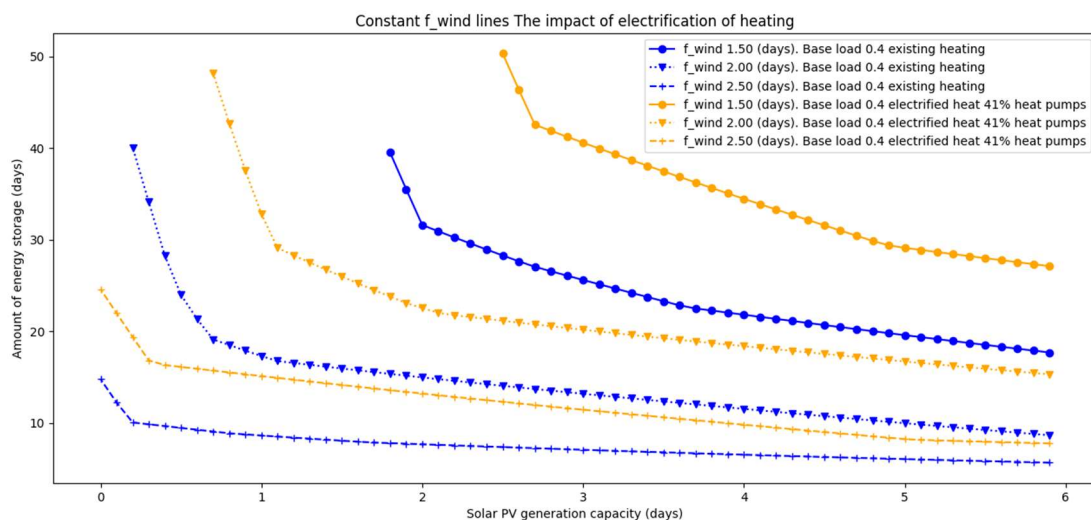


Figure 9-3 Lines of constant wind capacity showing points at which storage requirements climb sharply as PV capacity drops.

Figure (9-4) shows lines of constant PV capacity. For heating electrification, the amount of energy storage required starts to climb at a lower amount of wind energy also reflecting the higher wind share for heating electrification. After these inflection points, adding more wind capacity does not reduce the storage requirement very much.

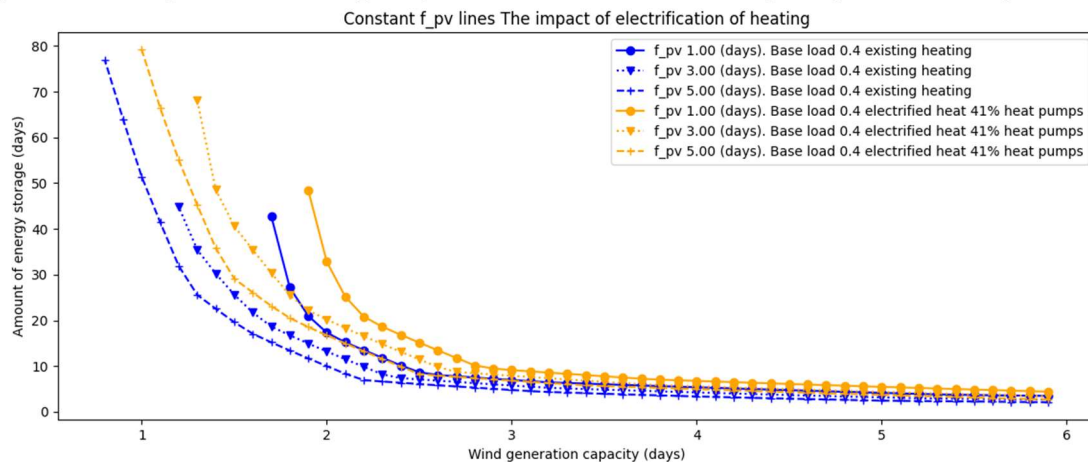


Figure 9-4 Lines of constant PV capacity showing the point at which storage capacity increases sharply as wind capacity declines.

Increased wind capacity reduces storage required more than increased PV for both the existing heating technology and 41% heat pumps.

9.3 Baseload

The configurations analysed to far have a baseload of 0.4 based on likely projections of future base load. In this section the effect of different amounts of baseload capacity is considered.

In figure (9-5) each line joins configurations requiring 30 days minimum storage. It can be seen that as the base load capacity reduces, the lines move to the right showing that more wind generation is required.

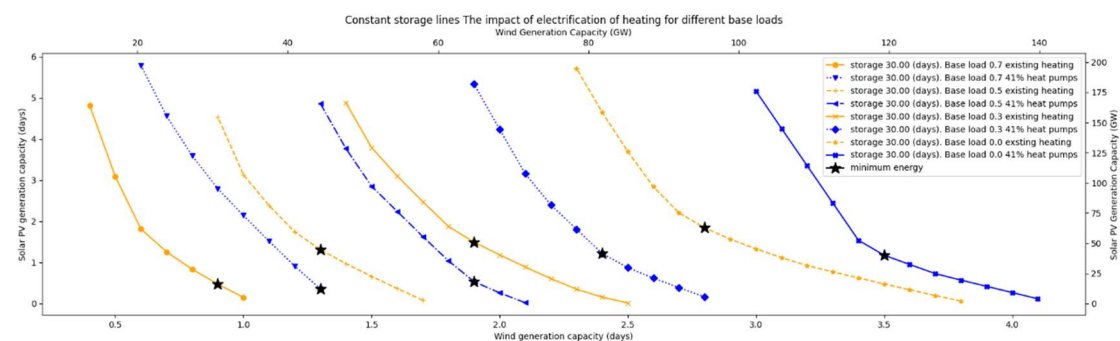


Figure 9-5 Lines of constant storage for different base load for existing heating and 41% heat pumps

Table (9-3) shows how different base load impacts storage requirements, cost and wind energy fraction. For the minimum cost configuration assuming hydrogen storage at today's cost, it shows the storage, cost and wind energy fraction for each base load. It can be seen that as the base load increases, the minimum storage requirement declines. However, the cost increases as the amount of base load capacity increases because the base load cost is using the cost of nuclear from table (5-3) which is about twice as

expensive as wind. Also, increases in hydrogen storage capacity only make a small difference to cost because most of the cost is due to charge, and discharge equipment (ie rate of charge and discharge, rather than capacity). As the baseload capacity increases, the wind energy fraction increases. This is because the storage also decreases, so more energy must be used when it is generated, and demand is greater in winter when there is more wind. The fact that baseload 0.0 and baseload 0.3 for heat pumps have the same wind energy fraction is showing that there is not really an optimum wind energy fraction in this case.

Table 9-3 How variation in base load affects storage, cost and wind energy fraction.

Baseload	Storage for the minimum cost configuration (days)		Cost £/kWh for hydrogen storage at todays costs.		Wind Energy Fraction for minimum cost configuration	
	Existing heating	heat pumps	Existing heating	heat pumps	Existing heating	heat pumps
0.0	80	79	0.073	0.070	70%	75%
0.3	64	77	0.082	0.080	75%	75%
0.5	58	69	0.088	0.086	78%	83%
0.7	45	56	0.094	0.093	83%	89%

Figure (9-6) shows the relationship between baseload and storage requirements for the minimum cost configuration in table (9-3). As baseload increases the required amount of storage for both the existing heating technology and for 41% heat pumps declines. In general, a 0.1 day increase in baseload capacity, reduces storage requirements by about 5 days.

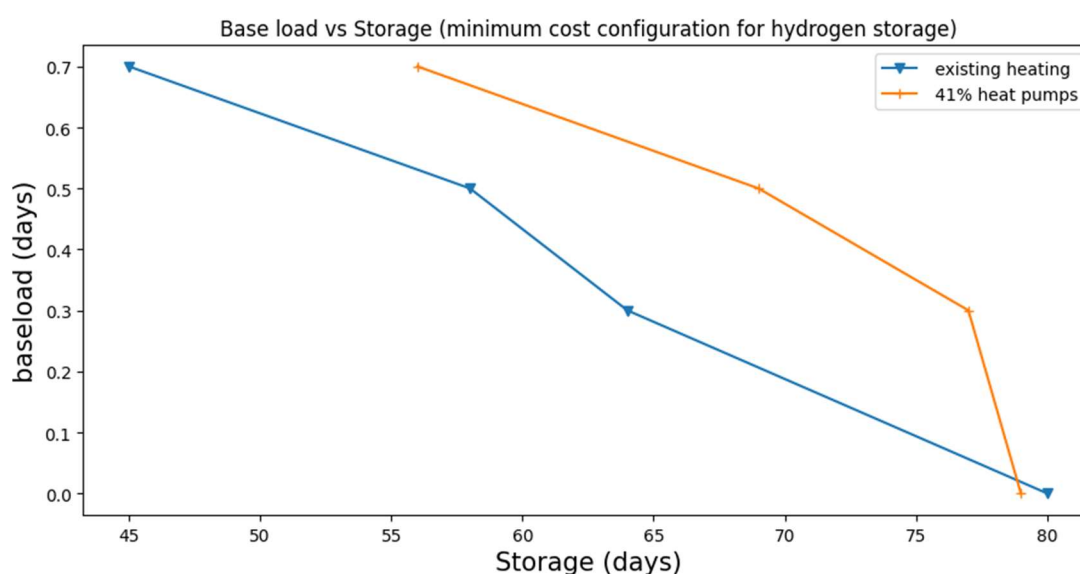


Figure 9-6 Relationship between base load and storage requirements for the configurations with the minimum cost of electricity at today's prices.

Figure (9-7) shows that as base load increases the wind energy fraction on the minimum energy point for the 30-day storage contour changes. However, for higher base loads there is no obvious optimal wind energy fraction as the lines are fairly flat. The existing heating technology always has a lower wind energy fraction than the 41% heat pumps case.

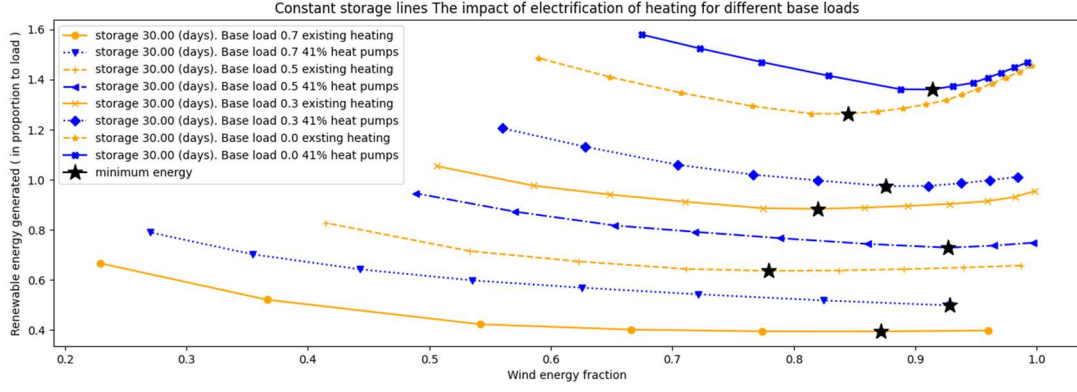


Figure 9-7 Wind energy fraction for 30 days storage and different base loads

The results of this section have shown that a lack of energy storage can be compensated for by increase in baseload, for both the existing heating technology and 41% heat pumps. The cost model used in this project which assumes the baseload to be nuclear with current costs, shows a similar increase in the cost of electricity for both the existing heating technology and for 41% heat pumps when using base load instead of storage.

9.4 Lost Energy

There are two reasons that energy generated may not be used to satisfy the load.

1. Energy is lost or wasted due to curtailment when more energy is generated than can be used or stored. The energy curtailed is calculated using equation (42) from 6.3.4. This occurs as a consequence of design choice in the power system to have additional generation capacity for periods of high demand or low generation due to weather.
2. The additional energy that must be generated due to the inefficiency of charging and discharging the energy store using equation (43). This occurs because of a design choice in the power system to store energy when it is generated for use in the future.

Excess energy (curtailed) was calculated using equation (42):

$$E_{excess} = C_b + E_{renewable} + E_{dispatchable} - E_{sl} - 1.0 \quad (42)$$

Where E_{excess} is the excess energy not required to service the load, C_b is the baseload generation capacity = 0.4 days, 1.0 is the demand, $E_{dispatchable}$ is the mean daily dispatchable energy generated and $E_{renewable}$ is the sum of the mean daily wind energy and mean daily solar energy generated. E_{sl} is the energy lost due to the round-trip efficiency of the store, and is given by equation (43)

$$E_{sl} = E_{charge} \left(\frac{1 - \eta_c}{\eta_c} \right) + E_{discharge} (1 - \eta_d) \quad (43)$$

Where E_{charge} is the mean daily energy added to the store, η_c is the charge efficiency, $E_{discharge}$ is the mean daily energy taken from the store and η_d is the discharge efficiency. Unless otherwise stated, $\eta_c = \eta_d = \sqrt{\eta}$ (round-trip efficiency).

Figure (9-8) shows the additional energy that must be generated to the efficiency of charge and discharge to the store. More additional energy is required at configurations of very high solar generation and low wind generation. This is because more solar

energy is generated in the summer, but more energy is used in the winter, and therefore more energy needs to be stored, and so there is more additional energy needed to be generated due to the storage inefficiency.

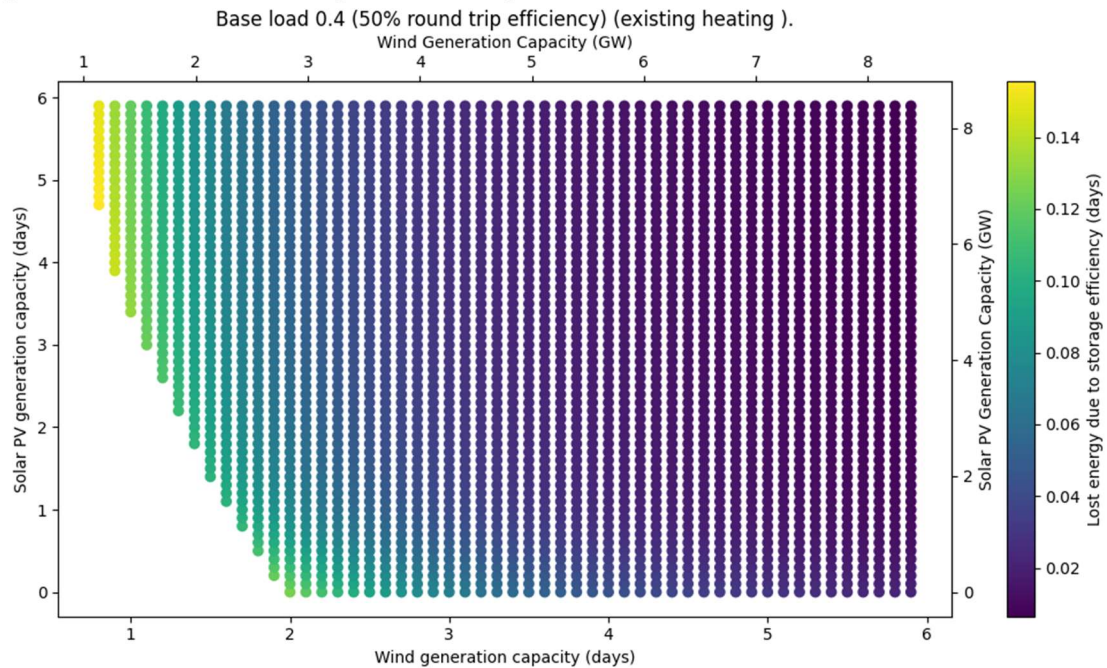


Figure 9-8 Additional energy needed due to the inefficiency of the energy storage for different wind and solar capacities.

Figure (9-9) shows the energy curtailed for different combinations of wind and solar generation capacity for the existing heating technology. It can be seen that more energy is curtailed at large generation capacities which will have low amounts of storage. With small installed capacity, less energy is curtailed. The amount of energy curtailed with increasing solar generation capacity is less because mean solar capacity factors are lower. It can also be seen that compared to figure (9-8) above that the energy lost due to curtailment far exceeds the additional energy that needs to be generated due to the inefficiency of the energy storage.

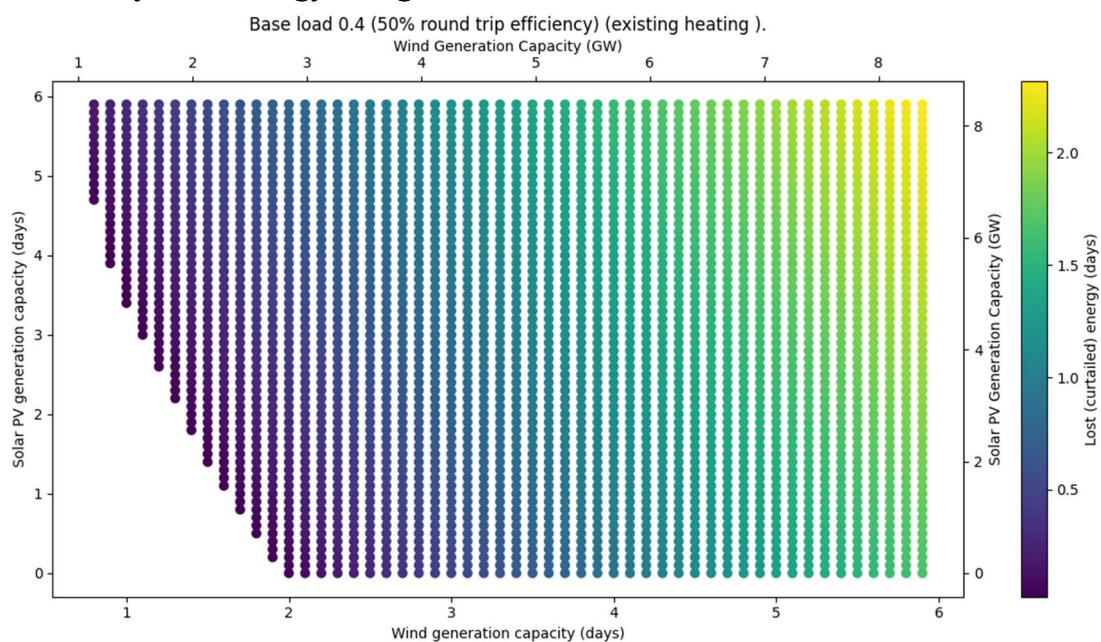


Figure 9-9 Energy curtailed for different wind and solar capacities.

Figure (9-10) shows the relationship between storage capacity and the energy lost through curtailment. This was generated using the minimum energy configurations from those that have storage of 10,20,30,40 and 50 days. It can be seen that as storage capacity increases, less energy is required to be generated and therefore less is curtailed.

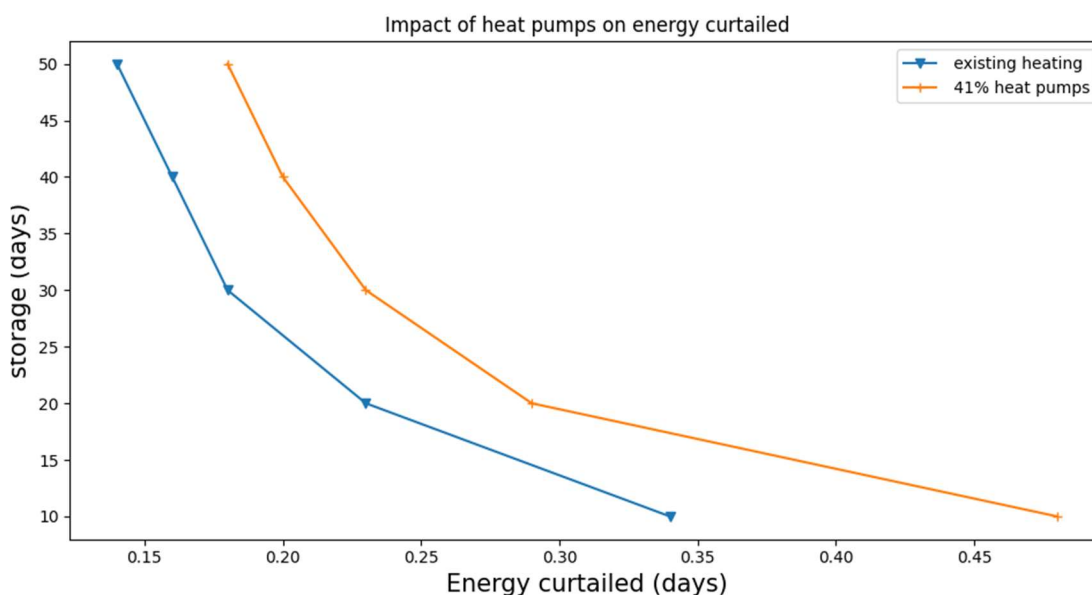


Figure 9-10 Variation in energy lost due to curtailment with storage capacity.

The energy lost due to curtailment exceeds the additional energy required to overcome the inefficiency of the energy store by an order of magnitude. This suggests that the efficiency of the storage might be less important than its capacity. If the capacity were greater, then this curtailed energy could be stored. If the charge efficiency were lower, there is still a lot of curtailed energy available to charge the store. However, lower discharge efficiency effectively means less energy is stored for the same capacity. Charge efficiency and discharge efficiency would need to be modelled separately to study this further.

9.5 How long the energy store stays full

The objective of this section is to investigate the state of charge of the store over time. Does the energy store spend most of the time full or is the store empty for long periods? If the store is empty for a long period, then this is of interest from an economic perspective because there is an underused, possibly expensive asset. If the store is full for a long time, then there are technical implications. For example, if part of the energy store were 10 pumped hydro storage lakes, and 9 of them were full for several years, is this technically feasible? would there be evaporation of water? If the storage were hydrogen, would it be better to use it for another purpose and then replenish it later?

Figure (9-11) below shows the store history for a configuration with wind capacity 1.7 and PV capacity 1.3 with the existing heating and wind capacity 2.0 and PV capacity 1.1 with 41% heat pumps chosen so that they have similar storage requirements (28.9 and 29.1 days respectively). It can be seen that there are long periods when the store is at a high state of charge, but others where it is almost empty.

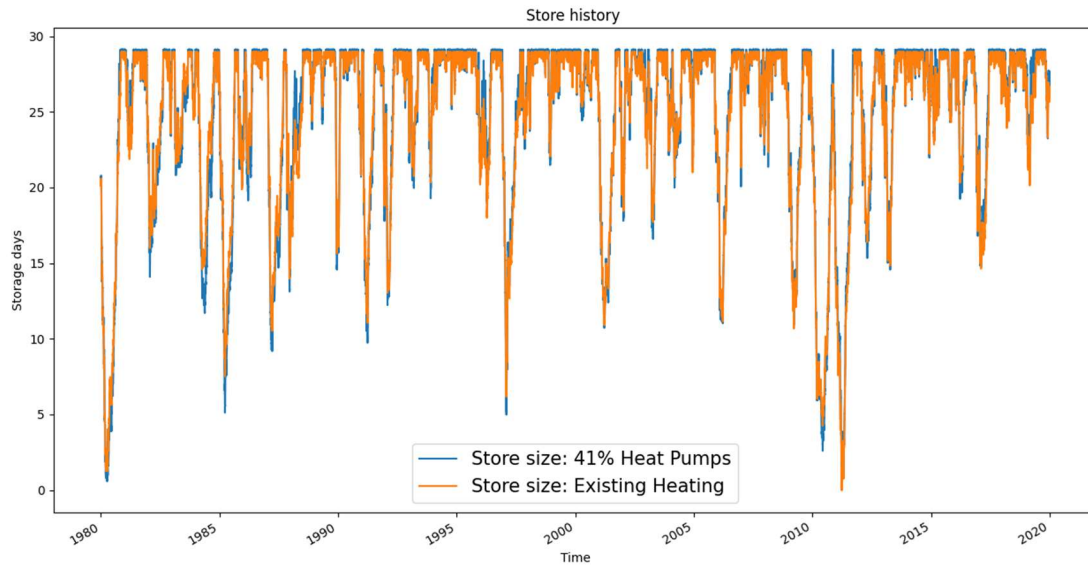


Figure 9-11 Example of the energy store state of charge over 40 years for configurations needing about 29 days storage capacity (wind 1.7, PV 1.3 existing heating), (wind 2.0, PV 1.1 41% heat pumps)

Figure (9-12) below shows the store history sorted by state of charge, rather than time, so it shows a load duration curve showing how many days the store was at a particular energy level (state of charge) for this same configuration. It stays at a high level most of the time for example above 25 days of storage for 250,000 hours which is 28 years out of the 40-year time period.

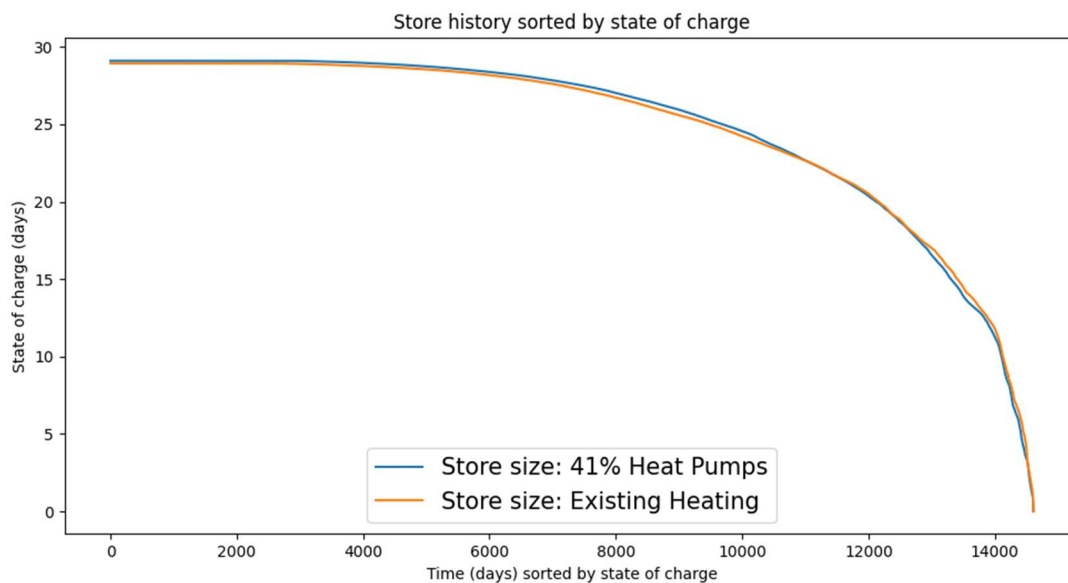


Figure 9-12 Load duration curve created by sorting the store history by the state of charge. Shows the number of hours that the store was at a particular state of charge for the same configurations as figure (7-18)

Figure (9-13) shows how long the energy needs to be stored for. It can be seen that for most of the time, the store is full.

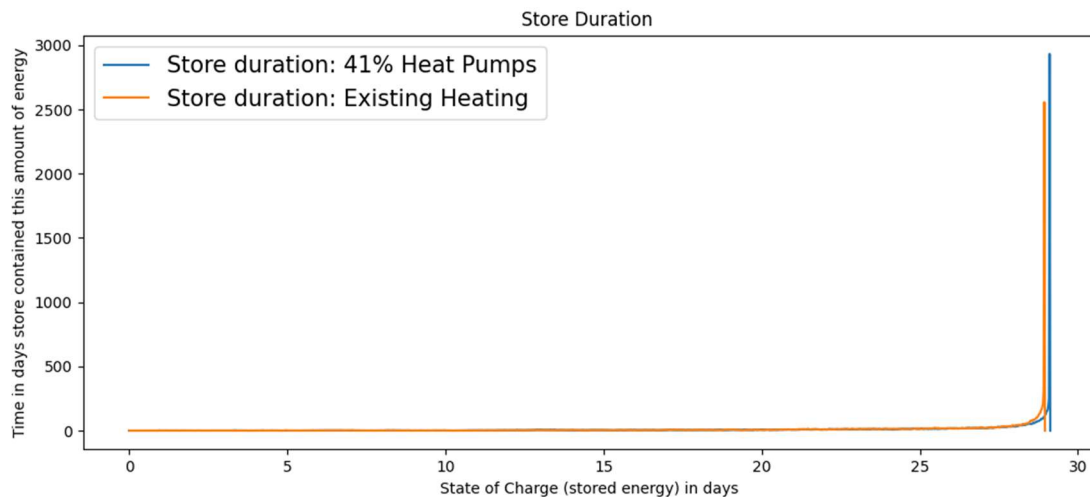


Figure 9-13 How long the energy store was at a particular state of charge for sample configurations with a storage capacity of 29 days for both the existing heating technology and with 41% of heating provided by heat pumps.

The energy store is full most of the time. The implications of this are:

- Energy loss through storage inefficiency may be less important because there is plenty of time to top it up. This is particularly true of charge efficiency. Discharge efficiency effectively means that less energy is stored for the same capacity.
- There could be loss through self-discharge if energy is stored for a long time.
- The storage medium must be capable of storing energy for long periods of multiple years.

The simplified model used here only has one energy store. The real power system will consist of a number of different storage technologies with different characteristics. As discussed in the background section, batteries are suitable for a period of a few hours, CAES and pumped storage are suitable for 6-10 hours, and power to gas such as hydrogen are suitable for long term storage. The implication of the energy store in the model being full most of the time, suggests that the real power system should contain more long-term storage such as hydrogen, than shorter duration storage technologies.

Limitations of the model being used are that it does not take into account the rate at which stored energy is lost (self-discharge) or consider the charge and discharge efficiencies separately. These should be considered in future research.

No other study has been found that quantifies how long energy needs to be stored for. Storage duration is discussed in [52] but it refers to how long it would take to discharge the energy store at its maximum discharge capacity.

9.6 Correlation between supply and demand

9.6.1 Background

The capacity of energy storage required in an energy system is related to the correlation between the demand and supply. In other words when the energy is needed compared to when the energy is generated. In a purely renewable power system or one including a baseload below the minimum demand, if the pattern of renewables generation matched the demand curve exactly then it would only be necessary to install enough

capacity to generate the energy to satisfy the demand and no storage would be required, or excess energy generated (curtailed). When there is a mismatch between the pattern of supply and the pattern of demand then this must be compensated for by either larger generation capacity or energy storage or a combination of the two. More storage is required for a purely solar PV system than wind because wind matches the demand curve better [52].

9.6.2 Methods

The correlation of the two electricity demand time series from chapter 4 with each of the various generation time series used in this thesis was calculated using Pearson's Correlation Coefficient R. The objective is to see if there is any relationship between the findings regarding wind energy fractions and correlation.

9.6.3 Results

The table (9-4) below shows how closely the normalised generation curves match the normalised demand curves for the existing heating, 41% heat pumps and all heat pumps. It includes Wind and PV generation time series from Fragaki et. al. (section 6.3) and those from Renewables Ninja (section 1.2.7 and 1.2.8). As well as the near-term wind generation from Renewables Ninja used in this study it also shows the current and future wind generation time series.

The Fragaki et. al. data is only available as a daily time series, hence hourly correlation is not shown in this table. Also, this project is more concerned with long-term storage, so the intra-day correlations are of less importance. However, the hourly wind time series are less correlated with the demand (eg 0.13 to 0.15), but the PV series are more correlated 0.23 for the existing heating.

Table 9-4 - Correlation of renewable generation and electricity demand

Generation	Correlation (R) of demand to generation 1984-2013					
	Existing heating		41% heat pumps		All heat pumps	
	Daily	Monthly	Daily	Monthly	Daily	Monthly
Wind Fragaki et, al.	0.19	0.56	0.16	0.53	0.13	0.50
PV Fragaki et. al.	-0.53	-0.78	-0.55	-0.80	-0.54	-0.77
PV Renewables Ninja	-0.64	-0.82	-0.67	-0.85	-0.65	-0.81
Wind Onshore Ninja near term	0.22	0.61	0.19	0.58	0.16	0.55
Wind Offshore Ninja near term	0.26	0.66	0.24	0.64	0.21	0.60
Wind combined Ninja near term	0.26	0.66	0.24	0.64	0.20	0.60
Wind Ninja future	0.25	0.66	0.23	0.64	0.20	0.61
Wind Ninja combined current	0.24	0.64	0.22	0.61	0.18	0.58

From this table we can see that with the addition of 41% heat pumps the demand curve would become less correlated with both wind and PV and so we would expect more storage to be needed based on the pattern as well as the increased generation.

The daily correlation of the Ninja near term offshore wind of $R=0.26$ to the demand curve is greater than that of onshore with $R=0.22$. A similar pattern is seen with the monthly correlation. For this reason it might be expected that less storage would be needed for offshore wind even when scaling to account for the lower capacity factor of onshore wind. This was indeed what was found in chapter 6.

The last 3 rows of the above table indicate that when near term future wind farms come online that the wind generation will become slightly more correlated ($R=0.26$ compared to $R=0.24$) with the demand curve, but then as the long-term future wind farms come online the correlation will decline ($R=0.25$). The monthly correlation of demand with wind generation is higher suggesting that being able to store energy over monthly periods might ease the mismatch between demand and generation.

A similar exercise was done to compare the 9-year wind generation time series created in section 7.4. This used the actual national grid wind farm generation for 2011-2019 factored by the quarterly increase in generation capacity [113]. This time series was found to have the same correlation values as the Wind combined Ninja time series. It is not added to the table above because since it is for a different (shorter) time period all the correlation values are different. In fact, although they show the same trend that offshore wind correlates better than onshore wind with the demand, using this shorter time period, the correlation coefficients R are all about 0.08 lower.

The renewable power generation time series is a combination of different capacities of the wind and PV time series. Using the Renewables Ninja combined near term wind and PV generation time series the correlation with demand was investigated for different wind energy fractions. Figure (9-14) shows how the correlation of the normalised demand time series with the generation time series varies for different wind energy fractions. It can be seen that the higher the proportion of wind energy the greater the correlation. With the addition of 41% heat pumps, the demand becomes less correlated with the generation, so that we might expect more energy storage to be required.

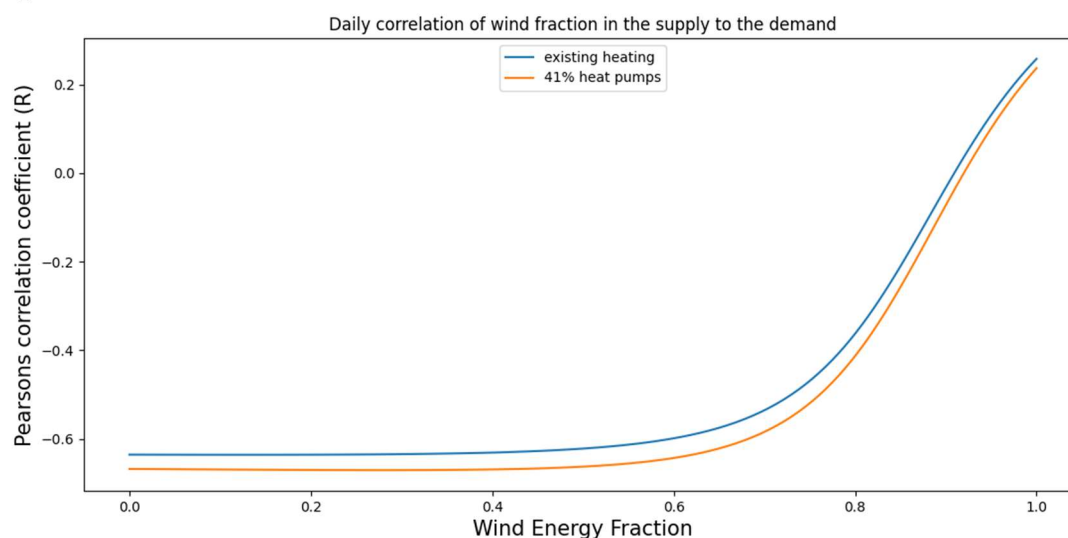


Figure 9-14 Correlation of normalised demand with power generation time series based on different wind energy fractions.

9.6.4 Summary and Conclusions

Wind correlates better with the demand than PV and the addition of heat pumps reduces the correlation with demand. The reduced correlation would be expected to lead to increased storage. This matches the findings in earlier chapters that the addition of heat pumps needs more storage.

9.7 Wind Energy Fraction

This section investigates methods of finding the wind energy fraction without using an energy balance model. It compares two alternative methods against the various wind energy fractions found using the energy model in this thesis. The different wind energy fractions and their assumptions are reviewed.

The section starts with a brief review of previous work determining the optimal wind/solar generation ratio. This is followed by two mathematical methods for estimating this ratio. The results section then compares all the optimal wind energy fractions from this thesis with these methods. The chapter finishes with some conclusions about the wind energy fraction.

9.7.1 Background

The optimal mix of wind and solar PV depends on the assumptions and objectives. It is usually expressed as a percentage of the combined wind and solar generation as in equation (33). Previous studies that use energy balance models including energy supply, demand and storage have found:

- That 55% wind is the ideal mix for Europe by using an energy model with the historic electricity demand [95] assuming pumped hydro storage.
- 84% wind is the optimal mix for the UK by finding the minimum cost configuration at today's prices [52] assuming a round trip efficiency of 70% for compressed air storage.
- The ideal mix for Europe is 70% wind assuming an excess generation of 50% and assuming the round trip efficiency of hydrogen storage is 36%.[96]

The energy balance models in this thesis have also found different mixes of wind and solar based on different assumptions, such as using a constant value of storage, excess generation, and optimum cost.

Some studies did not use an energy model at all. One study that had the objective of reducing the variability of generation [12] calculated the combination of wind and solar PV that minimized the standard deviation of simulated power generation time series. They found that on a seasonal basis the optimum for the UK was 67% wind and over a multidecadal time scale that the optimum was 46%. However, that study did not look at the seasonal variation of demand which tends to be larger in winter. Another study [95] that did consider demand, used the same method of minimising the standard deviation. However, they used the time series of demand net of wind and solar generation instead of just the generation time series. They found that 62% wind is the ideal mix for Europe. However, with energy storage, it is not just the extremes of net demand that are important but how long these extremes last. In this section another

possible method of identifying the optimal wind-solar mix without using an energy model is investigated.

The optimal mix of wind and solar generation is determined by the mismatch between electricity supply and demand. This mismatch is illustrated in figure (9-15) which shows a small part of the normalised demand net of renewable generation N_t from equation (28) from section 5.2

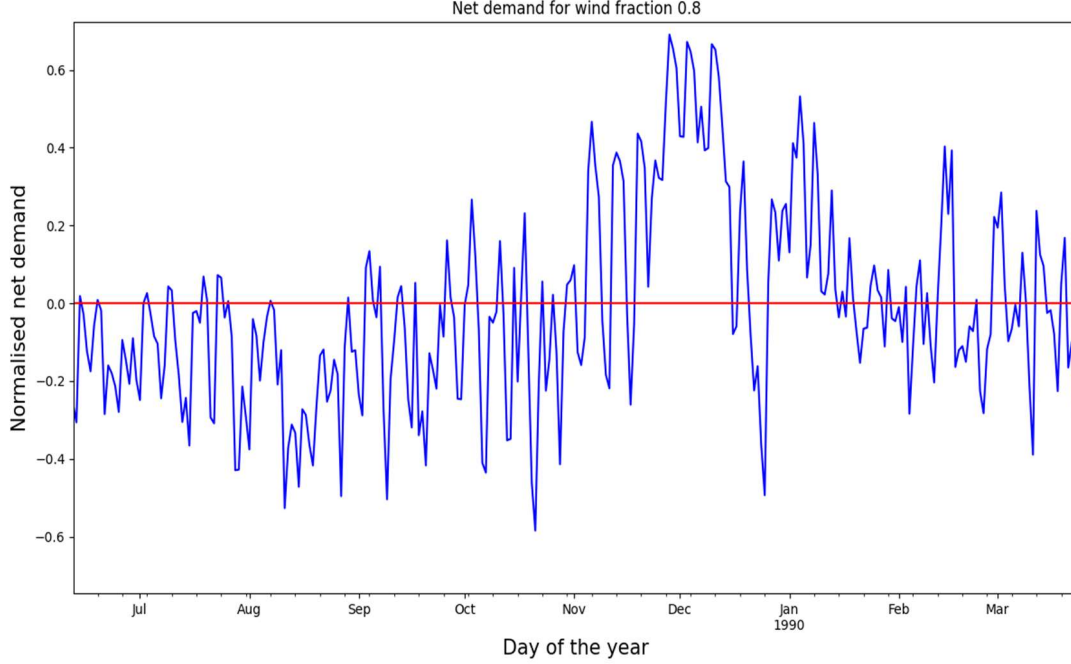


Figure 9-15 Normalised net demand with the existing heating technology, net of renewable generation with 80% wind and 20% solar PV

In this example the generation is made up of 20% Ninja PV and 80% Ninja wind. When the net demand (blue line) rises above zero (red line), energy needs to be taken from the energy store. For example, it can be seen that net demand stays positive in December 1990 for a period of about 1 month, indicating that the demand would be met from energy perhaps stored in August. This suggests energy needs to be stored for periods of at least months. The higher the net demand is, combined with the longer it stays above zero, determines how much energy needs to be stored and leads to the idea of using the area under the curve as an indicator of how much storage is required. This will be tested out in this chapter.

9.7.2 Methods

A set of different hourly net demand time series were created for different wind energy fractions using equation (44).

$$N_t = D_t - W_f W_t^{cf} + (W_f - 1) P_t^{cf} \quad (44)$$

Where N_t is the net demand time series, D_t is the 40 year electricity demand time series with the existing heating technology from 4.2.2, W_f is the wind energy fraction given by equation (33), W_t^{cf} is the time series of wind generation capacity factors from

Renewables Ninja combined (onshore and offshore) near term future (1.2.7) and P_t^{cf} is the time series of PV generation capacity factors from Renewables Ninja (1.2.8). D_t , W_t^{cf} and P_t^{cf} were all normalised to that their values ranged between 0 and 1. The wind energy fraction was varied $0 \leq W_f \leq 1$ in steps of 0.01 creating a set of different net demand time series. For each net demand time series, the following were calculated:

- The standard deviation of the net demand time series $\sigma = \sqrt{\sum \frac{(N_t - u)^2}{NT}}$ where N_t is the net demand time series from equation (44), u is the mean of N_t and NT is the number of values in N_t .
- The area between the blue curve and red zero line from figure (9-15). First each negative value in the time series was set to zero and then the trapezium method was used to calculate the area.

9.7.3 Results

Figure (9-16) shows the first of these methods of identifying the optimal wind fraction. This method used in previous work is to minimize the standard deviation of the normalised demand net of renewable generation. In figure (9-16) it is plotted against the wind energy fraction. The idea is that the minimum standard deviation indicates less extremes. Less extreme values in the net demand time series mean either lower additional generation or lower energy storage requirements. For the existing heating the minimum occurs at a wind energy fraction of 95% and for 41% heat pumps it occurs at 92%.

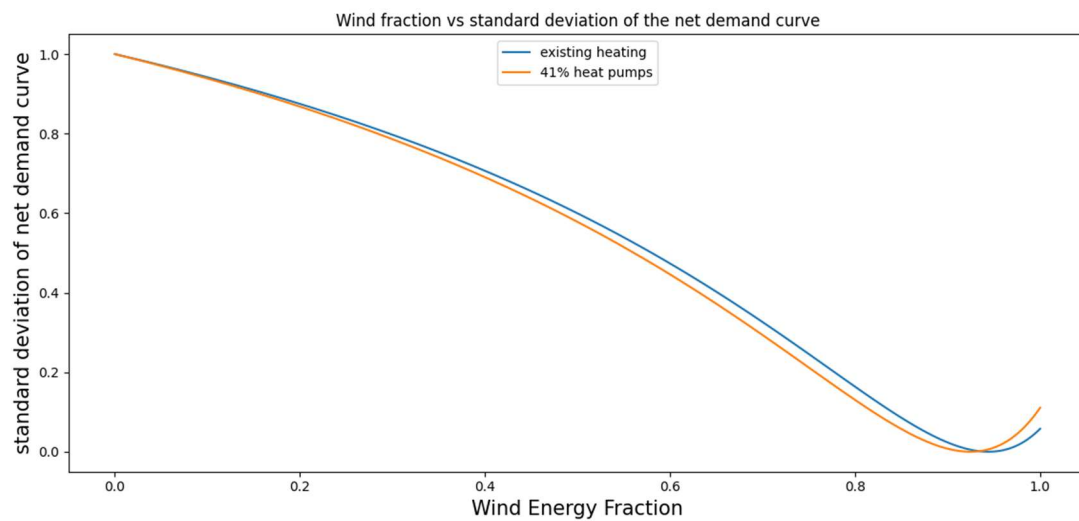


Figure 9-16 Optimum wind energy fraction from the standard deviation of the net demand time series

Figure (9-17) shows the area under the normalised demand net of renewable generation plotted against the wind energy fraction. The minimum area for the existing heating occurs at a wind fraction of 93% whereas for 41% heat pumps it occurs at 94%. It makes sense intuitively for more wind to be needed. Since wind is more correlated with the demand than PV, a generation mix containing more wind will correlate better with the demand, leading to lower energy storage.

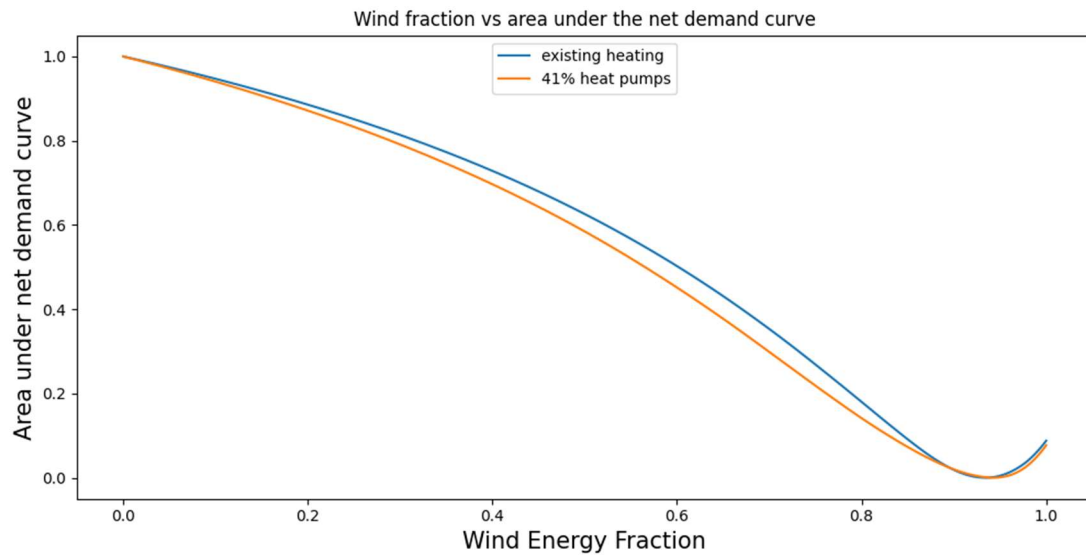


Figure 9-17 Using the area under the normalised net demand curve to estimate the ideal ratio of wind to solar PV energy generation.

Figure (9-18) shows wind energy fraction found using lines of constant storage minimum energy point plotted against that found using the area under the net demand curve. It can be seen that although they do not match, that these is a fairly linear relationship. This shows that this is useful method for identifying the wind energy fraction.

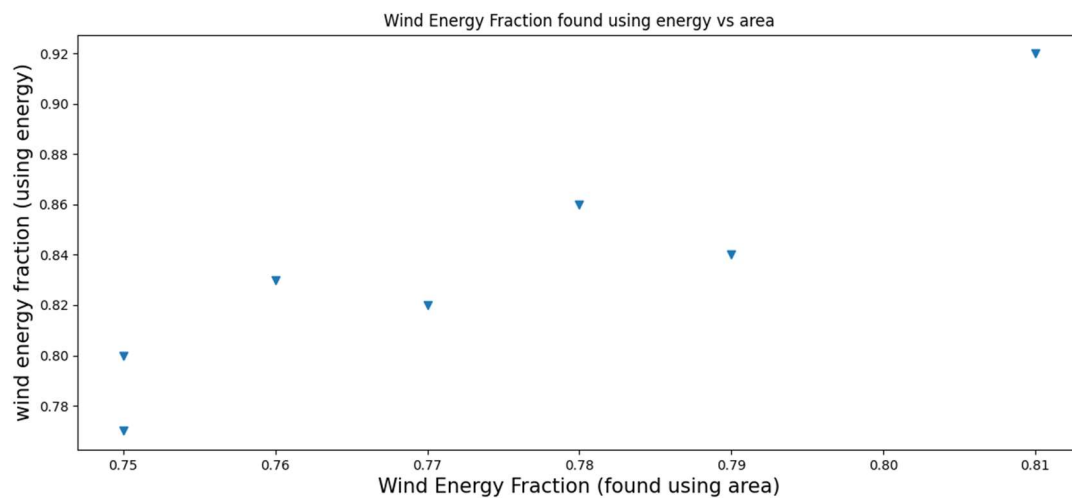


Figure 9-18 Wind energy fraction found using minimum energy compared to using area under the net demand curve for lines of constant storage

Table (9-5) compares these two mathematical methods of finding the wind energy fraction with the other methods used in this study. This illustrates the range of different wind energy fractions found in this thesis. These would not be expected to be the same because they are based on different assumptions. For example, the Fragaki 30 days storage has a large 90% fraction because of using onshore wind and large energy generation of 30% excess. The 50% excess is a lot of energy, which leads to lower storage, so that energy must be used closer to when it is needed. Since more energy is used in winter, when more wind energy is generated, this leads to a higher wind energy fraction. Increasing baseload has more impact in the summer because summer has lower energy requirements and therefore means less PV is needed. All these methods are based on different assumptions, but they consistently find that 41% heat pumps require a higher wind energy fraction.

Table 9-5 Different methods and assumptions of finding the optimal wind energy fraction produce a range of values. Those from this thesis have the section they occurred in shown in brackets.

Method	Thesis Section	Wind Energy Fraction	
		Existing Heating	41% Heat Pumps
Minimum standard deviation of the normalised demand net of renewable generation	9.7	95%	92%
Minimum area under the normalised demand net of renewable generation	9.7	93%	94%
30 days storage. minimum energy	6.3.3	83%	87%
This study 30 days storage, minimum cost	6.3.3	87%	91%
50% excess energy	6.3.4	96%	99%
Hydrogen Cost Optimal	6.3.5	88%	91%
CAES Cost Optimal	6.3.6	87%	92%
Baseload 0.0 min cost hydrogen	9.3	70%	75%
Baseload 0.3 min cost hydrogen	9.3	75%	75%
Baseload 0.5 min cost hydrogen	9.3	78%	83%
Baseload 0.7 min cost hydrogen	9.3	83%	89%

The method using the standard deviation calculates a high looking value for the wind energy fraction for the existing heating of 95%. However, the wind fraction of 92% for 41% heat pumps is lower which contradicts all the other results in the table. This could be because the addition of heat pumps to the demand increases its standard deviation and if the peaks in the wind generation do not match the demand peaks then the optimal wind fraction could be in less.

The new method of using the area under the net demand curve is consistent with the other methods in finding that 41% heat pumps need more wind. However, it is also slightly high compared to the other values. Therefore, the conclusion is that using the area under the curve is a better method of finding optimal wind energy fraction than using the standard deviation. Finding the area under the net demand curve requires much less computational power than running the full hourly model. It runs in seconds on an ordinary PC, compared to a few hours for the daily energy model or a few days for the hourly energy model. It provides a useful quick method of estimating the optimum wind energy fraction.

However, neither the standard deviation nor the area under the curve method take account of efficiency. An energy balance model will produce a more accurate result if it considers energy lost for efficiency of storage and the timing of when the periods of high demand occur relative to those of high generation and if the energy store can be refilled before the next such period. The methods using the standard deviation and the area under the curve are using normalised time series, which means that they are equivalent to a minimum over generation case.

9.7.4 Summary and Conclusions

As an alternative to using an energy model, a new mathematical method of finding the optimum wind fraction has been proposed. This is to minimize the area under the demand net of renewables. It has been shown to be more accurate than minimizing the standard deviation, a method proposed in previous work. It runs much faster than an energy model and has a approximately linear relationship with the optimum wind energy fraction found using constant lines of storage. The new method finds that heating electrification increases the wind energy fraction by 5% whereas other experiments in this thesis have shown the energy fraction increasing by between 4% and 6%. All configurations from table (9-5) show that the UK should have more than 70% wind and that the addition of electric heat pumps increases this fraction.

9.8 Summary and Conclusions

To simulate the migration away from today's system, the capacity of dispatchable generation was gradually reduced with a varying mix of wind and solar. In contrast to the system with only baseload, wind and solar, there is no clear optimal wind energy fraction. However, as dispatchable generation is reduced with today's amount of storage, more wind energy is needed. As the amount of dispatchable generation is reduced, modelling a migration towards renewable generation, it was found that energy storage is required after about 20% renewables with 50% excess generation.

Heating electrification does not change the relationship between energy curtailment and storage. The efficiency of the energy storage might be less important than its capacity, due to two factors: (i) the energy lost due to curtailment exceeds the additional energy required to overcome the inefficiency of the energy store by an order of magnitude (ii) the energy store is full most of the time. A full energy store implies curtailment, so a lower charge efficiency does not matter if there is plenty of excess energy. However, a low discharge efficiency effectively reduces storage capacity. The energy store must consist of technology storing energy for long periods of multiple years suggesting that there could be loss through self-discharge. It should also be noted that storage capacity tends to be determined by extreme events. Future research should consider charge and discharge efficiency separately.

A lack of energy storage can be compensated for by increase in baseload, for both the existing heating technology and 41% heat pumps. The cost model used in this project which assumes the baseload to be nuclear with current costs, shows a similar increase in the cost of electricity for both the existing heating technology and for 41% heat pumps. An increase in baseload increases the wind energy fraction for both the existing heating and 41% heat pumps.

10 Conclusions, contributions, and further work

The main research question in this thesis is: How the future decarbonization of heat and transport will impact the mix of solar, wind and storage in a power system with a high penetration of these technologies? To answer this question three 40-year UK electricity demand time series were created: for the existing technology, with 41% of heating provided by heat pumps, and with most transport as EVs. A novel method for incorporating heating electricity into the historic electricity demand was developed allowing the impact of heat pumps alone to be studied. The method accounts for long-term weather effects, whilst keeping socioeconomic and technological factors constant. These electricity demand time series were used in a high-level energy model to calculate the minimum energy storage required for a generation mix including wind, solar, base load and dispatchable power sources. It was found that heating electrification increases the proportion of wind energy required by between 3% and 5%. In contrast, a change to providing most transport by electric vehicles does not significantly change the optimum proportion of wind energy required. For an example configuration generating 80% excess energy above the load, 41% of heating provided by heat pumps requires 2 days more storage, whereas most transport provided by EVs requires 15 more days storage.

Before the main research question could be answered, four subsidiary questions were posed. The main conclusions for each are summarised below, followed by the main question. Then the conclusions from the additional case studies are summarised. The main contributions to knowledge are listed. This final chapter concludes with suggestions for further work.

10.1 Electricity demand incorporating changes to heating alone.

The first subsidiary research question was: how electricity demand including changes to heat pumps alone could be generated. This was answered by chapters 2-4.

Chapter 2 compared four methods of generating daily heat demand time series which has not been done before. The methods have been validated against national gas demand time series, including a regression to show that the unknown portion of the time series is not heating. The methods were also validated against heat pump measurements and gas smart meter data, data sources not previously used for this purpose. It was found that using previous days' temperatures to account for thermal inertia of buildings and population weighting all improved the results, but that using a finer weather grid did not bring significant improvements. The BDEW method based on the when2heat dataset performed best and was therefore chosen. This is an important result because this method has already been used to provide the UK heat demand input for several previous studies by other authors.

Chapter 3 used the daily heat demand series from the best method identified in chapter 2 to generate 40-year hourly electricity demand time series for both the existing heating technology of 2018 and future technology with electric heat pumps. UK COP curves were used, and an hourly profile derived from UK heat pump trial data instead of one derived from gas boilers as had been used in previous work. Heat demand was

converted to electricity demand based on assumptions about current and future proportions of heat pumps and hybrid heat pumps from UK National Grid Future Energy Scenarios. Actual measurements from a UK heat pump trial show higher electricity demand than that predicted by the model. However, there is a large variability in heat pump trial COP making comparisons difficult.

Chapter 4 used the two heating electricity time series created in chapter 3 to generate two 40-year UK electricity demand time series enabling the impact of heating electrification to be studied independently of other factors. Previous work has kept socioeconomic and technological factors constant either by using linear regression to replace the electricity for the heating sector in one year's historic electricity demand based on multiple years weather or has simulated all sectors. In contrast the method used here replaces the electricity for the heating sector with a heating electricity time series from chapter 3 based on detailed calculations for current or future heating. The new method can generate time series for recent years more accurately than those used in previous work. Analysis of the historic electricity demand justifies the assumption that removing the heating electricity removes its weather dependence. These generated time series show that 41% of heating provided by electric heat pumps would double monthly demand for electricity leading to an increase in about 30TWh for each winter month. Year to year variability of electricity demand due to weather will increase by 37%. The research also revealed that the sensitivity of generated peak electricity demand to the hourly profiles and heat demand methods used in modelling leads to uncertainties in the estimations of peak electricity demand which vary over a range of 25 GW. This is quite significant compared to estimates of future peak demand of between 40 and 100 GW reported in research. Such inaccuracies have not been quantified in previous research.

10.2 Finding the minimum energy storage

The subsidiary research question: how should the required energy storage be found? was answered in chapter 5. A simplified power system model including 10 improvements over previous UK studies was developed. This included a new algorithm to find the minimum required energy storage for a simplified power system model. The model includes a specified amount of baseload and dispatchable generation combined with different proportions of simulated wind and solar power generation from 40-years' historic weather. The algorithm for finding the storage was validated against a model used by a previous study and found to match apart from small differences which can be explained by the differences between the two models. The model accurately predicts the amount of storage used by today's energy system. The model has been used to show the pattern of energy storage requirements for a range of different wind and solar generation capacities for a system with a base load capacity of 0.4 days.

Chapter 7 investigated the sensitivity of the model to different inputs. It was shown that whilst daily time series are adequate for estimating the required storage, that hourly time series are needed for estimating wind energy fraction and system cost. Experiments suggest that for large amounts of storage, using a few years' data including a cold spell is adequate and that it does not matter which decade of data is used. However, for small capacities of storage, these choices in the data make a much larger difference to the results. A sensitivity analysis on the impact of the different model inputs from two previous studies found that the most significant difference was caused

by using different wind generation data. Using a comparison between onshore and offshore wind as an example, it was also found that as well as the higher capacity factor from offshore wind, that the pattern of wind generation modelled in different ways can have a large impact on the amount of storage required. Although previous work has considered how different siting of wind turbines might result in higher capacity factors, no previous study has been found that notes the impact that a different *pattern* of generation can have on storage requirements. In other words, the impact of when the energy is *generated* compared to when it is *needed*. However, the significance of this effect depends on the particular configuration being studied. For example, a power system with 105 GW wind generation capacity based on the pattern of onshore wind requires 7 TWh more storage than one based on the offshore wind pattern. But with a wind capacity of 245 GW, it requires 1 TWh less storage. Energy modellers need to be wary of this possibility because it may mean that their models are less accurate and not comparable with models using different wind generation data.

Chapter 7 also used the new model from this thesis to update the results of two previous UK studies. Whilst Fragaki et. al found that 30% more energy generated for 30 days pumped hydro storage could power the UK for 30 years, here it was found that only 15% more energy is needed. This difference is mainly attributed to the different wind generation data used. Whilst Cardenas et. al. found that the cost optimal configuration for CAES at today's prices generated 15% excess energy and required the 43 TWh storage, using the methods from this project found 11 TWh of storage with 21% excess energy generated. The wind energy fraction found here of 84% was the same as that found by Cardenas. Although they also used different wind generation time series, it does not fully explain the difference and further work is needed.

10.3 Assessing the results

The subsidiary research question: How can the results be assessed was discussed in chapter 6. Chapter 6 used the electricity demand time series generated in chapter 4 to investigate the impact of heating electrification alone on the UK power system model developed in chapter 5. The 40-year electricity demand with the existing heating technology was compared to that with 41% heat pumps. There is a wide range of different combinations of wind generation, solar generation and energy storage capacities that can supply both these alternative UK electricity demands. Two quantities were used to assess the impact of heating electrification: energy storage capacity and wind energy fraction. The configurations to compare were identified using configurations with the same storage, the same excess energy, or minimum cost. The wind energy fractions between 83% and 96% for these different comparison configurations, show a similar variation to those of the 7 different plans from other studies discussed in the background section. The minimum energy generation configurations for constant storage are close to but not the same as the minimum cost configurations.

10.4 The impact of the electrification of heat

The heating part of the main research question: how does electrification of heating impact shares of wind, solar and storage? was also answered in chapter 6. It was found that heating electrification requires a higher wind energy fraction for the same amount of storage, for example an increase by 4% for 25 TWh storage. For a baseload of 13.6

GW and hydrogen storage, the lowest costs configuration of the model representing today's demand is for a wind capacity of 48 GW, PV capacity of 58 GW and 39 TWh of storage. With heating electrification this is wind 54 GW, PV 68 GW and storage 47 TWh or 58 days. For comparison the UK currently has 9 days of gas storage. For CAES or hydrogen storage, 41% of heating provided by heat pumps increases wind energy fraction by 3% and storage by 11 TWh. Conversely, with a fixed wind energy fraction, for example the configuration that generates 50% excess energy, 41% heat pumps requires 5 days more storage. To look at it another way, increased wind capacity reduces storage required more than increased PV. This is logical because more heating energy is required in the winter when there is also more wind and less PV energy available. For both the existing heating technology and 41% heat pumps, the amount of storage required increases if less energy is generated and the wind energy fraction decreases. For lower amounts of storage, the difference in wind energy fractions between the existing heating technology and 41% heat pumps is greater.

With 41% heat pumps, if the PV capacity is zero, then viable configurations include 78 GW wind with 38.5 TWh of storage and 190 GW wind with 5 TWh of storage. The minimum cost configuration for hydrogen storage is the former. For zero wind, 340 GW PV capacity requires 104 TWh of storage with the existing heating and 130 TWh after heating electrification. Whereas 2.7 TW of PV generation capacity requires 1.6 TWh of storage with the existing heating and 2.9 TWh with heating electrification. So, if PV and storage were sufficiently cheap, a solution with PV only and a large amount of storage would be possible. However, the optimal solutions are a combination of wind and PV.

Chapter 8 updated the energy storage model to enable a comparison between supplying heating with electric heat pumps and hydrogen boilers to be made. It was assumed that if the energy storage medium is hydrogen, then the hydrogen can also be used to supply heating using hydrogen boilers. It was found that for hydrogen boilers there is no obvious optimum wind energy fraction. If the electricity to create green hydrogen is included, then heat pumps use about 10 times less electricity than hydrogen boilers and have an electricity cost less than 20%. However, this model does not take account of the cost of upgrading boilers and the gas network to use hydrogen and installing heat pumps for all heating to be provided by heat pumps. No previous work including hydrogen boilers under long-term weather variation has been found. However, a previous study of a 3-year period found that architectures based on district heating and electric heat pumps need about four times less electricity per unit of heat and have a whole system cost 33% lower than those providing 70% of heating using hydrogen boilers.

10.5 Electric vehicle time series

Chapter 8 also answered the subsidiary research question: how should an electricity demand time series incorporating the impact of EVs alone be generated? Weather dependent EV electricity demand time series were added into an electricity demand with the heating technology of 2018. This enabled the storage model from chapter 5 to be used to study the impact of transport electrification alone. The model has shown that electrification of transport increases the annual electricity demand from 371 TWh to 489 TWh. The seasonal impact is less significant for that of heating electrification: with electricity demand varying over a range of 10 TWh between years without EVs and 14

TWh with EV's included. Previous work including EVs into generated electricity demand time series does not take the weather into account. The power system configuration with the minimum cost for EVs occurs with a 72% wind as opposed to 88% without EVs and uses 15 fewer days (12 TWh) of storage. This contrasts with heating where the proportion of wind increases. This could be because most of the cost of hydrogen storage is due to charging and discharging. Heat pumps have a big impact on peak demand and so could lead to high charge rates, whereas EVs are being modelled as charging partly overnight. The minimum energy point on the 30 days' storage contour also occurs at higher proportion of PV with electric vehicles. This is likely to be due to heat pumps requiring more energy in the winter, but EV charging is spread more evenly across the year. No other studies have been found that look at the impact of electric vehicles on the proportions of wind and solar.

10.6 Changes to power generation

Chapter 9 included several case studies using the model. It was found that:

- Energy lost due to curtailment exceeds the additional energy required to overcome the inefficiency of the energy store by an order of magnitude. This excess energy could compensate for losses due to charging the energy store and losses due to self-discharge. This suggests that the charge efficiency of the energy storage is less important than its discharge efficiency. The energy store is full most of the time, suggesting its storage capacity tends to be determined by extreme events.
- There is no clear optimal wind energy fraction with today's generation mix. Nevertheless, as the capacity of dispatchable generation is reduced, modelling a higher proportional of renewable generation with today's amount of storage, more wind energy is needed. Energy storage is required after about 20% renewables with 50% excess generation.
- For both the existing heating technology and 41% heat pumps, a lack of energy storage can be compensated for by an increase in baseload. Both heating technologies show a similar increase in the cost of electricity for increasing proportion of base load assuming nuclear power at today's prices.
- Wind generation correlates better with electricity demand than PV generation, so it would be expected that more wind generation would be needed. The addition of heat pumps reduces the correlation of electricity demand with both wind generation and PV generation and consequently more storage is needed. Increased wind capacity reduces storage required more than increased PV for both the existing heating technology and 41% heat pumps.
- A new method of finding the optimum wind energy fraction by minimizing the area under the demand net of renewables was proposed and shown to be more accurate than minimizing the variance, a method used in earlier work. The wind energy fraction found by this new method and the other three comparison methods used in this thesis, with different assumptions about base load and storage technology all show a 4% increase due to heat pumps.

10.7 Original Contributions to Knowledge

The original contributions to knowledge from this thesis are listed below:

- The heat demand method used by the when2heat dataset was found to be the best from four heat demand methods tested. This is a useful result as this method has already been used for several studies.
- The heat demand methods were validated against measurements from heat pump trials and smart meters, data not previously used for this purpose.
- The novel method of incorporating heating electricity into the historic demand was developed allowing the study of the impact of heat pumps alone.
- The hourly profile derived from measured heat pump data rather than gas boilers was used.
- The finding that peak demand is very sensitive to the hourly profile or heat demand method used.
- The seasonal and interannual impact of heat pumps were quantified, rather than just the peak demand as is usual in most studies.
- The finding that heating is the only significant weather dependence of the UK electricity demand.
- The new iterative algorithm to find the minimum required storage, and improved modelling inputs over previous studies.
- The impact of the electrification of heat and transport on wind energy fraction and storage
- The methodology to assess the impact of changes to demand from the perspectives of energy, cost and storage.
- The sensitivity analysis of different modelling inputs used by this, and two previous studies found that different wind generation time series had the most significant impact. Different wind generation time series can have a significant impact on storage requirements. This could apply to actual wind turbine locations.
- The updates to the findings of two previous studies using the new methods.
- The study of the impact of hydrogen boilers on wind energy fraction.
- Showing that area under the net demand curve is a useful alternative way of finding optimum wind energy fraction.
- The finding that energy lost due to curtailment exceeds storage losses by an order of magnitude.
- That storage becomes necessary after about 20% renewables.
- That the energy store is full most of the time

10.8 Further Work

This section lists possible future work that could be undertaken in this project.

10.8.1 Heating

More realistic heat pump measurements are required in the future to be able to properly validate time series of heating electricity from electric heat pumps.

10.8.2 Storage

The energy storage algorithm defined in chapter 5 could be improved to find the optimal initial state of charge, rather than specifying it.

One limitation of the energy storage model is that although it finds the minimum storage capacity it does not try and minimize storage power. Since the cost of some long-term energy storage technology, for example hydrogen is much more dependent on the cost of the charging and discharge equipment, than the actual capacity, modelling power curtailment might give cheaper solutions. The energy store could be charged up more slowly. This could also be the case for transmission line constraints.

Based on previous work, this study has assumed that much more long-term storage is required than short-term. However, the model could be improved to consider two types of storage in a merit order: one short-term with high cost and high throughput, one long-term with lower cost and lower throughput. This might enable the optimal proportion of long- and short-term storage to be established.

Rather than choosing to base the cost model on today's costs for a particular technology, a more technology agnostic approach could be taken considering the relative costs of wind, solar, energy storage, charge, and discharge. This could give an indication of the relationships between the costs of different technologies might influence the optimal configurations. The costs of geothermal and tidal power could be used rather than nuclear. It would be interesting to find out if there are many configurations close to the cost optimal one, and to provide a range of wind energy fractions.

Some previous studies have found that storage efficiency is important. However, others say that cost is the most important factor. A new model combining relative costs, storage power curtailment and efficiency could establish how important round-trip efficiency is, considering the findings here that the energy lost due to efficiency is an order of magnitude lower than that lost due to curtailment.

Rather than finding the minimum cost configuration, another method of looking at the optimum wind energy fraction would be to find the configuration with the minimum CO₂ emissions. This could use an estimate of the current lifecycle emissions of wind, solar and nuclear.

Another improvement that could be made to the model is to consider self-discharge. Thermal storage could also be included in the model.

This work makes the implicit assumption that the weather of the past is a guide to the weather of the future. The methods used in this study could be used with climate projections.

The model used in this study treats the energy system as a single node. It could be expanded to use different supply and demand time series for different parts of the country and include transmission constraints in the model.

10.8.3 Reproduction of Cardenas

An experiment was done to try to reproduce the Cardenas model as closely as possible using the methods described in chapter 5. It is recorded in the future work section because the result did not agree with the model used in this thesis, and further work is required to explain it. Table (10-1) summarises the input parameters.

First the Cardenas et. al study was repeated as closely as possible without any assistance from the authors. The same solar PV generation data from Renewables Ninja was used. The wind generation data was derived from national grid figures in the same way. The actual wind generation data from Elexon [114] was added to the embedded half hourly wind generation from National Grid [83] and converted to capacity factors by dividing by the quarterly capacity from government figures [104]. It was then converted to hourly by aggregating. The power generation data for the years 2011-2019 was created in the same way as Cardenas did. The historic electricity demand for 2011 – 2019 taken from [83], was scaled by multiplying each year so that it had 335 TWh annual demand. The cost model from Cardenas was copied exactly. The algorithm from Cardenas to calculate the minimum storage was not reproduced here due to the uncertainty of being able to replicate the complex algorithm without access to the computer code. Instead, the algorithm from this study was used.

Table 10-1 Experiment to reproduce the results of Cardenas (see 5.3.1 for terminology)

Experiment Objective: Reproduce results of Cardenas et. al. as closely as possible. Baseload: $C_b = 0.0$ Dispatchable: $C_v = 0.0$ Wind $0.0 \leq C_w \leq 5.9$ Solar $0.0 \leq C_p \leq 5.9$							
Experiment	Frequency	η	Demand	Storage	Wind	PV	Years
1	Hourly	70%	Historic Mult	Iterative	NGrid	Ninja	2011-2019

Figure (10-1) shows the results of this experiment. The amount of energy storage required is plotted against the wind energy fraction for lines of constant energy generation. Figure (10-2) shows a copy of Fig. 17 from Cardenas et. al which shows the same thing. The pattern of the lines is similar to Cardenas et. al. with the minimum storage occurring at the same wind energy fraction, but some of the actual storage values are different. For the energy 1.10 line (10% over generation) the minimum is 65 days storage which at 60 TWh matches what Cardenas found. The 1.15 energy line (15% over generation) has a minimum of about a 40 days storage which translates to 37 TWh which is not far off the 43 TWh of their cost optimal solution. However, for the 1.25 energy line (25% over generation) Cardenas get just under 40 TWh whereas here 5 TWh was found sufficient.

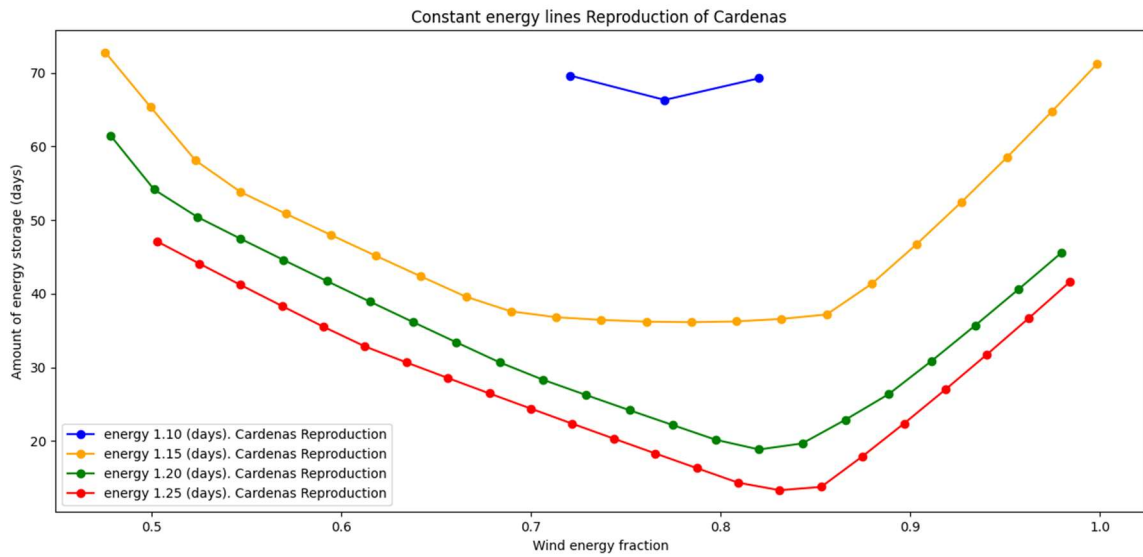


Figure 10-1 Reproduction of Figure 17 From Cardenas et. al.

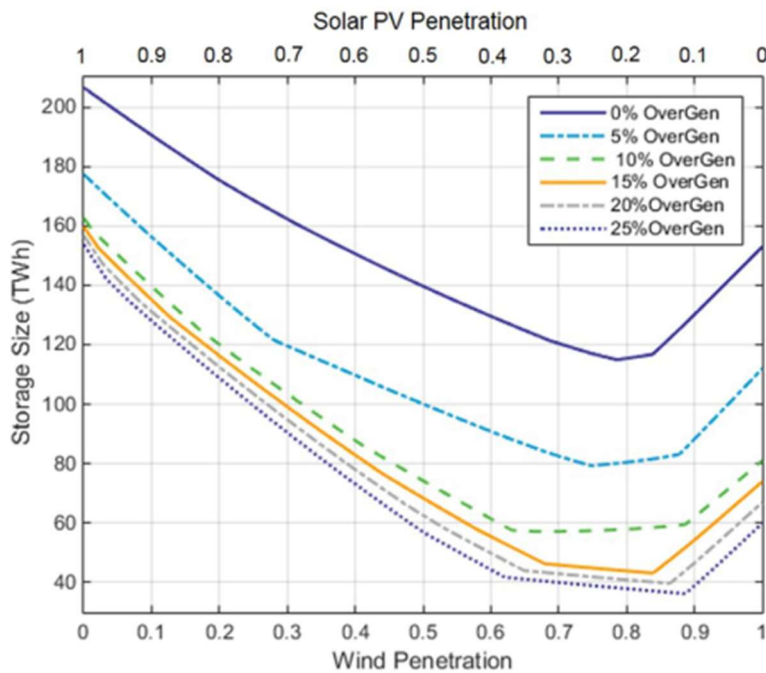


Fig. 17. Effect of over-generation on the energy storage capacity required for a renewable penetration of 100%.

Figure 10-2 Figure 17 from Cardenas et. al. by permission from Elsevier: Order no 5522081314340.

Table (10-2) summarises these findings. It seems that the more excess energy is generated, the more the findings of Cardenas diverge from that found in this thesis. The amount of energy storage found by the model in this thesis compares well to that found by Fragaki et. al. Also it seems strange that as the amount of over generation in figure (10-2) increases that the required storage does not decrease by more. It would be expected that generating more energy would eventually lead to needing no storage at all. It therefore seems possible that the Cardenas model is not finding the most optimal solutions for higher energy generation.

Table 10-2 Comparison of storage required in this thesis to the findings of Cardenas et. al.

Energy generated	This thesis	Cardenas et. al.
1.10	60 TWh	60 TWh
1.15	37 TWh	43 TWh
1.25	5 TWh	40 TWh

Other possible factors which could account for the difference in the results found here are:

- The electricity generation data used here is taken from [83] rather than directly from Elexon and National Grid. However, when plotted, it appears that the difference is small.
- The wind generation data may have been scaled in a slightly different way.
- The energy store is assumed to start 70% full in this model and it is not known how full it was in the Cardenas model. However, experimenting with starting the store between 50% and 90% full at the start did not make any difference to the storage requirements. Having the store start 30% full increased the storage requirement to 43 days, and 20% full increased it to 65 days.
- Cardenas et. al. use a more complicated procedure to find the minimum storage which involves modifying the net demand time series to account for the energy lost due to storage round trip efficiency in one go, rather than splitting it up into charge and discharge. The model used here simply applies an equal charge and discharge efficiency calculated as the square root of the round-trip efficiency when adding or removing energy from the store. It is noticeable that the Cardenas result has the same charge rate, but a lower discharge rate. Here the discharge rate has been calculated based on the energy removed from the store, not the energy supplied to the load which is lower due to efficiency losses.

In summary, although the amount of storage found here for an excess energy generation of 15% above the load matched that found by Cardenas, it diverged more from the result found by the model used here the more the excess energy generation. Yet section 5.4.2 showed that the model used here gives almost the same energy storage requirement as the Fragaki study. It seems more likely therefore that the Cardenas model is not finding the most optimal solutions for higher energy generation. Further research is required to confirm this.

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Appendix A Developed Software

In the course of this work, many python programs were developed. The three main programs are briefly described here:

- Heat and heating electricity time series generation
- Modelling of net demand, generation, and storage requirements
- Comparison of output from storage modelling and plotting.

Appendix A.1 Heat and heating electricity time series generation

The python program used for generating heat and electricity demand time series is available at <https://github.com/malcolmpeacock/heat>

The software generating the heating electricity demand time series can use any historic year's weather available from the ERA 5 reanalysis on two different grid resolutions. It can also read the adverse weather scenarios files from the UK met office. It can generate heat demand using four different methods, using a specified number of days previous temperature. The hourly profile and the proportions of different types of heating are a user supplied input. It can generate hourly heat demand, COP or heating electricity demand time series for any European country provided an annual heat demand is supplied as in input. The input parameters are summarised in table (11-1).

Parameter	Description
ref	Reference year
weather	Weather year
version VERSION	Version - subdirectory to store output in, defaults to year.
method METHOD	Heat demand calculation method: B BDEW, W :Watson, S : HDD 15.5, H : HDD 12.8
grid GRID	Grid I=0.75,0.75; 5=0.25,0.25
profile PROFILE	Hourly profile
adverse ADVERSE	UK Met office adverse weather scenario file in the adverse sub director within the weather directory
country COUNTRY	Country one of: AT BE BG CZ DE FR GB UK NI HR HU IE LU NL PL RO SI SK
nopop	No weighting by population
plot	Show diagnostic plots
climate	Account for climate change
electric	Generate an electricity time series
interim	Use ERA-Interim instead of ERA5
tdays TEMP_DAYS	Number of previous days temperature to use (1 to just use current day).
eta EFFICIENCY	Factor to multiple by annual demand by to take account of efficiency.
ceta CETA	Factor to multiple COP demand by to take account of real World conditions

Figure 11-1 Parameters for the program to generate heat and electricity demand time series

The software implementing the storage model can already be used to read in different sources of wind and solar power generation data, including future adverse weather scenarios from the Met Office. It has 3 different algorithms for finding the minimum storage. It can read electricity demand from two different sources and scale it in three different ways. The program writes out a file containing various parameters for each combination of wind and solar generation, including the amount of storage required and energy generated. The input parameters are summarised in table (11-2)

start START	Start Year
end END	End Year
reference REFERENCE	Reference Year
adverse ADVERSE	Use specified Adverse scenario file of the form a5s1 where a=warming, 5=return period, s=severity or d=duration, 1=event. The possible warmings are: a=12-3, b=12-4, c=4
scenario	• P All Heat Pumps • F FES Net Zero Hybrid Heat Pumps • G 41 percent Heat Pumps • H Half Heat Pumps • R Existing heating provided by Heat Pumps • B All Hydrogen Boilers • N No heating • E Existing Heating based on weather
dir DIR	Output directory
plot	Show diagnostic plots
cplot	Show climate related plots
dmethod	Method of creating a multiyear demand series: • Add: add a varying amount to each year as per Fragaki et. al. • Multiply: multiply by a varying amount as per Cardenas et. al. • Baseline: add the heating electricity to baseline demand.
hourly	Use hourly time series
climate	Use climate change adjusted time series
base	Use range of baseload shares
Ev	Include Electric Vehicles
genh	Assume hydrogen made from electricity and stored in the same store
Normalise	Factor to normalise by (ie converting to days): • annual: mean annual demand. • peak: the peak demand

	• scale: use the value passed in
scale SCALE	How to scale: • average (energy over the period) • reference (by the reference year) • or a value passed in.
storage STORAGE	Storage model: • Kf Fragaki et. al • New iteratively find the wind and solar for each value of storage • All iteratively find the storage for each combination of wind and solar
constraints CONSTRAINTS	Constraints on new storage model: new or old
eta ETA	Round Trip Efficiency.
etad ETAD	Discharge Efficiency. If this is specified nonzero, then eta is the charge efficiency
npv NPV	Number of points in pv grid
nwind NWIND	Number of points in wind grid.
baseload BASELOAD	Base load capacity.
step STEP	Step size. Between different wind and solar capacities.
cfpv CFPV	PV capacity factor to scale to, default is to leave unchanged
cfwind CFWIND	Wind capacity factor to scale to, default is to leave unchanged
shore SHORE	Wind time series to use: • On Use only onshore wind • Off only offshore, • all all
ninja	Which ninja to use: near, current, future
kfpv	Use PV generation from Fragaki et. al.
Kfwind	Use wind generation from Fragaki et.al.
ngwind	Use National grid wind generation scaled by quarterly capacity
demand	Electricity demand data source: espini, kf or national grid
shift	Shift the days to match weather calendar
wind WIND	Wind value of store history to output
pv PV	Pv value of store history to output
days DAYS	Example store size to find for store hist plotting

Threshold THRESHOLD	Threshold for considering 2 wind values the same in new storage model
variable VARIABLE	Amount of variable generation, default=0.0
store_max STORE_MAX	Maximum value of storage in days, default=80.0
heat_electric HEAT_ELECTRIC	Proportion of heat in electricity demand, default=0.11
contours CONTOURS	Set of values to use for contour lines

Figure 11-2 Parameters for the program to calculate storage requirements for different demand and generation

Appendix A.3 Comparison of output from storage modelling and plotting.

This program reads in the files created by the previous program and creates plots.

rolling ROLLING	Rolling average window
decimals DECIMALS	Number of decimal places
plot	Show diagnostic plots
inrate	Base the charge rate on the energy input, not energy stored
mcolour MCOLOUR	Plot min point marker in black
nolines	Do not plot the contour lines
markevery MARKEVERY	Marker frequency
compare	Output comparison stats
pstore	Plot the sample store history
features	Print feature correlations
pdemand	Plot the demand
pnet	Plot the net demand
heatdiff	Create a heat map as difference of 2 scenarios
pfit	Show 2d plots
pmin PMIN	Plot minimum point of given variable
dcolour	Use same colour for same number of days
yearly	Show Yearly plots
rate	Plot the charge and discharge rates
stype	Type of Storage for cost calculation: pumped, hydrogen, caes.
min	Plot the minimum generation line
annotate	Annotate the shares heat map
scenario SCENARIO	Scenario to plot
days DAYS	Days of storage line to plot
sline	Method of creating storage lines: interpolation from x-variable or y-variable or both, option to smooth, or just take the nearest value.
cvariable CVARIABLE	Variable to contour, default is storage

cx CX	X Variable for contour creation, default is f_wind
cy CY	Y Variable for contour creation, default is f_pv
sx SX	Variable to plot on the X axis, default is f_wind
sy SY	Variable to plot on the Y axis, default is f_pv
adverse ADVERSE	Adverse file mnemonic
last LAST	Only include configs which ended with store: any, full, p3=3 percent full
shore SHORE	Wind to base cost on both, on, off. default = both
excess EXCESS	Excess value to find minimum storage against
normalise NORMALISE	Normalise factor to override the one from settings
tenergy TENERGY	Total energy to pass to cost calculation instead of total electricity demand.
variable VARIABLE	Variable to plot from scenario
heat HEAT	Variable to plot a heat map of
surface SURFACE	Variable to plot 3d surface with
pwind PWIND	Print points with this wind proportion
ppv PPV	Print points with this PV proportion
costmodel	Cost model: current or future costs

Figure 11-3 Input Parameters for program to compare outputs and plot contour lines

Appendix B POD challenge energy forecasting competition

The author took part in the Presumed Open Data (POD) Challenge energy forecasting competition. Organised by The Energy Systems Catapult which is a publicly funded body set up to improve collaboration between academia and industry and Western Power Distribution (WPD) which is a Distribution Network Operator (DNO). The details and results of the competition are available at https://codalab.lisn.upsaclay.fr/competitions/213#learn_the_details-overview

Appendix B.1 Background

High resolution monitoring of electricity usage can be expensive and requires processing of large amounts of data. The features important to power system modelling are the peaks and troughs in electricity demand. The aim of the challenge is to find out if some of the features of high-resolution demand, particularly the maximum and minimum can be estimate accurately given only the 30-minute averages and weather data. The aim is to estimate the maximum and minimum demand at minute resolution for each 30-minute period for a whole month. Figure (11-4) shows the mean demand (in blue) over a half hour period in blue from a substation which has a large amount of embedded PV generation attached. The objective is to use this, along with weather data to estimate the maximum and minimum demand (shown in orange and green respectively).

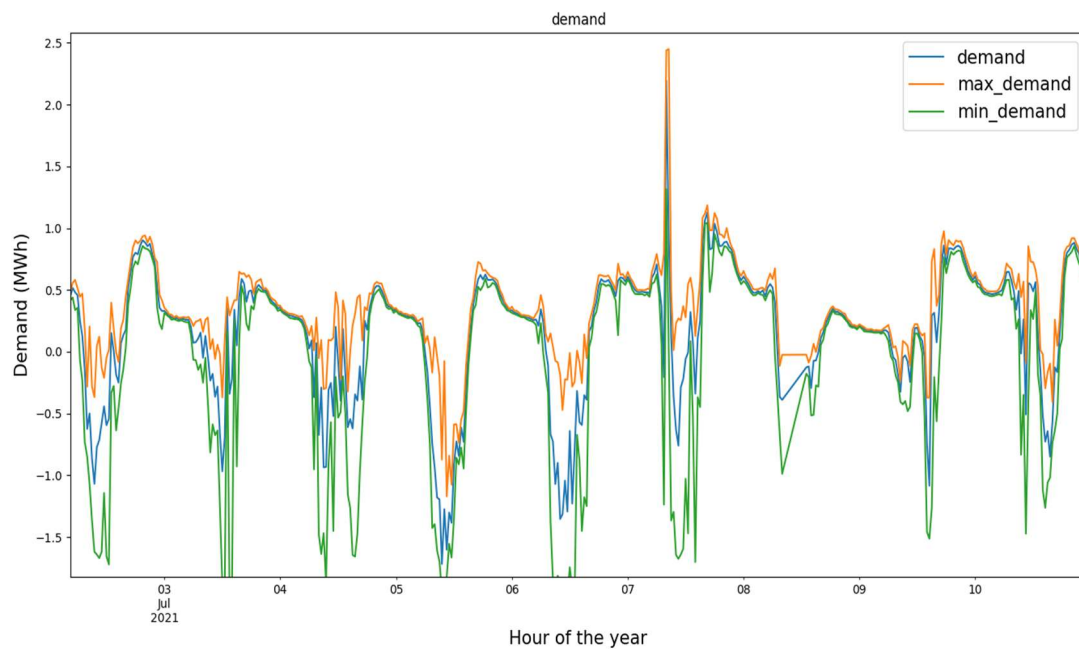


Figure 11-4 Half hourly demand, maximum and minimum for a period in July 2021

The data values supplied are summarised in table (11-1).

Table 11-1 Data supplied to POD challenge participants

Data Value	Availability
Half-hourly mean demand	2 years of consecutive values, followed by the forecast month
Half-hourly minimum demand	2 years of consecutive values
Half-hourly maximum demand	2 years of consecutive values
Hourly Temperature	2 years, followed by the forecast month
Hourly Solar irradiance	2 years, followed by the forecast month
Hourly Windspeed north component	2 years, followed by the forecast month
Hourly Windspeed east component	2 years, followed by the forecast month
Hourly Pressure	2 years, followed by the forecast month
Hourly Specific humidity	2 years, followed by the forecast month

The weather parameters were supplied for 5 geographic locations. The objective of the competition was to predict the half hourly maximum and minimum value for the forecast month that were not supplied. Participants were allowed several attempts to estimate these values. Each attempt was assigned a skill score defined as the ratio between the RMSE of the forecast divided by the RMSE of a benchmark. The benchmark was to use the half hourly mean values as both the maximum and the minimum. 35 teams took part. The author competed as a team of 1 person.

Appendix B.2 Methods

Additional variables were created (engineered features) by combining the given parameters in conjunction with the time stamps. For example:

- **demand_lag1** means the demand for the previous half-hour period.
- **Solar_irradiance1** means the solar irradiance measured at weather location 1
- **Cs_ghi** means clear sky global horizontal irradiance. The solar irradiance expected at the earth's surface based on the position of the sun calculated from the time of day and day of the year and geographic location of the substation.

Since it was known that there was a lot of PV generation attached to the substation, it was thought that this might be affected by cloud cover. Therefore, an engineered feature called **cloud** was created defined as the difference between **cs_ghi**, the theoretical solar irradiance and the actual solar irradiance. The features used in the final prediction are listed in table (11-2)

Table 11-2 Features used in the machine learning forecast.

Variable	Description	Used For
Demand	Half hourly demand	Both
demand_diff	Difference between successive demand values	Max
demand_lag1	Previous half hour demand	Both
cs_ghi	Clear sky global horizontal irradiance	Max
demand_lag2	Demand from 2 half hours back	Max
Trend	Monotonically increasing counter	Max
Zenith	Solar zenith angle	Max
Cloud	Cloud estimate. Cs_ghi – solar irradiance1	Both
solar_irradiance1_diff	Differenced between successive solar irradiance1 values.	Max
Presyd	Pressure from yesterday	Max
demand_lag4	Demand from 4 K periods back	Max
Presdb	Pressure from day before	Max
K	Half hour of the day	Both
solar_irradiance_var_lag1	Variance of solar irradiance amongst weather stations for previous k	Both
spec_humidity_var_lag1	Variance of humidity	Max
windspeed_var_lag1	Variance of windspeed previous k	Max
windspeed_var	Windspeed variance	Max
Wd	Day of the week	Max
spec_humidity_var	Variance of speculative humidity	Max
Solar_irradiance1	Solar irradiance at weather location 1	Min
Solar_irradiance_var	Variance of solar irradiance at different locations	Min
Wind_speed_east1	East component of windspeed at location 1	Min
Wind_speed1	Magnitude of windspeed at location 1	min
Dailyhume	Daily humidity at location 1	Min
Solar_irradiance2	Solar irradiance at location 2	Min
Windspeed1_diff	Difference between successive wind speeds at weather location 1	Min

The features were chosen by systematically adding those features suggested by the Lasso method to see which ones improved the forecast. Figure (11-5) shows those the important features positively and negatively correlated with the maximum half-hourly demand.

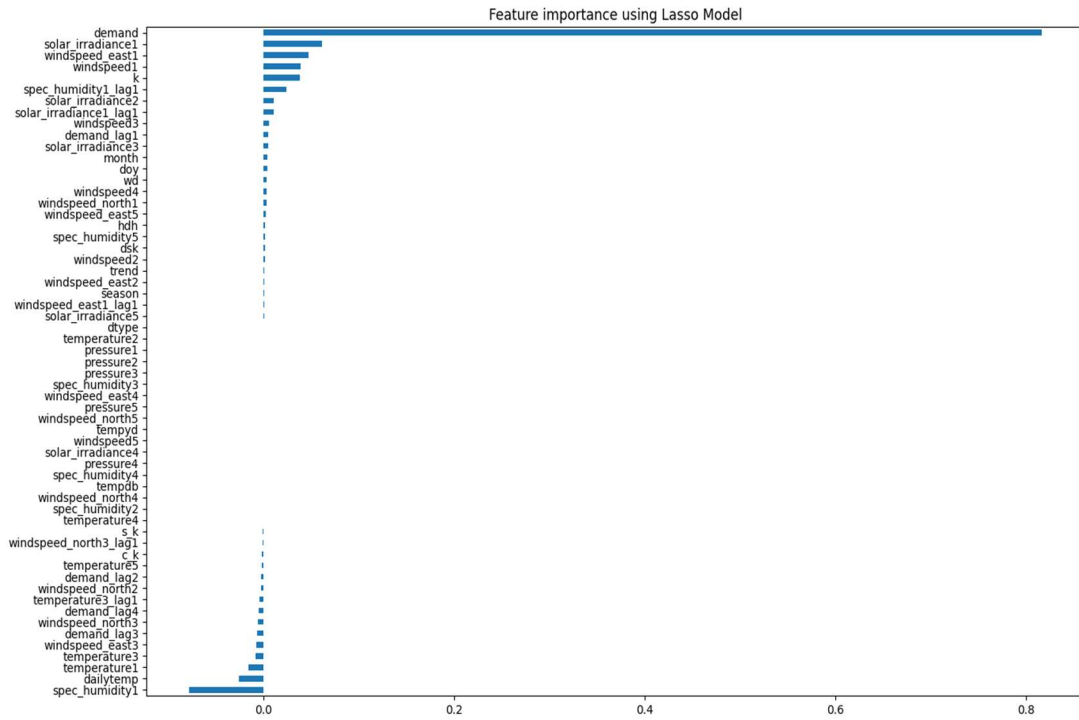


Figure 11-5 Feature importance using the Lasso Model

The following machine learning methods were tried to see which one gave the best forecast:

- A Multilayer Perceptron (MLP)
- Gaussian Process Regression (GPR)
- Random Forest (RF)
- Light GBM (Gradient Boosting Machines)

To use these methods, the engineered features had to be supplied to the method along with various tuning parameters. All the features were normalised. Success in the competition would therefore be a combination of method selection, tuning and choice of which features to use. Solutions were programmed in Python. The methods were trained by trying to predict the maximum and minimum values from the previous supplied data.

A Multilayer Perceptron (MLP) is a type of feedforward Artificial Neural Network (ANN). The MLP used in this project had a linear input layer, a sigmoid layer equation (A1) and a leak-relu layer equation (A2)

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (A1)$$

$$L(x) = \begin{cases} x, & \text{if } x \geq 0 \\ s x, & \text{otherwise} \end{cases} \quad (A2)$$

Where slope $s=0.01$

Gaussian Process Regression (GPR)[115] is a supervised learning method. Its advantage is that it produces a probabilistic prediction in terms of a value and a confidence interval and can refit parts of the model if the confidence interval is too low. It can be interpreted as a bayesian version of Support Vector Machines (SVR). Its

disadvantage is it is not sparse (ie uses all samples) and inefficient with a large number of features.

Random Forest (RF) is an ensemble method which takes the average of many decision trees. A decision tree is a method of subdividing the data based on the values of certain variables. Individual decision trees tend to overfit, but RF overcomes this limitation by averaging the predictions of many trees.

Light GBM (Gradient Boosting Machines) is an open source framework for predictions originally developed by Microsoft. Like RF it is also based on decision trees, but with histogram-based algorithms that bucket continuous feature values into discrete bins.

Appendix B.3 Results

Figure (11-6) shows an example of one of the forecasts. The maximum half hourly demand is shown in blue compared to the actual maximum in orange.

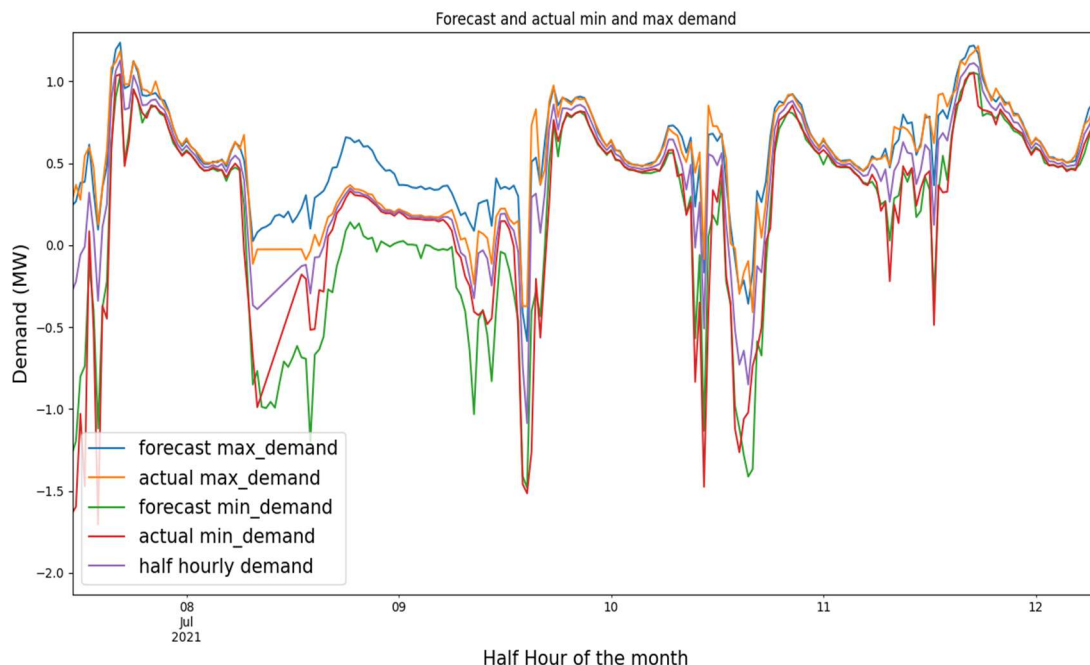


Figure 11-6 Example of forecast minimum and maximum demand

It was found that LGBM gave the best forecast. The competition took place over a period of 2 weeks. During the practice sessions 36 teams from all over the world took part. By the time of the actual competition this was down to 17 as those who were not doing well dropped out. On Monday of the 2nd week the author was in the lead in the competition as shown in figure (11-7)

Results					
#	User	Entries	Date of Last Entry	Team Name	skill ▲
1	malcolm	1	12/02/21	u_cvml	0.473 (1)
2	alefianrahman	1	11/30/21	ESDA Dream Team	0.480 (2)
3	burrowsej	1	11/30/21	ghd-not-the-hair-straightener	0.483 (3)
4	satrughna	1	12/02/21	code_green	0.493 (4)
5	wpd_challenges	1	11/26/21		1.000 (5)
6	AyrtonB	1	11/28/21		1.545 (6)

Figure 11-7 POD Challenge standings on Monday of the 2nd week

However, during the last week several of the other teams improved their forecasts. So, the author dropped to 6th place at the end as shown in figure (11-8)

Results					
#	User	Entries	Date of Last Entry	Team Name	skill ▲
1	flziel	6	12/10/21	LFCE - Load Forecasting Crew Essen	0.426 (1)
2	jw99	6	12/10/21	WOJJ	0.436 (2)
3	satrughna	6	12/03/21	code_green	0.437 (3)
4	AyrtonB	6	12/10/21	Random Forresters	0.443 (4)
5	burrowsej	5	12/10/21	ghd-not-the-hair-straightener	0.459 (5)
6	malcolm	5	12/08/21	u_cvml	0.460 (6)
7	arvinlim	4	12/08/21	The Bad Bois	0.466 (7)
8	alefianrahman	1	11/30/21	ESDA Dream Team	0.480 (8)
9	ecureuil	5	12/09/21		0.486 (9)
10	Daniel	6	12/10/21	The Resistance	0.511 (10)
11	matthias	2	12/02/21		0.520 (11)
12	mklien	3	12/09/21	nzlads	0.537 (12)

Figure 11-8 Final POD Challenge standings

The winning team consisting of a professor and two PhD students from Essen University using Generalized Additive Methods (GAM) models, which performed better than their two MLPs. The 2nd placed team, 4 PhD students from Imperial College also used GAMS. A team of 5 from a company in Pune India was 3rd.

Appendix B.4 Conclusions

The competition was a good learning experience, and 6th place was not bad considering I was a team of 1 competing against multi-person teams who were perhaps machine learning experts.

Appendix C Corrections following viva.

This appendix contains a list of the changes made to the thesis following the viva.

There are three tables:

- (11-3) Minor corrections listed in the examiner's response.
- (11-4) Table of corrections arising from the external examiner's annotated copy.
- (11-5) Other corrections identified by the author.

Table 11-3 List of minor corrections to the thesis requested by the examiners.

Comment from the examiners	How this has been addressed in the thesis
Pg. 20 Paragraph 4: Heating share of primary energy demand in the UK needs to be provided on top of the Europe figures to align with the context of the thesis	"and 36% in the UK" added to the paragraph with reference.
Pg. 21 Paragraph 1: A clear justification of how 40 years of data contribute to the accuracy and reliability of the developed models needed. Discuss why such dataset does not add to the uncertainties of the models considering drastically changing weather patterns in the recent years.	The more variation in weather conditions, the more likely that periods where high demand and low generation occur at the same time are captured. For example, a model developed using a warmer year with lower heating demand, or a windy year with high power generation might not cope with a cold, calm year. In this study 40 years of historic weather data are used, on the assumption that the weather patterns of the past give a guide to those of the future. Other research [12] has found the multi-decadal variability of wind generation based on historic weather to be greater than climate change impacts predicted by modelling, and [13] that the impacts on PV generation in Europe will be lower.
Pg. 21 Paragraph 2: Discuss with clarity what is the rationale behind keeping all factors constant other than weather. Focus on technological advances that if ignored, can affect reliability of the developed methodology.	If heating technology were changing over the analysis period, as it would be if historic electricity demand were used, then it would not be possible to tell which changes were due to weather and which to technology. Although the methodology developed here is used to study the impact of current heat pump technology it could equally well be used to keep technology constant at future

	levels, for example if heat pump COP and housing insulation improves.
Pg. 25 Last Paragraph: More clarification needed on what a single node national energy system means and what are the implications of such simplification on model outputs.	Pg. 27, paragraph 3 expanded: They consider the national energy system as a single node and do not take into account that it is a complex network connecting sources of supply and demand with varying transmission capacities. For example, wind generation in the north of the UK, might be needed to supply demand in the southeast and the network needs the capacity to do this. In rural areas, there may not be enough transmission capacity for houses to have both electric vehicles and heat pumps. The results of the models would be less accurate if the transmission network were not upgraded to have the necessary capacity. These simplified models will be referred to as energy balance models.
Pg. 27 Last Paragraph: Description of near- and long-term future series with reference to the source.	Page 29, paragraph 1: The near-term future series includes wind farms that are newly built, under construction or approved and has been used in the study. The long-term future series also includes planned wind farms but was not used because it does not separate onshore and offshore wind.
Pg. 29 Last Paragraph: cross-reference to detailed and critical analysis of the references mentioned would be useful in helping the reader navigate through the thesis.	Page 31: More detailed discussions on some of the references mentioned above are available in other parts of the thesis as listed below: • A study on how the UK could be powered by 100% renewable energy [34] is also discussed in section 2.1 in the background to heat demand and the HDD 12.8 method. • A study of seven plans for a UK net zero energy system [19] has already been mentioned in table (1-3) in the context of energy storage. It also features in a discussion on energy modelling in 1.2.5 and the relative proportions

	of wind and solar generation in 5.1 The two previous studies on the wind/solar/storage mix for the historic demand [41] and [52] are discussed in more detail in 5.1 and chapter 7.
Figure 2-3: The text above the figure needs modification to reflect HDD12.8 behaves differently to the rest of the methods	It can be seen that the HDD 12.8 method matches the gas time series less well, overpredicting at periods of high demand. In contrast, the other three heat demand methods over predict in summer and consequently under predict in winter.
Figure 3-4: The text below the figure needs modification to provide more details on why the yellow line doesn't look right.	As can be seen in figure (3-4) the shape of the RHPP derived COP curve (yellow) is different from the other curves. The COP should increase as the temperature difference declines, but this does not happen for lower temperature differences. Therefore, the RHPP curve was not used in the analysis.
Pg. 55 Last Paragraph: 'were used' repeated	3.3 Paragraph 1: Fixed
Pg. 77 Last Paragraph item 1: need modification '... and more will not change..)	Page 79. Fixed
Pg. 84 Table 5-4: Last column needs modification to reflect years in correct format.	Page 86. Done
Pg 85: Discussion needed around how realistic a baseload of 0.4 is, and cross reference to the sensitivity section discussing implications	Page 87 5.3.2: A figure of 0.3 for nuclear as assumed being between these two extremes. Potential UK tidal power generation is 0.8 days [19] consisting of tidal barrages, lagoons and stream generation. Here it as assumed that 0.1 days is built. This gives a combined nuclear and tidal value of 0.4 days. The consequences of varying this baseload are investigated in section 9.4.
Section 8.2.1 Pg.147: More discussion and clearer statement supported with evidence required around delivery of the hydrogen through existing gas pipelines.	Page 149 8.2. paragraph 1 extended: The industry led Leeds City Gate Project [22] proposed that the hydrogen could be produced from steam methane reforming of natural gas (called grey

What are the changes necessary, is it cost effective, is the whole approach practical or probable?	hydrogen). The report states that both the medium pressure and low-pressure gas distribution networks have been modelled using network analysis software and that the gas networks “have the capacity to 100% hydrogen with relatively minor upgrades”. A new transmission system to connect hydrogen production into the gas network at a cost of £230 million would be required. Appliances need converting and there are already hydrogen ready gas boilers on the market. Whilst the approach seems to be practical, since this process emits CO ₂ , it would be difficult to achieve a net zero energy system. It has to be combined with CCS to capture the emissions, which is described as blue hydrogen. A previous study on blue hydrogen [23] found that boilers using hydrogen from natural gas with CCS cannot achieve net zero. The alternative is to use hydrogen produced by electrolysis of water which is termed green hydrogen. This is what is assumed here. It should be noted that in a review of the evidence [111] (conducted after the work described below was completed), it was found that none of the 32 independent studies identified hydrogen as a viable solution for decarbonizing space and water heating in buildings.
Possibly renaming the section conclusions and summary and having a one main conclusion for the thesis towards the end.	Done
In addition, marked up comments and corrections to be addressed are provided on an electronic copy of the thesis provided by the external examiner.	See table (11-4) below

Table 11-4 Corrections arising from the external examiner's annotated copy.

Examiners comment	How it was addressed
Page 3, para 5. Best in terms of what?	"was the best" changed to most accurately predicted the measured data
Page 20, para 4, what about demand side management?	The intraday variability of wind and solar can be mitigated to a limited extent by demand side management, but to cope with the seasonal variability, they need to be complemented by energy storage.
Page 20, para 4, rephrase	This move to renewable power sources such as wind and solar will result in a migration away from burning fossil fuels for kinetic energy and heat energy to delivery of energy in the form of electricity.
Page 21, para 2, rephrase	Page 21: • How should electricity demand time series incorporating heating electrification under long-term weather variation be generated which allows heating alone to be studied? • How should an electricity demand time series incorporating electric vehicles under long-term weather variation be generated which allows the impact of EV's alone to be studied?
Page 23, para 1, power rating	1.2.2 • Charge rate: how quickly the energy can be stored. • Discharge rate: how quickly the energy can be used (related to power rating)
Correct capitalisation of kWh, MWh, GWh, TWh	Checked all
Page 23, para 3, write out plans	Page 24: New table (3-1) added
Fig 2-2 Y axis should just be TWh	Page 43: Plot fixed
Comment for Fig 2-6	Page 46: Amended seasonality and mentioned HDD 12.8
Axis labelling For Fig 2-8 bias plots	Page 48: Axis labels modified

2.3.5	Comment added to explain grid resolution
Fig 3-1 “ERA 5 reanalysis weather”	Page 51: Changed to “ERA5 reanalysis data”
P54 fig (3-5) show FES hybrid heat pump plot?	Page 57, paragraph 1: Reworded to include figure number from referenced report, since it is not clear if there is permission to reproduce the plot from the government report.
P56 any info about if hot water by heat pumps alone?	Page 58: but this is not the case for at least 4% of the houses
Equations (22), (23) summation?	Page 26: Changed to use a union operator although it seems unclear what the correct mathematical notation for concatenation of 2 time series is.
4.3.1 need to add nRMSE for 2017. Are plots available?	Page 63: Reworded to show nRMSE applies to both years. New plot added as Fig (4-2) resulting in renumbering of remaining figures in chapter (4)
Text below fig (4-6), now (4-7)	Page 72: Expanded to mention weather dependent GHI
P76, para 2: express in percentages, rather than TWh. Added a sentence	Page 78: These variations are 187%, 196% and 91% respectively.
P79 reference to Natural gas generated from electricity	Page 81: Reference added to Sabatier process in comment following equation (28)
Renewables ninja future changes? Sentence added after equation (29)	Page 82: The near-term future time series is used which includes wind farms which are under construction and planned in addition to those that already exist.
Fig (5-1) add more arrows	Page 83: More arrows added
Consistency of η as %	Updated tables at start of sections.
Which other studies use days?	Page 87, 5.3.2, paragraph 4: Reference added
Fig (5-3) scale £/kWh	Page 89: Scale corrected
Fig (5-3) Question about production of too much energy.	Page 89: The high cost of the configurations with large amounts of wind and PV is due to curtailment.

Fig (5-4) overplot both sets of results?	Page 92: New fig (5-6) added and remaining figures in chapter 5 renumbered.
5.4.2 Why is max deficit different at high PV?	Page 93: This is probably explained by the energy store emptying, as shown in figure (5-8) and discussed in the following section.
5.4.4 charge rate GWh /h ??	Page 94: Changed to GW
Check apostrophe in years' 6.1	Page 98: Checked
Fig (6-7), (6-8) common axis scale?	Page 106: Plots amended to show cost on the same scale
Table (7-2) comment on effect of finite ramp rates (w.r.t daily vs hourly)	Page 114: For daily time series the charge and discharge rates will be averaged over a longer time period and so their maximum values will be smaller. Using daily time series averages the charge rate across the whole day leading to lower calculated ramp rates.
Comment after (fig 7-4) – why does decade make more difference at smaller storage capacities.	Page 115: The bigger difference at small storage capacities is probably due to variations becoming smoothed out a large amounts of storage because there is more energy available to cope with short term variation.
Fig (7-9) comment on large PV difference at large PV configurations.	Page 120: This could be because the Fragaki time series model more PV panels in the south where the weather is sunnier, whereas Renewables Ninja model a PV panel at each weather grid point.
Fig (7-11) different scale so can't tell it is not as large a difference as onshore vs off?	Page 122: Fig (7-11) and Fig (7-10) redone so they have the same contour lines and comparable scale.
Fig (7-12) implications for storage?	Page 123: This would be expected to result in lower storage requirements.
Fig (7-14) how does pattern vary?	Page 125: Reference forward to 9.6
Fourier Transforms to confirm storage pattern? Comment added in 7.5 penultimate paragraph.	Page 135: One possible area of future work might be to analyse the patterns in store state of charge shown in fig (7-20) and fig (7-21) using Fourier series to see if there are any underlying cycles (such as yearly).
Fig (7-23) Onshore offshore patterns vs demand?	Page 133: Reference forward to 9.6

13.67 days future wind potential seems small? P133	Page 135: The existing capacity of offshore is 0.3 days with a potential 23 days [19] in the future.
Wind is very unpredictable - rephrase P133	Page 136 Wind patterns are due to a complex interaction of many factors
Table (9-2), why no consistent pattern? New paragraph added.	Page 157: These two configurations have a small amount of storage, and a large capacity of dispatchable generation which can be supplied at any time of year. Therefore, the dominating factor in determining the optimal wind solar mix becomes how much energy is curtailed, rather than generating energy close to when it is need as has been seen in previous sections. The amount of curtailed energy is determined by how long the generation exceeds the demand.
Figure (9-8) storage scale should have units	Page 162: Units added
Figure (9-9) storage scale should have units	Page 162: Units added
Figure (9-12) should units be days?	Page 164: Units changed to days on the x axis
9.6.3 what happens with hourly correlation, table (9.4)?	Page 166: The Fragaki et. al. data is only available as a daily time series, hence hourly correlation is not shown. Also, this project is more concerned with long-term storage, so the intra-day correlations are of less importance.
9.6.3 where have I shown that offshore wind correlates more closely with demand curve?	Page 167: Paragraph extended to reference specific values from table (9-4) in paragraph below
Figure (9-16) 83% and 75% comment, don't seem to match the plot. Also plot says all heat pumps not 41%.	Page 170: Fig (9-16) and Fig (9-17) changed to be the 41% heat pumps ones to match the text. Values of wind energy fraction updated in text, table (9-5), and conclusions.
Why is standard deviation a worse method for heat pumps?	Page 172: This could be because the addition of heat pumps to the demand increases its standard deviation and if the peaks in the wind generation do not match the demand peaks then the optimal wind fraction could be in less.
Future work 10.0.2	Page 180: Ramp rate, transmission constraints.

Table 11-5 other corrections identified by the author.

P62 Paragraph 2. 4.3.4 “cooling degreed days” changed to “cooling degree days”
P70 Fig 4-7 Y axis scale should be TWh
P93 Table 5-11 One day’s energy should have TWh as units.
P103 Table 6-3 41% fraction should be also 96%
P144 Fig 8-3 Y axis scale should be TWh
P128 table 7-14 had some incorrect values and has been updated.
Equation (35) corrected. In 7.1
Fig (9-14) had all heat pumps, yet text described 41% heat pumps. Figure corrected.