Programme Area: Smart Systems and Heat

Project: EnergyPath Operations

Title: EnergyPath Operations – EPO Analysis Plan and Results

Abstract:

This report contains the analysis plan and results from the first run of analysis from EPO including the design run documents for the analysis plan and the results and insights from the analysis.

Context:

DNV GL and a partnership between Hitachi & EDF worked independently on a functional specification to develop the first phase of EnergyPath Operations - a software tool that allows designers to better understand the information and communications technology (ICT) solutions they will need to implement to deliver new home heating solutions.
A first version of this tool is now being developed by DNV GL and the Energy Systems Catapult. EnergyPath Operations will provide knowledge to users on how to design ICT systems, the cost implications of such designs and the viability of various systems.
This project compliments the EnergyPath Networks software modelling tool which will be used in the planning of cost effective local energy systems.

EnergyPath® Operations Analysis Plan and Results

Sub-deliverable ID: WP3-6 and WP3-18

Document Control

ESC programme name	Smart Systems and Heat Phase 1
ESC project number	ESC00050 and ESC00053
ETI project number	SS9011 and SS9014
Version*	1.0
Status	**Approved**: Contains reviewed and approved content. (delete as appropriate)
Restrictions*	Open / Internal use only (delete as appropriate)
Release date	18/05/2018
External release ID	WP3-6 and WP3-18

* Refer to the Information Classification Policy.

Review and Approval

	Name	Position
Author	Richard Brooks	Modelling Analyst
Reviewer(s)	Daniel Mee David Wyatt	Senior Manager – Energy Systems Architecture Consultant – Software Tools
Approver	Daniel Mee	Senior Manager – Energy Systems Architecture

Revision History

Date	Version	Comments
18th May 2018	V0.1	First draft of analysis plan and results
1st June 2018	V1.0	Released Version

Document Protection

Arising IP

Description	**Owner**	**Category**
AddressBase – Building Topology Data	Ordnance Survey	Public
Weather Data	University of Exeter	Public
Chaotic Occupancy Profiles	CREST	Public
Cambridge Housing Model	BEIS	Public
English Housing Survey	UK Data Service	Written Consent
Average Electricity Consumption for Domestic Properties	Elexon	Written Consent
Average Monthly Wind, Wholesales Electricity and Gas Prices	ICIS	Public

Background IP

Trademarks, licenses and disclaimers

Description	**Owner**	**Category**
EnergyPath is a registered trademark of the Energy Technologies Institute LLP	ETI	Trademark

Contents

1. Introduction

This analysis provides insights into how a candidate conceptual architecture would operate in a specific scenario.

The roles and behaviours of the actors in the energy system are based on the conceptual architecture. The scenario defines the research question and the boundary of operation.

This section describes the analysis with an example scenario. This considers how an Energy Service Provider (ESP) would balance the supply from a wind generator with consumer demand, if hybrid heat pumps (HHPs) were installed within a regional area.

The intention of the main body of the section is to present the report that would be handed to a stakeholder. The appendix provides further detail and justification to support the findings / decisions.

2. Use-Case Analysis

2.1. Workflow

The analysis is presented based on the workflow described in the Final Technical Summary Report.

- The analysis is proposed to a stakeholder, in this case the stakeholder was internal.
- An EPO model of the conceptual architecture is designed.
- The model is configured and checked to verify that it is an appropriate representation of the conceptual architecture within the expected area of operation covered by the scenario.
- A series of simulation runs are conducted and the results analysed to provide Key Performance Indicators (KPI), which are distilled into insights.
- The analysis is written up and presented to the stakeholder. This presents the findings based on the analysis proposed.

The process is often iterative depending on the findings. The stakeholder may want to either increase the scope or conduct part of the analysis with a different set of assumptions to improve the quality of insights.

The intention of presenting the analysis like this, is to provide a principled approach, where the stakeholder can understand and question any aspect of the analysis.

At each stage of the analysis, the key assumptions, decisions and methodology for performing the analysis are described. In subsequent interactions of the analysis, the assumptions relating to any aspect can be revised based on the results of the previous pass.

2.2. Propose Analysis

2.2.1. Scenario

The scenario analyses the ability of an ESP to manage the delta between the demand for electricity and the available supply from the wind generator using storage.

The ESP supplies a group of domestic properties either having gas or electric heating. The demand is dependent on the behavior of occupants, the heating appliance and the weather.

The ESP has a relationship with a wind generator, whose supply is dependent on the weather.

The ESP requests charging from a storage operator when there is a surplus of generation, or discharging when there is a deficit. The ESP purchases energy from a spot market (of consolidated generators), whenever additional supply is required.

2.2.2. Actor Relationships

The scenario considers:

- One ESP responsible for supplying electricity to a group of domestic properties, with A mixture of combi-gas boilers and HHPs.
- One wind generator owning a wind farm delivering energy based on environmental conditions
- One storage provider owning a battery farm that can take excess energy (by charging) or provide additional energy (by discharging).
- One spot market that can supply instantaneous generation capacity.

2.2.3. Disturbances

The wind impacts generation and temperature impacts demand. The time horizon and time step of the model need to be set based on the impact of these disturbances on the scenario.

The scenario will look at storage measures to handle wind integration on the grid for ramp and voltage support and off-peak storage. The table below show the attributes of the storage devices used for these applications, taken from (Akhil, et al., 2013).

Description	Size	Duration	Cycles	Desired Lifetime
Wind integration ramp and voltage support	1 – 10 MW (distributed) 100 – 400 MW (centralized)	15 min	5k – 10k full energy cycles per year	c. 20 yr.
Wind integration off peak storage	100 – 400 MW	5 – 10 hours	300 – 1500 full energy cycles per year	c. 20 yr.

The scenario needs to consider time horizons of between 15 minutes up to 1 day. It therefore has representations of wind and demand variability on a minute by minute basis.

2.2.4. Evaluation Outputs

The scenario will evaluate:

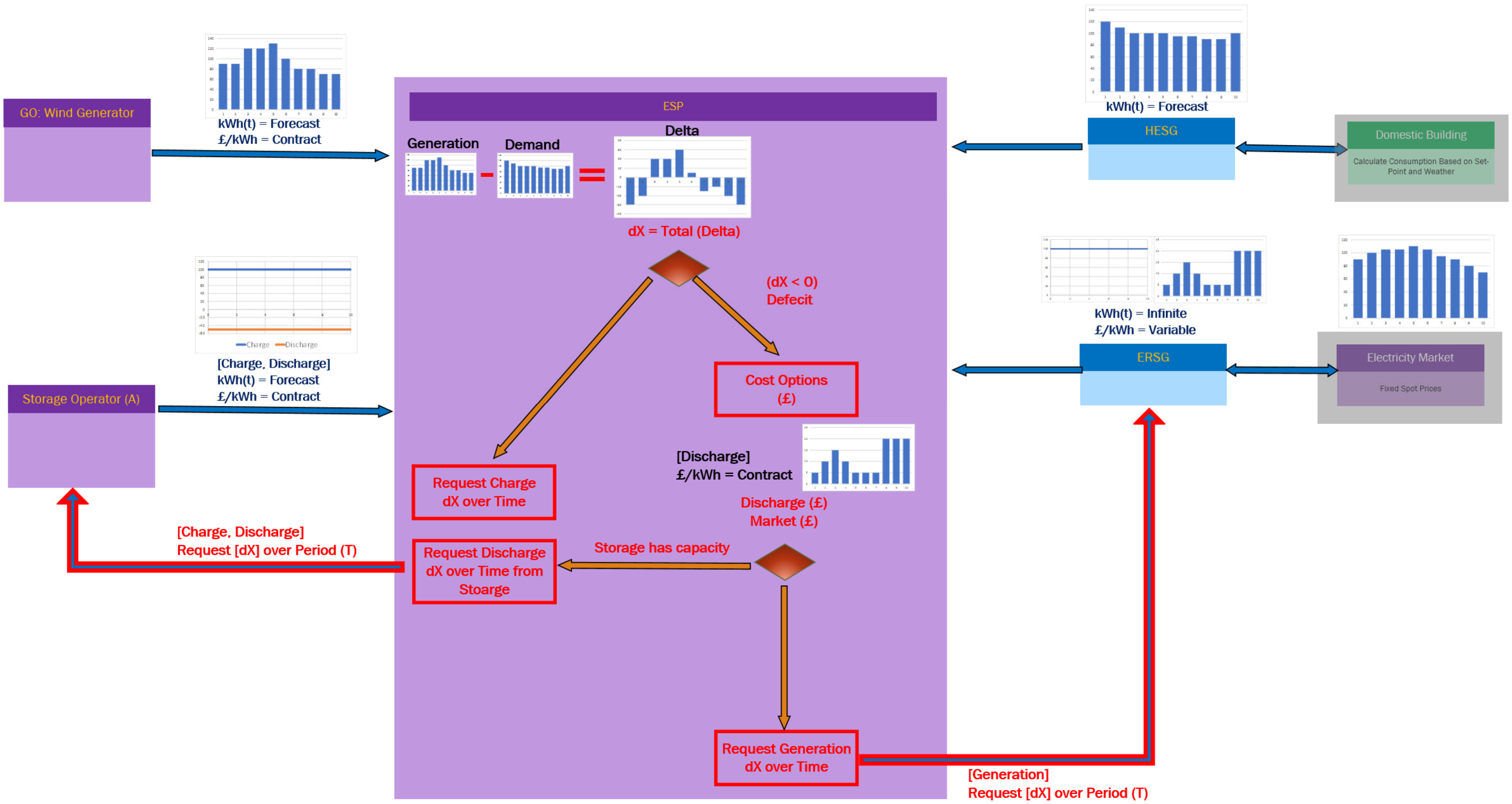
- The cost to the ESP of supplying energy (electricity and gas).
- The tolerance to which the delta between ESP supply (from generator / storage discharge) and demand (from houses / storage charge) can be maintained.
- The storage capacity required to handle the integral of the delta between electricity demand and supply.
- The total energy supplied to the domestic properties that comes from the wind generator, relative to spot market and gas. This will give an indication of the decarbonisation that is achieved.

2.2.5. Physical Representation

- The balancing looks at the delta supply / demand from the perspective of the ESP.
- The scenario looks at a set of domestic properties within a regional area. These are defined on a basis to allows comparison to the national distribution.
- The ESP supplies a group of properties that have a mixture of combi gas boilers (gas heating) and HHPs (electric heating).
- The spot market generators supply the ESP instantaneous power on request.
- The storage devices supply charging / discharging as requested by the ESP. There are limitations on the power rate of charging and discharging. The storage capacity is considered infinite.
- The ramp-rate for charging and discharging has not been considered in this analysis.
- The distribution / transmission networks are not considered in this scenario.
- The localised geography of weather conditions is not considered in this scenario

2.2.6. Business Representation

- The decision making used by the ESP to balance supply and demand is shown in the diagram over-leaf.
- The ESP receives a forecast at (1) minute resolutions, every (15) minutes forecasts over the next (15) minutes at (60) second intervals:
- The wind generator forecast from the wind generator,
- The aggregated demand profile of the ESPs consumers from the HESG,
- When the forecasted wind generation is greater than demand, the ESP requests the storage operator to take the excess.
- When the forecasted wind generation is less than demand, the ESP requests the storage operator to provide the deficit. If the deficit is greater than the maximum power, the ESP purchases additional energy from the spot market.


GO: Wind Generator
kWh(t) = Forecast
£/kWh = Contract
ESP
Generation
Demand
Delta
dX = Total (Delta)
(dX < 0)
Defecit
Cost Options
(£)
Request Charge
dX over Time
[Discharge]
£/kWh = Contract
Discharge (£)
Market (£)
Storage has capacity
Request Discharge
dX over Time from
Stoarge
Request Generation
dX over Time
[Generation]
Request [dX] over Period (T)
Storage Operator (A)
[Charge, Discharge]
kWh(t) = Forecast
£/kWh = Contract
Charge
Discharge
[Charge, Discharge]
Request [dX] over Period (T)
kWh(t) = Forecast
HESG
Domestic Building
Calculate Consumption Based on Set-Point and Weather
kWh(t) = Infinite
£/kWh = Variable
ERSG
Electricity Market
Fixed Spot Prices

2.3. Analysis Design

2.3.1. Key Performance Indicator (KPI) Definition

The analysis uses the following Key Performance Indicators (KPIs) to provide the outputs proposed, refer to Section 2.2.4.

2.3.1.1. Energy from Wind

The intention of this KPI is to understand the decarbonisation achieved.

This will be defined by the proportion of the total energy supplied to domestic properties that comes from wind generation (as a % of total energy consumed).

$$\sum_{t=1}^{t=End} \frac{E_{Wind}}{E_{Wind} + E_{Spot} + E_{Gas}}$$

This could be decomposed further to estimate impact on carbon emissions. The would require assumptions about the generation mix and transmission losses to account for the electricity from the spot market.

2.3.1.2. ESP Cost

The intention of this KPI is to understand whether the scenario is an attractive financial proposition.

The price for energy from wind generation, spot market and gas are constant (£ per kWh).

The storage operator charges the ESP a fixed margin for charging / discharging energy (£ per kWh).

$$ESP\ Cost = \sum_{t=1}^{t=End} C_{Wind}\,.E_{Wind} + C_{Spot}.E_{Spot} + C_{gas}.E_{gas} + (C_{wind} + C_{margin}).E_{discharge} - (C_{wind} - C_{margin}).E_{charge}$$

Where t = time step (1 minute), C = Cost (£ per kWh), E = Energy (kWh)

2.3.1.3. Demand Supply Delta

The intention of this KPI is to determine whether the proposition will sufficiently balance to reduce the risk of voltage issues on the distribution network, (within normal non-fault operation).

This considers the imbalance in supply purchased and demand provided (from the perspective) of an ESP (kW).

$$Imbalance = \left\{ \sum_{i=1}^{i=i+15} \{E_{Wind} + E_{Spot} + E_{discharge} - E_{charge} - E_{demand}\} \right\}_{t=1}^{t=End}$$

A 15-minute moving average was chosen as this is the interval over which imbalances are likely to cause voltage problems on a distribution network, refer to Section 2.2.3.

2.3.1.4. Storage Capacity

The intention of this KPI is to understand the storage capacity (energy) required to facilitate this proposition.

This is represented as the integral of the delta between the discharge and charge provided. This is the energy that will reside within the storage device (kWh).

$$Storage = \int_{t=1}^{t=End} E_{discharge} - E_{charge}$$

The accumulated storage will give an indication of the financial viability of the proposition from the perspective of the storage operator.

The scenario assumes the storage provider can provide infinite capacity (to the ESP). The storage devices for voltage support and off-peak storage, in reality, have cycles where the device is emptied / filled multiple times over the year, as shown in the table in Section 2.2.3.

This is a necessary simplification at the moment and future versions will add restrictions.

The maximum delta in energy storage over a given period provides an indication of the capacity of the device and how often it would need to be filled / emptied, (from other sources outside the boundary of the analysis).

2.3.2. Experimental Variable Definition

The analysis definition and methodology needs to appropriately represent the patterns and values of the experimental variables (inputs and disturbances), that impact the KPI.

The variables that have a strong impact on this scenario are:

- The physical properties of the domestic stock on heat storage and losses.
- The impact of the weather, on wind generation and heat losses from the building (and subsequent heating demand). The seasonal change in heating usage based on annual weather patterns.
- The chaotic and cyclic behaviour of users. The impact of daily and weekly cycles. The difference between users. The impact that the aggregated behaviour has on the aggregated demand.
- The predictability and forecasting of the demand / generation profiles, (based on the above effects).

The patterns of the experimental variables are inherently chaotic. It is therefore difficult to define a base simulation run that has 'average' conditions. It was decided to base the analysis on a contextual scenario (actual location and weather). This was selected to be considered 'typical'. This would allow an understanding to apply the results, at a high level to other potential contextual scenarios.

2.3.2.1. Domestic Topology

The analysis considers domestic properties within a specific geographic region. This approach was chosen because at distribution level the topologies are inherently unique and it provides a contextual example that is expansible for further analysis.

The data was taken from the Energy Path Networks (EPN) analysis of Bridgend County Council. This is defined based on information from Ordnance Survey, Valuation Office and English Housing Survey. This source also has information on the distribution network connectivity / topology, which can be used when the network is incorporated in future scenarios.

The domestic properties are defined using archetype classes from the English Housing Survey (EHS), which allows comparison to national data / other regions.

2.3.2.2. Weather

The weather was defined by the hourly observational data relating to the location of the topology.

2.3.2.3. Occupant Behaviour

The occupant behaviour, particularly the requirement for thermal comfort, impacts the heating demand. This requires an 'occupancy category' to represent occupant behaviour that can be mapped onto a regional topology.

There is a field of work that has demonstrated that socio-economic factors have a strong impact on the energy use in residential buildings, including both the total annual consumption and its short-term temporal profile. The behavioural factors alone can account for a doubling of building energy demand and the diversity between occupants can have an even stronger effect, (McKenna & Thomson, 2016; McKenna, Hofmann, Merkel, Fichtner, & Strachan, 2016; Nijhuis, Gibescu, & Cobben, 2016; Hauser, Evora, Kremers, Hernandez, & Hernandez-Tejera, 2016; Huebner, et al., 2013; McKenna, Djapic, Weinand, Fichtner, & Strbac, 2018).

The occupant demand was defined by running the CREST Stochastic Demand Model. This provides daily heating space set-points, hot water demand and background electricity based. This gives profiles for 'typical' weekdays and weekends based on occupant number. The analysis used 100 profiles generated by this model.

2.3.2.4. Forecasting

The ESP will forecast wind generation and demand to calculate the delta.

The demand from domestic properties, in this scenario, is not influenced by the ESP (i.e. no DSR).

The limitations of accuracy in the forecast is represented by distorting the actual wind generation and demand through a first order filter with a time constant, (default 180 seconds).

This representation provides a forecast that represents the general shape of the demand profile. This would not contain the detail of the volatilities (high frequency erratic spikes). These are caused by synergies in the chaotic behaviour of individual users, so would be difficult to predict.

2.3.3. Key assumptions

The analysis needs to appropriately capture the key phenomena that impact the KPI. The analysis will only be as credible as the definition of the weakest component. It is not appropriate to have a detailed definition in one area (data or model), if broad assumptions or poor-quality data are used in other areas that have a significant effect on the overall result.

The modelling assumptions are summarised below, and defined in detail in the project actor-specific Engineering Requirement Specifications (ERS).

Weather:

- The wind generation is a function of wind speed.
- The weather conditions are uniform across the region.
- The variation in conditions within the hour are ignored, (values calculated by interpolation).

Domestic Property:

- The heat loss from domestic properties is a function of dry bulb temperature only.
- The thermal properties of the building fabric (resistance and capacitances) are based on; property type, property age and floor area band classifications from the English Housing Survey. This provides a set of archetypes, which are unique of these combinations
- The impact of energy saving measures are not considered on an individual basis, but are lumped together within the categories.
- The consumer model was tuned so that each archetype gave ‘sensible’ temperature and energy consumption profiles in response to weather and set-point changes.
- This is scaled to consider the permutations of archetypes using values of overall resistance and capacitance from the Cambridge Housing Model, (Palmer, Tillson, & Armitage, 2013). This is based on the Government’s Standard Assessment Procedure for Energy Rating of Dwellings, (Standard Assessment Procedure (SAP 2012), 2014). This is described in Appendix Section 3.2.

Storage Device:

- The storage is represented as an energy flow with defined maximum absolute power and rate constraints.
- The storage device(s) have infinite energy capacity.
- There is no loss of energy during discharge / charge, (conversion of electricity to stored energy), or during situ within the device.

Occupant Behaviour:

- The occupant behaviour is defined by CREST stochastic demand model, (McKenna, Hofmann, Merkel, Fichtner, & Strachan, 2016). This assumes that the behaviour follows a repeated daily cycle. This is different for weekdays and weekends and is a function of number of occupants in a house. This does not consider; the change in use of heating between seasons, subtle changes in daily routine or special events, such as public holidays.
- The precise assignment of number of occupants to properties is unknown. It is defined as a probability based on floor area, derived from the English Housing Survey.

2.3.4. Base Run

The analysis considers a heating season running from the beginning of October to the beginning of April.

The analysis will be based on a region (cluster) within Bridgend supplied from one of the High Voltage substations (HV 560024). This has 7,484 domestic properties.

The comparison against the English Housing Survey (EHS) representation of England is shown in the appendix. The region has slightly larger houses, with fewer solo occupant and fewer flats, compared to the national average. This difference suggests that it is appropriate to take as a ‘typical’ contextual example for a semi-urban area. Refer to the appendix, Section 3.1 for details.

The wind generation is assumed to be supplied by a set of Siemens SWT-2.3MW-101m (MG) wind turbines. The number of wind turbines is specified to approximately match the domestic property demand, throughout the overall heating season. At the end of the season there is not a significant deficit or surplus of energy storage.

<table>
<tr><th>Case</th><th>Heating Appliance</th><th>Wind Turbines</th><th>Storage Power</th></tr>
<tr><td>1</td><td>All Gas Heating
100% Combi-Gas Boilers</td><td>2</td><td rowspan="2">Infinite Power Capacity</td></tr>
<tr><td>2a</td><td rowspan="2">Penetration of HHP
70% Combi-Gas Boilers
30% HHP</td><td rowspan="2">4</td></tr>
<tr><td>2b</td><td>10 MW Power Capacity</td></tr>
</table>

In properties with combi-gas boilers, this appliance provides all space and hot water heating.

In properties with HHP, the heat pump component provides all space heating, the combi-gas boiler component provides all water heating.

The appliances delivering space heating are switched on / off based on the room temperature. The power delivered is proportional to the temperature of the water in the heating system. Refer to section 3.2 for detailed description.

The size of the appliance and heating system is proportional to the size of the house. The capacity of appliances in the mid-sized houses, (floor band area 3), is 7 kW Heat Pump and 25 kW Combi-Boiler.

The precise assignment of heating appliances to properties is unknown. It is defined as a probability of HHP being installed in houses. None are installed in flats.

The penetration of HHPs in case 2a and 2b, was chosen so the electricity demand from heat pumps is equivalent to the overall background demand (electricity for non-heating purposes) from all properties.

The storage power limitation in Scenario 2b, was chosen so the storage operator can take the maximum power from the wind generator, so that energy never has to be 'thrown away'.

The energy prices were selected as 'reasonable starting values' for the first pass of the analysis. These are based on the day ahead prices from winter of 2016. A change was applied to reflect the trend of wind becoming cheaper, with base load electricity and gas prices becoming more expensive.

The storage margin price was an initial estimate. The analysis (in later iterations) could consider the relationship between the storage margin and energy prices that would make the strategy cost effective.

The prices used in the analysis are in the table below. These are the constants in the KPI, defined in Section 2.2.4.

Wind Generation	C_{Wind}	£46.5 MWh	25% less expensive than current on-shore generation cost in 2016 – Ref[3]
Spot Market	C_{spot}	£56.0 MWh	25% more expensive than current UK day ahead prices in winter months of 2016 – Ref[4].
Gas	C_{gas}	£13.6 MWh	25% more expensive than current UK day ahead prices in winter months of 2016 – Ref[4].
Storage Margin	C_{margin}	£10.0 MWh	Initial value chosen

2.3.5. Run Perturbations

The analysis considers an additional set of runs to assess the impact of forecasting.

The case 2b, was taken as the base run.

A series of runs were conducted where different time constants were specified. The longer the time constant, the lesser the extent to which the short-term volatilities in the profile are captured.

In future scenarios perturbations in HHP penetration and energy prices could be considered.

2.3.6. Data Sources

The data sources used in the analysis are presented in the table below.

Source	Usage in Analysis	Secondary Data	Reference
Energy Path Networks	Building Topology Information – Inputs to Allocation Function	Ordnance Survey Valuation Office English Housing Survey	Internal Project
University of Exeter	Weather Data (for topology – Cardiff)		University of Exeter (2012) - Observational Mean for 1961-1990 using UKCP09 Weather Generator: https://www.metoffice.gov.uk/climatechange/science/monitoring/ukcp09/methods.html
CREST	Outputs used to define Chaotic Occupancy Profiles		Centre for Renewable Energy Systems Technology (CREST), Stochastic Demand Model v2.2, http://www.lboro.ac.uk/research/crest/demand-model/
Cambridge Housing Model	Defining the thermal properties of buildings for different archetypes	English Housing Survey Government SAP Calculations	Cambridge Housing Model and user guide, v3.02 https://www.gov.uk/government/publications/cambridge-housing-model-and-user-guide **Note: BEIS allow usage noting that this is an unsupported deprecated model and the fore only appropriate for use in prototype development**.
English Housing Survey	Assessing the selected example topology with national data.		English Housing Survey - https://www.gov.uk/government/collections/english-housing-survey#2016-to-2017
Wind Power Program	Generation Curve for Wind Generator		Wind Power Program Data Sources, http://www.wind-power-program.com/download.htm

Source	Usage in Analysis	Secondary Data	Reference
Elexon	Typical Consumption Profile		Elexon Data – Average Electricity Consumption for Domestic Properties, www.elexonportal.co.uk
Ofgem	Average Monthly Wind, Wholesales Electricity and Gas Prices Annual Gas / Electricity Consumption Annual Gas / Electricity Cost to Consumer		Ofgem - https://www.ofgem.gov.uk/

2.4. Design Model

The EPO development is in its embryonic stages.

The library of component variant models has been configured specifically for this scenario.

These were configured from requirements defined by; the Case Study (what architecture needs to be represented), and the analysis (what is an appropriate representation).

Future versions of EPO shall have a set of library objects that can be used to represent each actor. The specific library object for each actor shall be selected based on the analysis requirements. The selection will be justified in the analysis report.

2.5. Configure and Check

2.5.1. Simulation Approach

The approach used to conduct the analysis is shown the figure overleaf.

The allocation script creates a batch of physical configurations, representing a batch of consumers (physical buildings, occupancy patterns and external loads) with slight variations. These 'variant configurations' represent the uncertainty in; the appliances assigned to houses, the number of occupants within each house and the exact behaviour of these occupants.

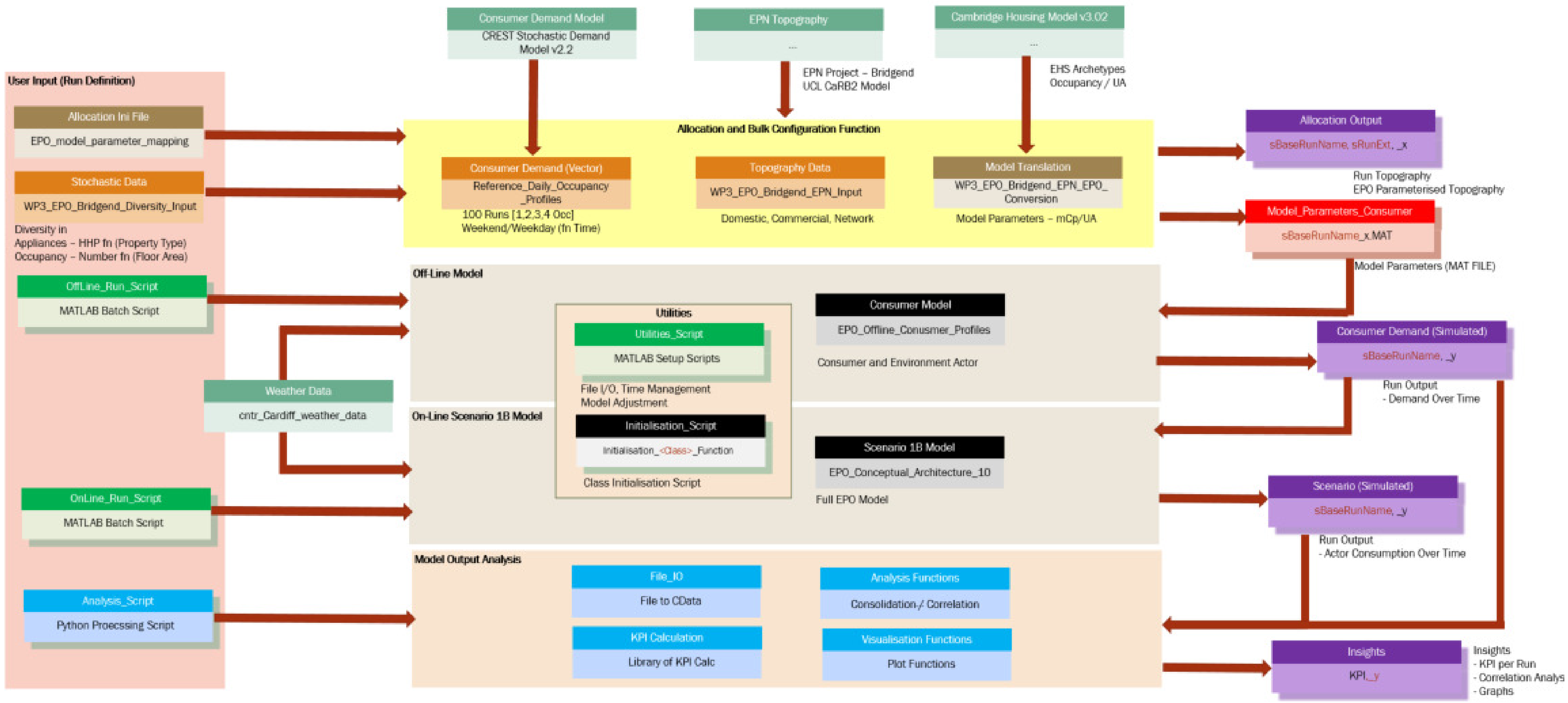
The bulk configuration functions then translate this into EPO parameters, based on a conversion sheet. This translates the configuration into physical parameters related to the consumer model that represents each building instance. The output is a set of MAT files which can be read into the EPO models configured in MATLAB/Simulink.

In the scenario, the consumer demand is only impacted by the occupier, and is independent of the other actors within the system.

An (off-line) consumer model was created, containing the consumer model, environment model and aggregation node. This takes in the MAT files, for each topology variant and weather data, to simulate the aggregated energy demand profile, (from all consumers).

The demand profiles are then fed into the (on-line) conceptual architecture model, along with the weather data (wind speed), to simulate the generation and storage charge / discharge.

The outputs are fed into the post-processing functions to calculate the KPI for variant runs. These are then analysed using a set of scripts to investigate; the KPI over the batch of runs, relationships between variables and visualisation of the results.


Consumer Demand Model
CREST Stochastic Demand Model v2.2
EPN Topography
...
EPN Project – Bridgend UCL CaRB2 Model
Cambridge Housing Model v3.02
...
EHS Archetypes Occupancy / UA
User Input (Run Definition)
Allocation Ini File
EPO_model_parameter_mapping
Stochastic Data
WP3_EPO_Bridgend_Diversity_Input
Diversity in
Appliances – HHP fn (Property Type)
Occupancy – Number fn (Floor Area)
OffLine_Run_Script
MATLAB Batch Script
Weather Data
cntr_Cardiff_weather_data
OnLine_Run_Script
MATLAB Batch Script
Analysis_Script
Python Proecssing Script
Allocation and Bulk Configuration Function
Consumer Demand (Vector)
Reference_Daily_Occupancy_Profiles
100 Runs [1,2,3,4 Occ]
Weekend/Weekday (fn Time)
Topography Data
WP3_EPO_Bridgend_EPN_Input
Domestic, Commercial, Network
Model Translation
WP3_EPO_Bridgend_EPN_EPO_Conversion
Model Parameters – mCp/UA
Allocation Output
sBaseRunName, sRunExt, _x
Run Topography
EPO Parameterised Topography
Model_Parameters_Consumer
sBaseRunName_x.MAT
Model Parameters (MAT FILE)
Off-Line Model
Utilities
Utilities_Script
MATLAB Setup Scripts
File I/O, Time Management
Model Adjustment
Initialisation_Script
Initialisation_<Class>_Function
Class Initialisation Script
Consumer Model
EPO_Offline_Conusmer_Profiles
Consumer and Environment Actor
Consumer Demand (Simulated)
sBaseRunName, _y
Run Output
- Demand Over Time
On-Line Scenario 1B Model
Scenario 1B Model
EPO_Conceptual_Architecture_10
Full EPO Model
Scenario (Simulated)
sBaseRunName, _y
Run Output
- Actor Consumption Over Time
Model Output Analysis
File_IO
File to CData
KPI Calculation
Library of KPI Calc
Analysis Functions
Consolidation / Correlation
Visualisation Functions
Plot Functions
Insights
KPI, _y
Insights
- KPI per Run
- Correlation Analys
- Graphs

The model was configured and checked concentrating on three components.

- the consumer model provided an appropriate and rational representation of the energy consumption profile of individual buildings,
- the off-line consumer model provided an appropriate and rational representation of the aggregated energy consumption profile,
- the on-line conceptual architecture model provided an appropriate response of the architecture over the range of operation in the analysis, and that emergent behaviours could be explained.

2.5.2. Consumer Model

The heating system, building and appliance control parameters were tuned to give a 'realistic' room temperature response and energy consumption profile, refer to section 3.2.

This provided confidence in the response from the range of building archetypes. This in turn provided confidence in the aggregated curve generated by the off-line consumer model. It also helped provide insight into emergent behaviours.

There is an ongoing piece of work looking at how the model compares and can be tuned against the more detailed Integrated Electric Heating (IEH) model (Energy Technologies Institute, n.d.). This should improve the realism of the response and provide confidence in the 'grey box' consumer model design (Bacher & Madsen, 2011).

The consumer model has thermal states that represent the average temperature of the radiators, building air and fabric. These are set at initial (close to average) values at the start of the run. The analysis suggests that it takes around 3 days for the model to soak, so that effect of the initial conditions do not significantly impact the electricity consumption profile.

2.5.3. Off-Line Consumer Model

The off-line consumer model populated by the allocation function for the domestic property topology was checked, refer to section 3.3.

This gave confidence that the model provided an appropriate response of the aggregated daily consumption.

- The curves produced followed expected daily trends.
- There was volatility caused by heating devices coming on-line, particularly in the morning and evening. There was a difference between weekend and weekday, due to greater mid-day occupancy.
- There was an inverse relationship between average daily usage and temperature.
- The average daily gas and electricity consumption on a per house basis were consistent with average consumption values, (from Ofgem). The response for heat pumps, where less data is available, was sanity checked by conducting a heat balance on daily average conditions.
- The building items of the same archetype in the topology can be bunched into groups of five, without significantly impacting the consumption profile. This gave a fourfold reduction in model run-time.

The shape of the curve was compared against a limited data set from the Consumer Lead Network Revolution (CLNR) project, (Love, et al., 2017; McKenna, Djapic, Weinand, Fichtner, & Strbac, 2018). These suggested that the volatilities in the simulation were more extreme than measured data. This could be because of; the representation of occupant behaviour, the size of the HHP devices and local control of devices.

2.5.4. On-Line Conceptual Architecture Model

The on-line conceptual architecture model, provided with demand inputs from the off-line consumer model was checked.

This gave confidence that the model performed appropriately.

- The wind generation followed patterns in the weather.
- The power from storage followed the delta between consumption and generation.
- The imbalance was centred around zero. The magnitude of the spikes appears to be greater during periods where the demand is most volatile.
- The storage appears to follow the demand forecast. This can be seen more clearly during periods when there is no wind, so storage discharge follows demand.

The graph below shows runs with two variant topologies over the course of a day, to illustrate the above. The wind generator is on full until 6pm, where it drops off and the storage operator starts discharging.

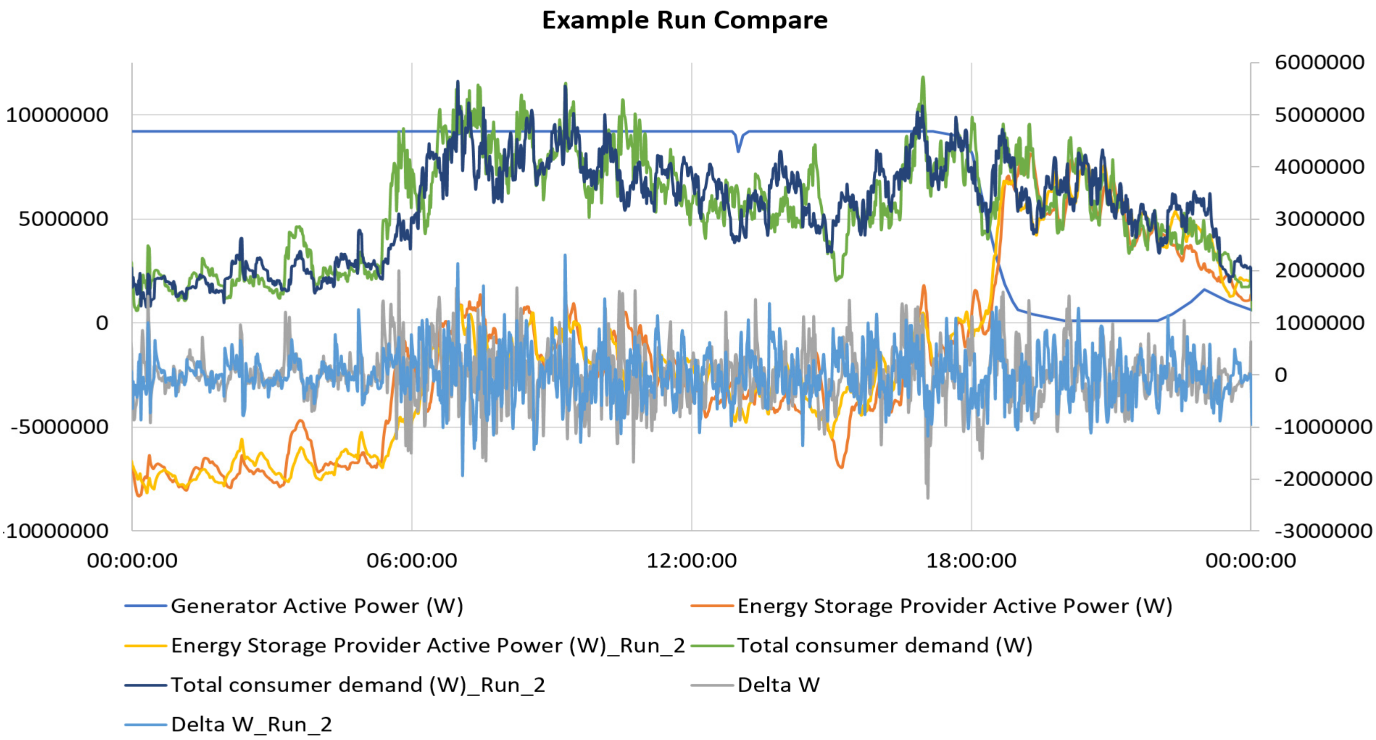


Figure 3 - Response of Storage and Imbalance for 2 Variant Topologies over an Example Day

The summarised plot of all the 132 variant topologies, presented and discussed in Section 3. provide further evidence to support that the model behaves as expected.

2.6. Analysis Workflow

The analysis work flow is shown in the figure below.

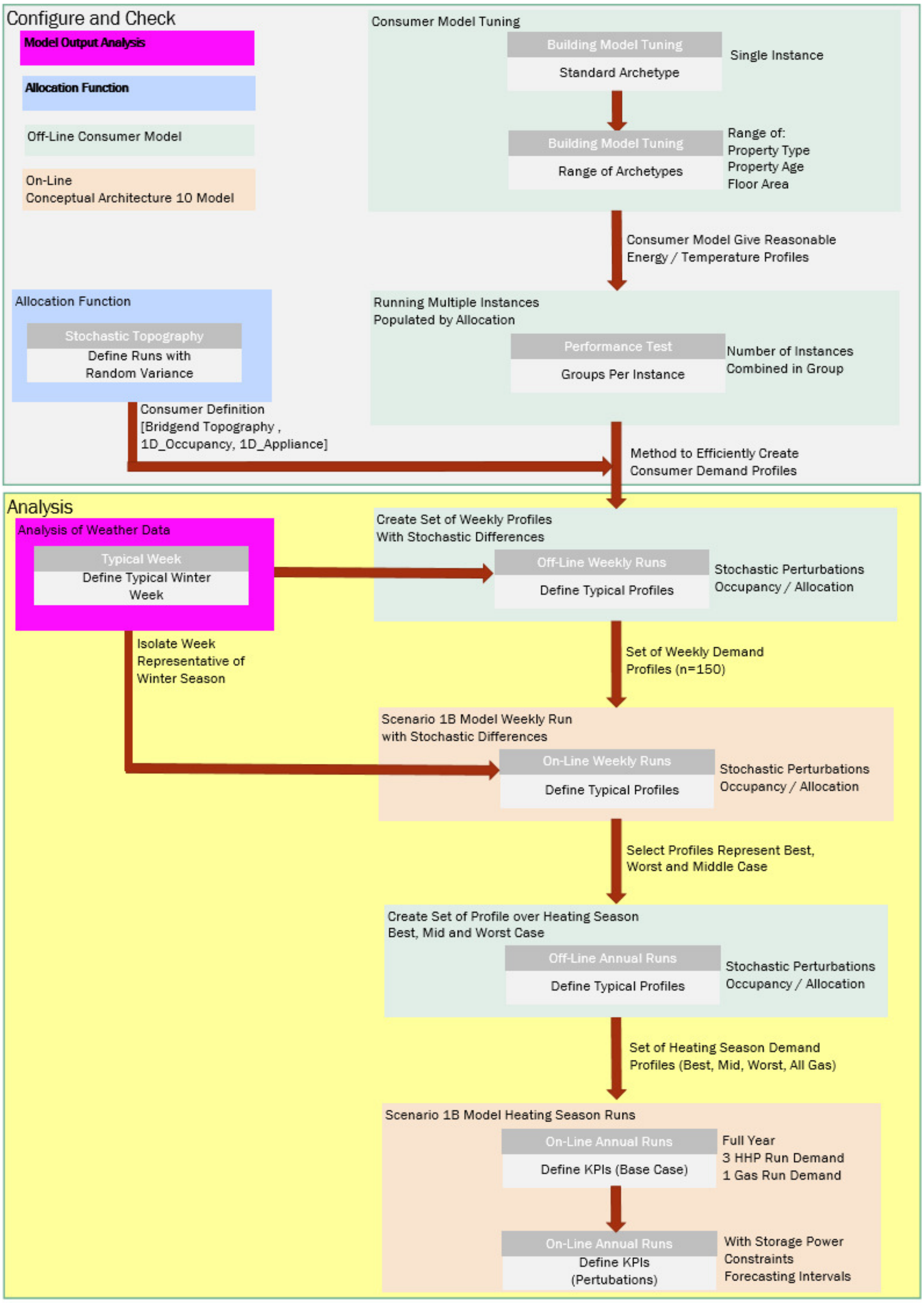


Figure 4 - Analysis Workflow (for this Scenario)

The analysis needs to consider both the impact of uncertainty in the topology and the changing weather over the heating season.

The run time of the off-line model, (1.5 hours to run one week), makes it prohibitive to run many variant topologies over the entire (28 week) heating season.

It was therefore decided to use an approach to de-couple these effects.

The first part of the analysis identifies instances of the variant topologies that give extremes and average behaviour. The profiles that give the 'best', 'mid' and 'worst' performance relative to KPI.

The second part of the analysis uses these topologies to assess performance over the heating season.

2.6.1.1. Selection of Typical Week

The typical week was selected by running the on-line conceptual architecture model using the average daily electricity demand, recorded by Elexon.

The typical week was selected base on; the deviation and mean in; weather conditions the imbalance KPI and the ESP cost KPI, Refer to section 3.4.

2.6.1.2. Off-Line Consumer Model Stochastic Differences

The candidate variant topologies were selected by running the off-line consumer model with 132 variant topologies generated with the Allocation and Bulk Configuration. These have different allocation of heating appliance, number of occupants and in turn the profile to define occupant behaviour. These were generated by random sampling from a proportional distribution, refer to section 6.3.2.

These were simulated using the off-line consumer model for a 'typical' one-week period. The runs were pre-fixed by a 3-day period to allow for soaking to remove the effect of the initial conditions.

The figure below shows that whilst the runs follow the same daily patterns, there is variability of demand between the variant topologies.

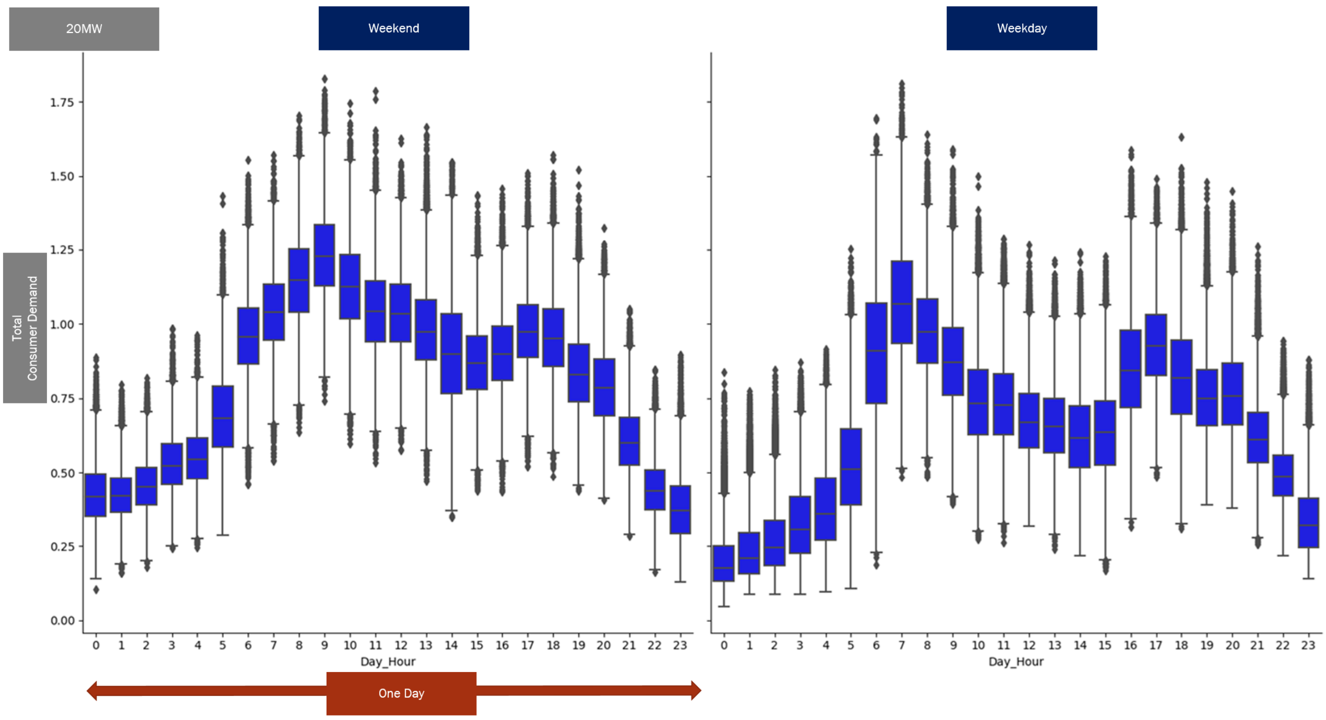


Figure 5 - Spread of Hourly Consumer Demand Across All Variant Topologies

2.6.1.3. On-Line Conceptual Architecture Model Stochastic Differences

The variant demand profiles were running through the on-line conceptual architecture model, over the ‘typical’ week.

The ‘best’, ‘mid’ and ‘worst’ performing variant topologies were selected based on consumer demand, the imbalance KPI and the ESP cost KPI. This is described in Section 3.5.

2.6.1.4. Off-Line Consumer Model Profiles over Heating Season

The ‘best’, ‘mid’ and ‘worst’ performing variant topologies were simulated through the off-line consumer model to give demand profiles over the heating season.

These were accompanied by an ‘all-gas’ topology, where heating is supplied by combi-boilers. This provides the base case, without any HHP penetration.

2.6.1.5. On-Line Conceptual Architecture Model over Heating Season

The ‘best’, ‘mid’, ‘worst’ and ‘all gas’ topologies were run through the on-line conceptual architecture model, over the heating season.

The outputs were analysed to determine the value and uncertainty of the base case proposition.

2.6.1.6. Scenario Permutations over Heating Season

The ‘best’, ‘mid’, ‘worst’ and ‘all gas’ topologies were used as a basis to evaluate the permutations of having different forecasting (time constants).

These were simulated by taking the same topologies, running the consumer model and feeding these demand profiles into the conceptual architecture model.

These were repeated with different forecasting (time constants). This could be repeated in future analysis to look other variables such as; HHP penetration, storage constraints or wind generation capacity.

2.7. Analysis Results

2.7.1. Base Run

The results from the overall heating season are presented in this section.

The trends of KPIs between each day, and over the heating season are shown.

2.7.1.1. Generation from Wind

The energy consumption over the heating season is shown in the table below.

The values are the average daily kWh per house.

CASE		Run	Electricity Sources		
			Storage	Wind	Spot
1	GAS	Std	**-1.91**	**11.12**	**0.00**
2a	30PC_HHP Infinite Power	Worst	-0.33	22.24	0.00
		Mid	**0.28**		**0.00**
		Best	1.04		0.00
2b	30PC_HHP 10 MW Power Limit	Worst	-0.48		0.15
		Mid	**0.07**		0.21
		Best	0.77		0.27

Electricity Consumption for Base Runs – kWh/house/day

The columns are Net from Storage, Wind Generation and Purchased from Spot Market. The negative values for storage indicate that there is more generation than demand, resulting in a net increase in energy held in the device at the end of the heating season.

CASE		Run	Consumption		
			Electricity	Gas	Total
1	GAS	Std	**9.22**	**69.24**	**78.46**
2	30PC_HHP	Worst	21.93	51.17	73.10
		Mid	**22.56**	**51.11**	**73.67**
		Best	23.32	48.96	72.28

Total Energy Consumption for Base Runs - kWh/house/day

The overall gas / electricity is the same in 2a and 2b.

The first table show that for combi-gas boilers (and two wind turbines), there is a surplus of energy provided, which is accumulated in the storage devices. When there is 30% penetration of HHP (and four turbines) the energy provided and consumed match closely. The absolute energy residing storage at the end of the heating season is within 5% of the total energy consumed.

The 10 MW limit on storage power was selected to match the maximum consumption from the wind turbine, so the ESP never needs to encourage curtailment of power. The second table shows that restriction only causes the ESP to buy around 1% of the energy from the spot market. This is transferred to additional energy accumulated in storage. The facility is only used on rare occasions where there is no wind during hours of peak consumption.

The deployment of heat pumps causes a 25% reduction in gas usage, (which is equivalent to 18 kWh/house/day). The strategy using storage with the 10MW limit allows nearly 99% of the electricity to come from the wind turbine.

2.7.1.2. ESP Cost

The cost to the ESP is shown in the tale below. The values are the average cost per house over the heating season (but includes all energy use – not just heating).

The reference values (yellow rows) are based on the ESP having no contract in place with wind generator or storage provide. They purchase all the energy based on the gas and electricity spot market prices.

Ref 1	GAS	Std	**242.79**	**322.99**	**565.78**
		Worst	577.57	238.70	816.27
Ref 2	30PC_HHP	Mid	**594.31**	**238.40**	**832.71**
		Best	614.34	228.39	842.73
1	GAS				
		Std	**223.34**	**322.99**	**546.33**
	[redacted]	Worst	523.61	238.70	762.31
[redacted]					
		Best	553.51	228.39	781.90
2b	30PC_HHP 10 MW Power Limit	Worst	523.68	238.70	762.38
		Mid	**537.89**	**238.40**	**776.30**
		Best	553.63	228.39	782.02
	Electricity Cost for Base Runs – £/house (over heating season)				

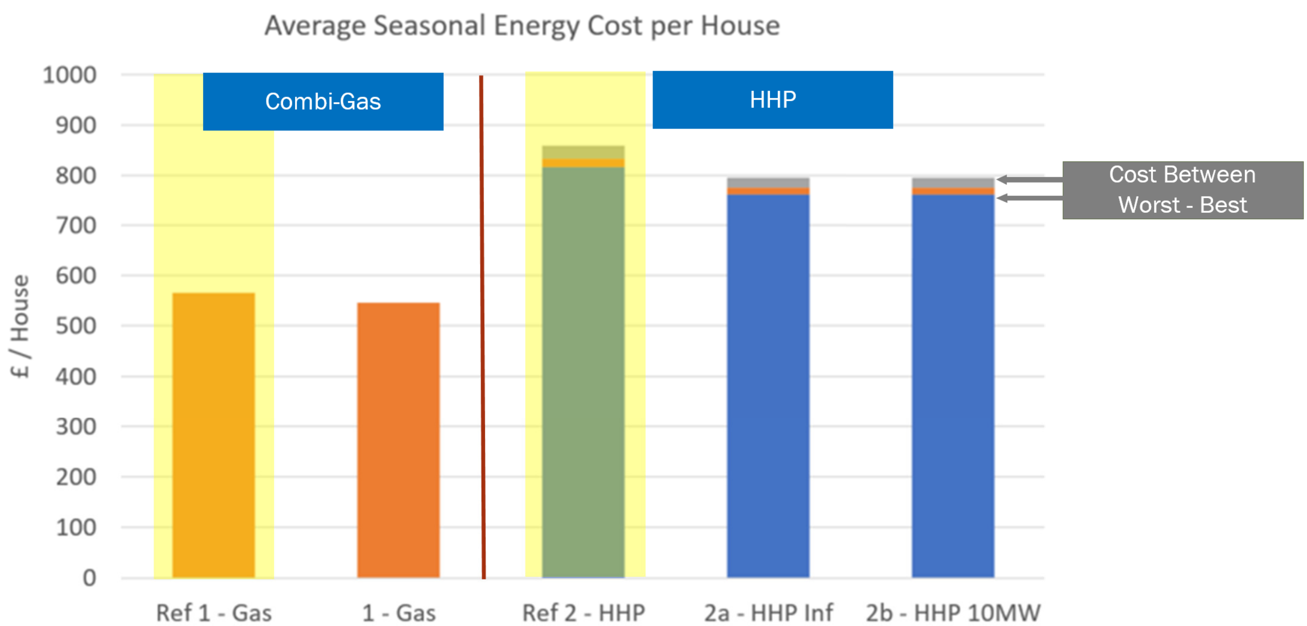


Figure 6 - Electricity Cost for Base Runs – £/house (over heating season)

The results show that, as expected, supplying energy with HHP is more expensive than combi-gas boilers. This suggests that for the proposition to be financially viable either, the price of wind needs to reduce relative to gas, or a subsidy provided. It should be noted that the prices in the analysis are based on rough estimates of price where, wind is 25% less expensive and gas is 25% more expensive than today, refer to section 2.3.2.

The proposition of using storage reduces the cost to serve. The reduction is 3% for combi-boiler heating, which rises to 7 to 9% when HHP are implemented.

There is a 4% difference in cost due to uncertainties in topology.

There is very little difference in cost when the storage power is restricted to 10 MW. This is because only a small fraction of the energy is purchased from the spot market.

2.7.1.3. Supply - Demand Imbalance

The storage power and supply delta over the winter season are shown in the tables below. The delta is difference between the total power supply and demand, over a 15-minute average.

CASE		Run	Mean	SD	MIN	5_PC	95_PC	MAX
1	GAS	Std	**-633**	**456**	**-3,994**	**-3,571**	**3,573**	**6,123**
2a	30PC_HHP Infinite Power	Worst	-118	358	-8,505	-7,125	9,346	15,978
		Mid	**69**	**374**	**-8,458**	**-7,161**	**9,590**	**16,479**
		Best	299	444	-8,473	-7,065	9,928	15,512
2b	30PC_HHP 10 MW Power Limit	Worst	-164	352	-8,505	-7,125	9,346	
		Mid	**5**	**354**	**-8,458**	**-7,161**	**9,590**	**10,000**
		Best	223	406	-8,473	-7,065	9,872	

Storage Power – kW (over heating season)

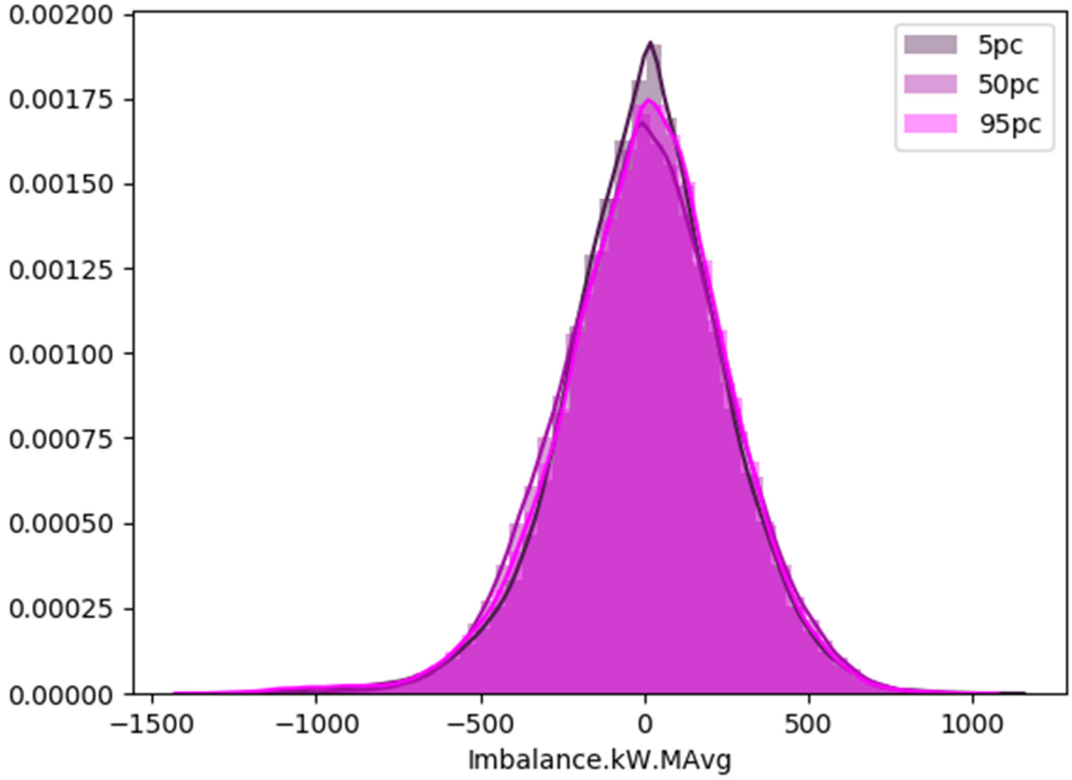
CASE		Run	Mean	SD	MIN	5_PC	95_PC	MAX
1	GAS	Std	**0**	**139**	**-465**	**-216**	**234**	**651**
2a	30PC_HHP Infinite Power	Worst	0	249	-1,272	-413	398	1,096
		Mid	**0**	**254**	**-1,130**	**-422**	**418**	**989**
		Best	0	259	-1,353	-433	402	993
2b	30PC_HHP 10 MW Power Limit	Worst	0	264	-1,272	-413	398	1,093
		Mid	**0**	**272**	**-1,127**	**-422**	**418**	**989**
		Best	0	273	-1,351	-433	402	993

Supply Imbalance - kW (over heating season)

The negative values denote charging to the storage devices when there is excess generation. Conversely positive values denote discharging when there is excess consumption.

Comparing the gas with the HHP runs, the imbalance appears to be worse when electric heating is introduced (even accounting for the doubling of consumption). This indicates that the behaviours associated with electric heating, which appears to be more chaotic to reach and maintain user-demands cause more imbalance problems than background consumption.

The graph below shows the probability distribution of the imbalance over the ‘worst’, ‘best’ and ‘mid’ runs, for Case 2b with the 10 MW power limitation.



The distribution is quite narrow with a long head / tail.

The maximum absolute delta is 1.2 MW, which relates to around 20% of the average power demand. The absolute delta for the 5th and 95th percentiles is however only a third of this value, (around 0.4 MW).

This suggest that there may be specific outlying conditions during the run where the balancing strategy is not very effective.

2.7.1.4. Storage Capacity

The scenario assumes that the storage devices have infinite energy capacity.

The table below shows the cumulative delta of the storage (in kWh) over the heating season. The tables show the difference between the maximum and minimum, and the 5th and 95th percentile.

CASE		Run	5 to 95% Range	Total Range
1	GAS	**Std**	**456,080**	**1,414,977**
2a	30PC_HHP Infinite Power	Worst	358,138	1,098,569
		Mid	**374,092**	**1,149,736**
		Best	443,727	1,294,015
2b	30PC_HHP 10 MW Power Limit	Worst	351,734	1,090,409
		Mid	**353,896**	**1,100,381**
		Best	405,899	1,207,129

Cumulative Storage (kWh) Over the Heating Season

In the HHP cases the average demand and generation closely match. In the gas case there is a notable (17%) surplus, so it will be ignored in the analysis.

The storage operator would need 1.3 GWh of storage to accommodate the cumulative delta over the entire heating season. If the storage operator had a mechanism of purchasing / selling for periods where there was either very little or significant wind (outside the 90%), this would fall to around 0.5 GWh of storage capacity.

2.7.2. Factors Impacting KPI

The analysis factors that have greatest impact on the KPIs are presented in Section 3.

Volatilities in Consumer Demand:

The volatilities in the aggregate consumer demand profile have a significant impact on ESP cost and imbalance.

The figure below shows the consumer demand taken from the 'mid' variant topology over a 'typical' weekday during the Case 2b run (HHP with power restriction).

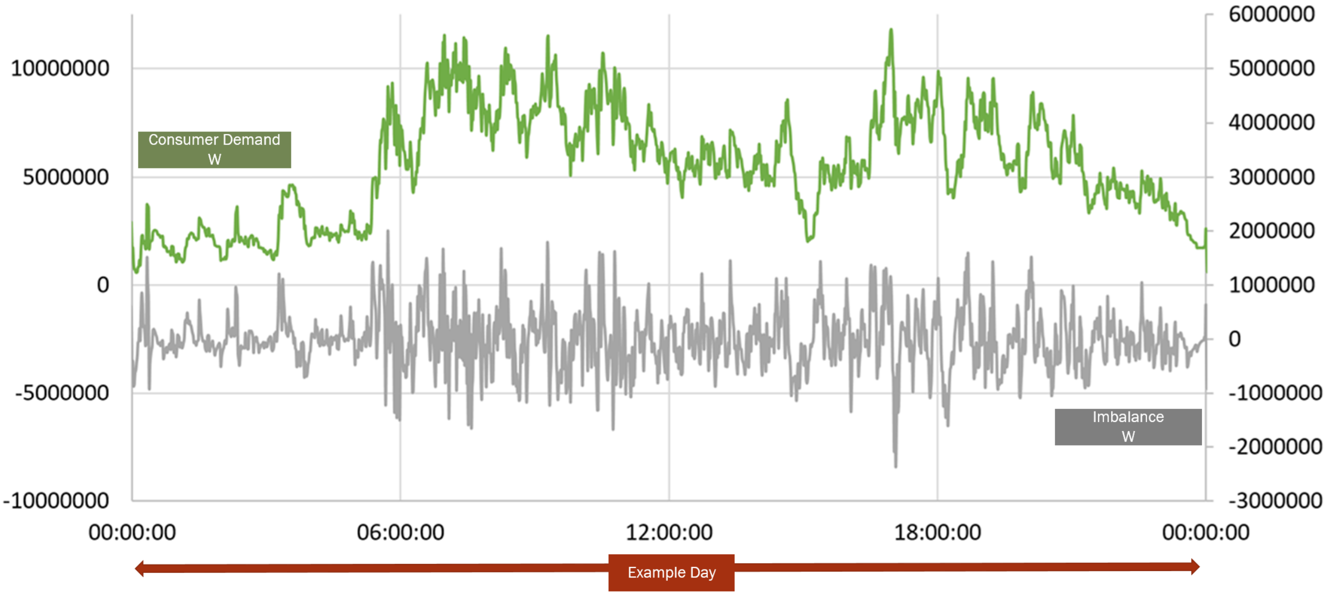


Figure 3 – Consumer Demand Against Imbalance (Example Day)

The spikes in the combined consumer load coincide with the significant imbalance spikes. This is hypothesised to be because the forecast does not see the immediate impact of the spike, so the storage response lags. The consumption spikes occur predominantly during the periods of peak heating demand, because of the co-ordination of many heat pumps switching on.

The figure below shows the daily variation in consumer demand and imbalance.

The plots show the distribution of the hourly demand. The 'worst', 'best' and 'mid runs are on the same graph in progressively darker colours, referred to a '5pc', '50pc' and '90'pc'.

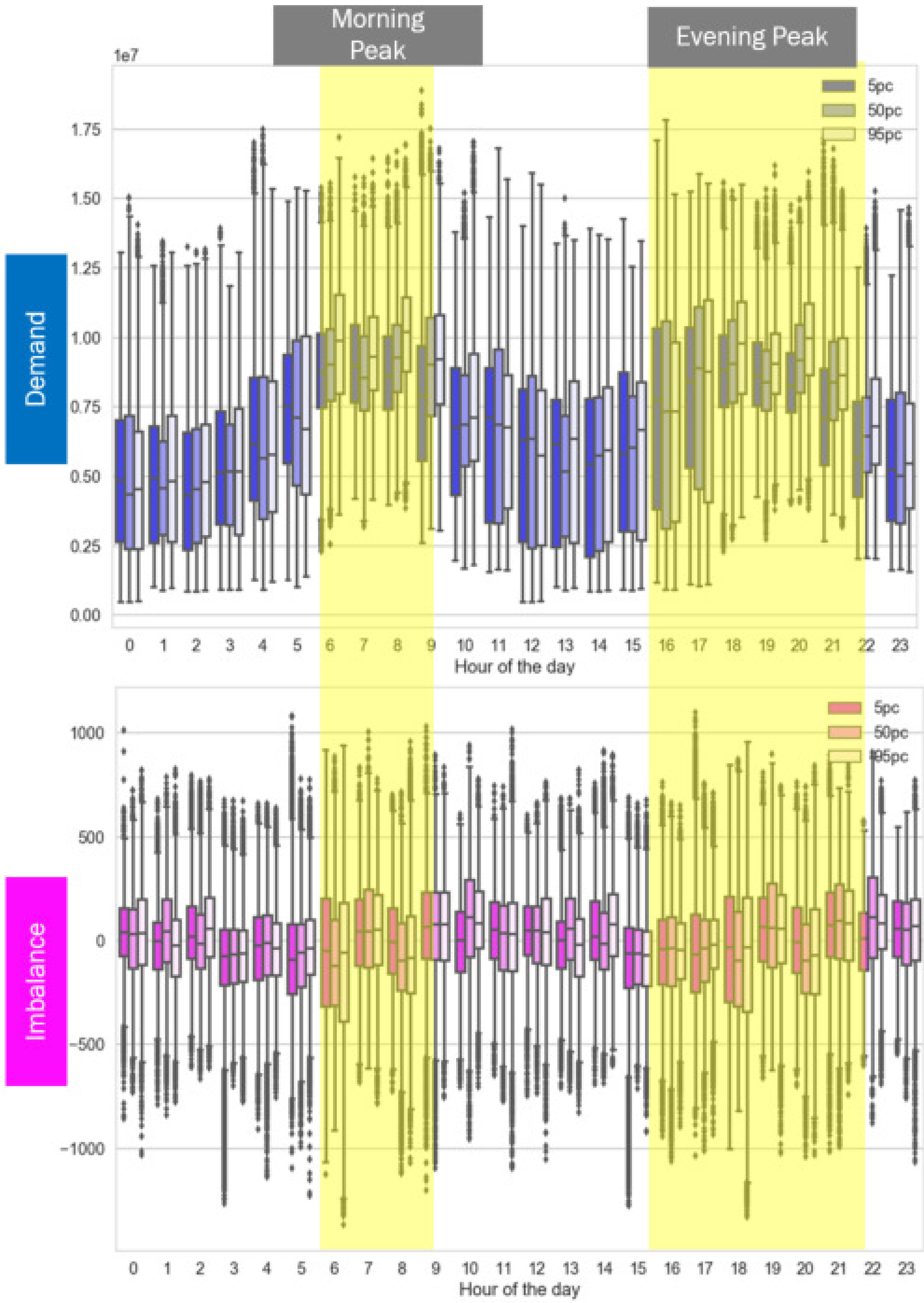


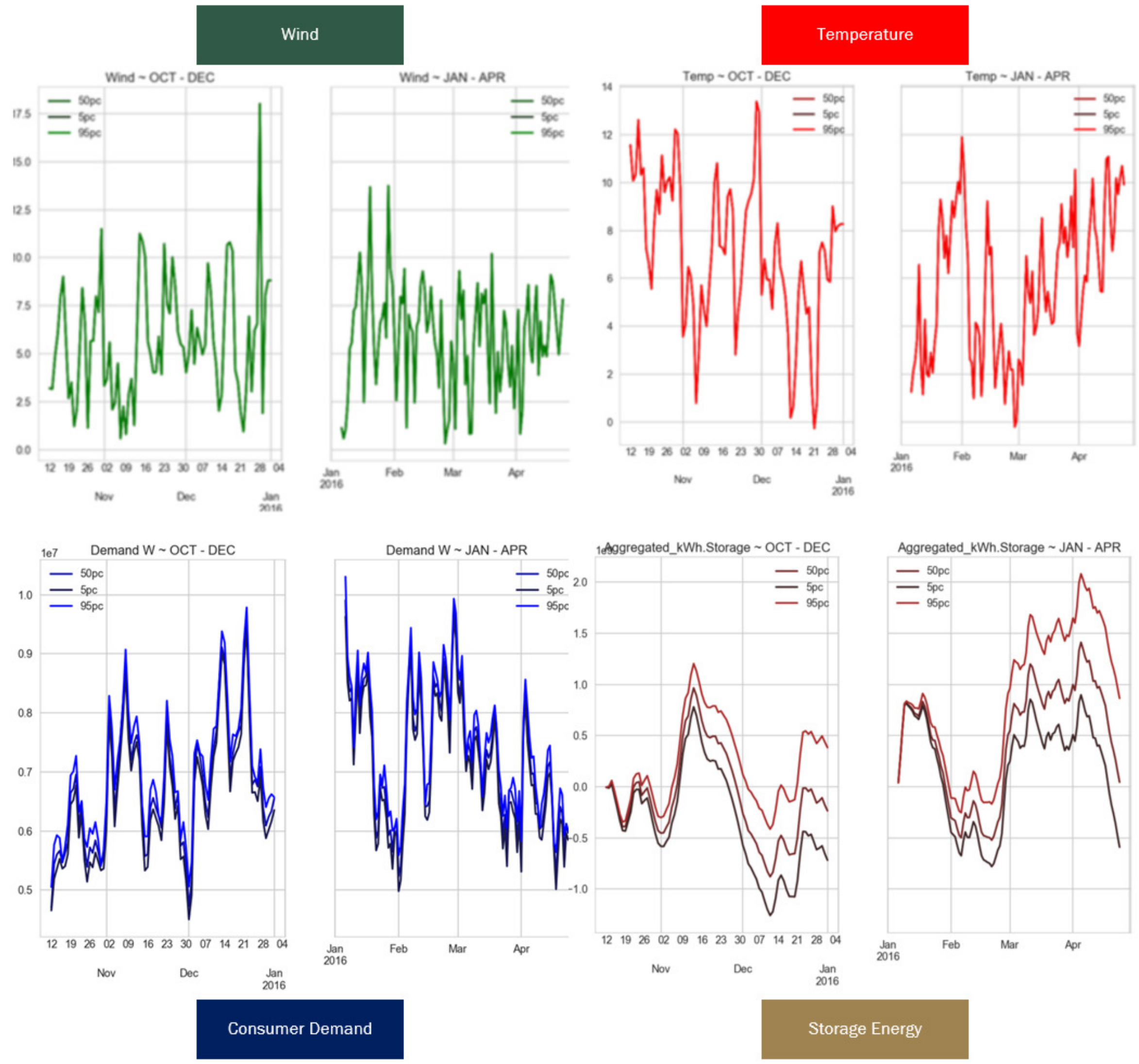
Figure 8 - Daily Consumer Demand and Imbalance over the heating season.

The graphs suggest that there is a greater occurrence of significant imbalance when there is greater deviation in the demand. This supports the hypothesis that the volatilities are likely to be caused by combined chaotic switching on of devices.

The periods however appear to be spread throughout the day, so not exclusively limited to the heating peaks, when the HHP have greater utilisation.

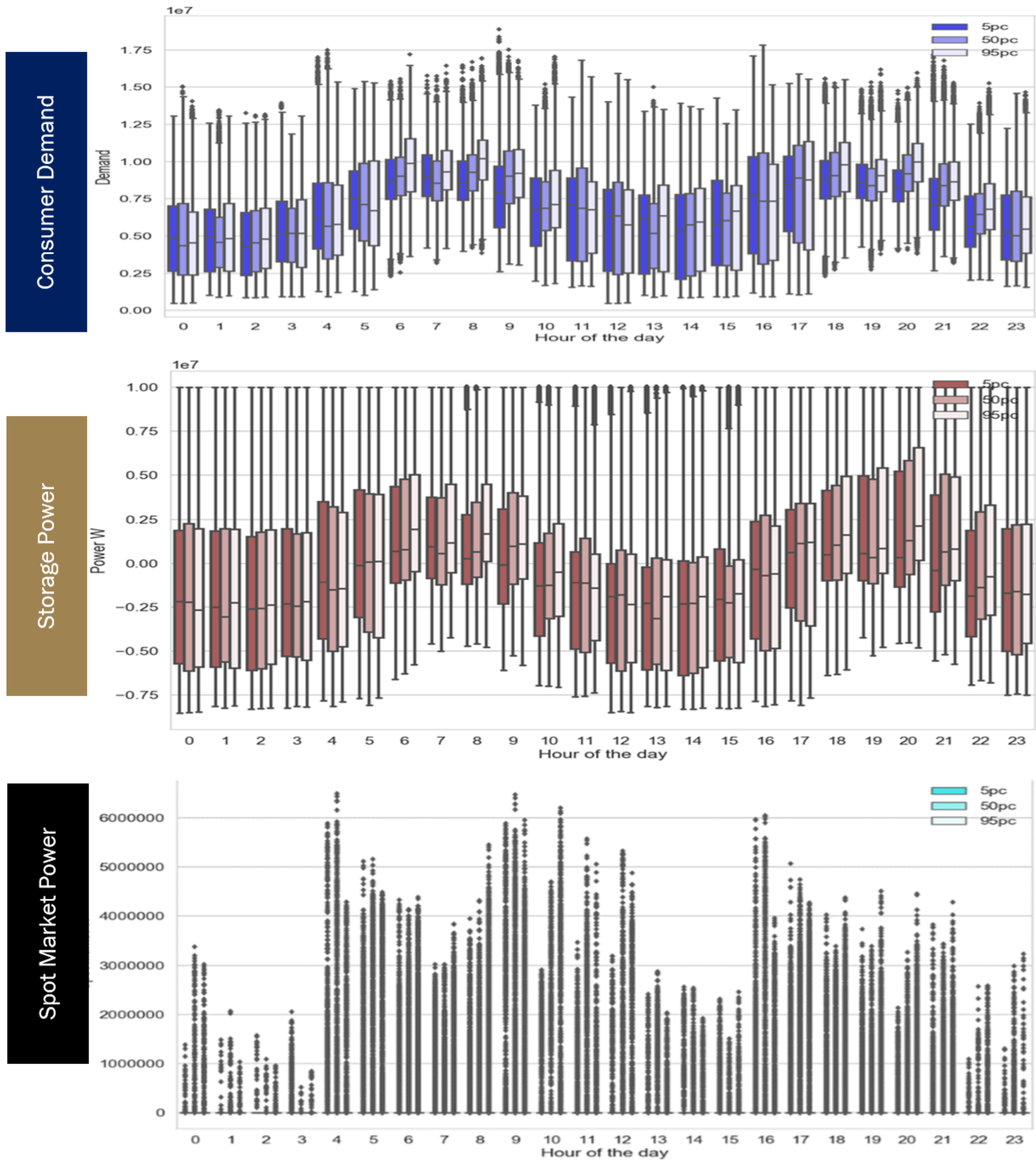
Impact of Weather:

The plots below show the variation in daily average weather conditions, demand and accumulated storage over the heating season.



The above shows that the change in accumulated storage, shows a distinct pattern influenced by weather. There is also a difference in energy accumulated in the storage device, between variant topologies.

The plots below show the variation in demand, and subsequent requests for power from the storage provider, then additional spot market generation.



The spot market is called upon less than 1% of the total time. This is on cold days with no wind, where energy is needed from the spot market, where the maximum demand is greater than the power that can be supplied from storage. The curves show that the spot market may be needed at any time during these days.

This suggests that it may not be appropriate for an ESP to have fixed volume energy contract with a wind generator over a heating season. A better strategy would be to purchase energy daily based on the weather. Storage may then be used to balance the demand within days, (Lawton, 2018).

2.7.3. Impact of Forecasting

The forecasting of the consumer demand is central to the strategy.

A set of runs were conducted with permutations in the time constant of the forecast. The smaller the time constant, the greater extent to which the forecast follows the volatility or spikes in demand. The analysis was with HHP and storage power limited to 10MW, (case 2b).

The graphs on the next page, show ESP cost and Imbalance as the forecast time constant increases from 15 seconds to 30 minutes (1,800 seconds).

The imbalance plot shows standard deviation, as we are interested in the absolute deviation away from the mean.

The graphs show that as the time constant is increased, there is a small linear decrease in the ESP cost, but a significant increase in the imbalance.

The imbalance is primarily caused by the volatility in consumer demand. The first order filter causes the forecast to lag the actual consumption, having an influence of what has just gone before. The forecasts with a lower time constant chase the short-term volatilities (spikes) in the consumption profile. This provides a closer fit to the consumption profile, despite the weighting in the filter to what has gone before.

The cost to the ESP is also slightly greater, because in order to chase the spikes, there is a short-term request for additional charge, followed by a request for discharge after demand falls. They incur a marginal cost for this.

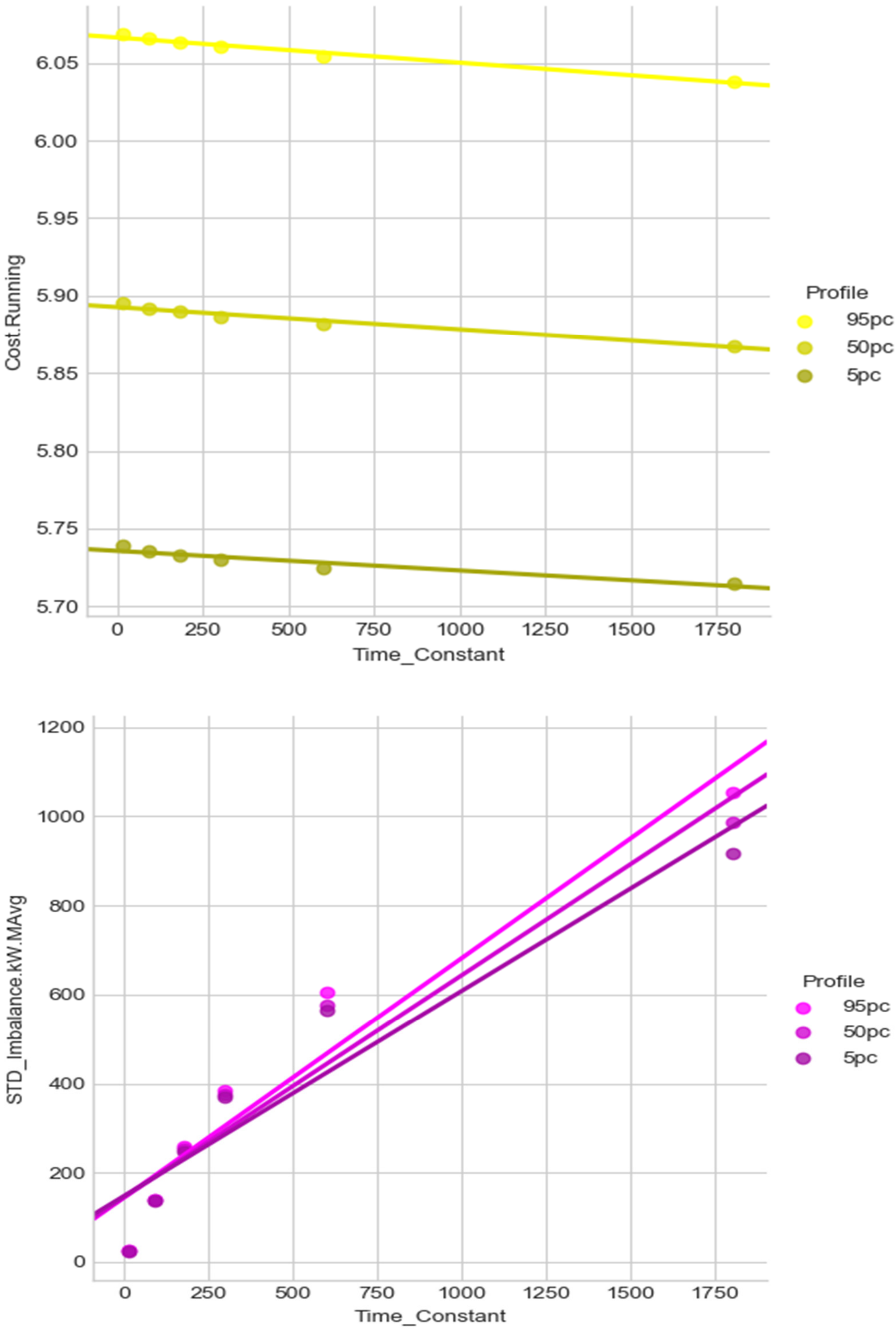

6.05
6.00
5.95
5.90
5.85
5.80
5.75
5.70
Cost.Running
0
250
500
750
1000
1250
1500
1750
Time_Constant
Profile
95pc
50pc
5pc
1200
1000
800
600
400
200
0
STD_Imbalance.kW.MAvg
0
250
500
750
1000
1250
1500
1750
Time_Constant
Profile
95pc
50pc
5pc

Figure 1

2.8. Recommendations

2.8.1. Value of Business Proposition

The value of the business proposition is evaluated against the five design principles of the conceptual architecture, defined in the D1-1 Solution Context, Goals and Objectives project document, (Energy Technologies Institute, 2017).

CONSUMER CENTRICITY: The scenario assumes that the consumer operates HHP and combi-boilers in the same way without restriction. The impact is assumed to be neutral.

SOCIETAL OBJECTIVES: The scenario facilitates decarbonisation, by increasing the utilisation of renewable energy (wind generation) and decreasing gas usage.

PHYSICALLY CONSTRAINED: The scenario requires storage facilities with power and storage capacities that are significantly greater than available on a local level.

The UK has 12.5 MW of power and 20 MWh of non-pumped hydro storage, either on-line or under construction (as of 2015), (Deign, 2015) The strategy requires 10 MW power and 400 MWh capacity to manage most of the load over the heating season, for just this small section of Bridgend. Although there is continued enhancements in storage technology, the relative scale suggests that this may not be economic.

The future scenarios would need to consider how the storage operator could provide this facility with smaller, (more economically viable), storage devices. This would need the storage operator to manage the inventory of energy held in their devices to allow multiple charge/discharge cycles over the heating season.

COMMERCIALLY ALIGNED: The operating costs to the ESP are higher when HHPs are introduced than supplying consumers with conventional combi-gas boilers by contracting energy from the day ahead market. This is dependent on the future price of wind relative to gas, and the storage margin.

The imbalance improves, but the cost to the ESP increases, as the forecast time constant decreases, as discussed in Section 3. The tolerance of the imbalance would need to be agreed by the actor whom it is likely to be most impacted, presumably the network operator. There would need to be an incentive, (based on this tolerance), to the ESP that would be greater than the cost of using additional storage to manage short term volatilities in demand.

The business processes of the storage operator would also need to be considered in future scenarios.

SECURITY AND RESILIENCE: The imbalance in supply and demand is significant. It is particularly pronounced during peak heating times when consumer demand has significant volatilities.

OTHER: The differences due to uncertainties in the potential variants in topology, (heat pump allocation and occupant behaviour), have a modest impact on the results (up to 7%). The sizing of the wind generation against the proliferation of heat pumps is likely to be more significant factor.

2.8.2. Analysis Limitations

CONSUMER BEHAVIOR REPRESENTATION: The volatilities (spikes) in consumer demand appear to have the greatest impact on imbalance and energy inventory within storage devices.

The comparison against published experimental data suggests that the EPO model simulates a profile with greater volatility (short term spikes), (Barteczko-Hibbert, 2015; Love, et al., 2017). This is however not a like for like comparison. The difference could be based on a combination of; the representation of consumer behaviour within the allocation function, the local control of the heat pump and the size of the heat pumps. This is discussed in the appendix, Section 3.3.

Given this is a key aspect of the model, it would be appropriate to investigate this further, looking at the body of work on the subject in academia and outcomes from the SSH phase 1 HEMS field trial and IEH project to improve this aspect of the model, (Nijhuis, Gibescu, & Cobben, 2016; Hauser, Evora, Kremers, Hernandez, & Hernandez-Tejera, 2016; Alfakara, 2017).

CONSUMER PHYSICAL REPRESENTATION: The physical consumer model is tuned to give sensible behaviour and is currently not validated. There is an ongoing scope of work to compare the structure of the model and improve tuning parameters against the IEH model.

The physical model does not currently include the impact of solar radiation, wind or orientation of the house, which may improve the representation of the building if appropriate data is available.

The spread of building parameters across archetypes is based on the Cambridge Housing model, (which is being superseded) and does not currently consider energy efficiency measures. This is discussed in the appendix, refer to section 3.2.

OTHER EFFECTS: Improving the behavioural and physical representation of consumer behaviour may cause inaccuracies in other aspects of the model to have greater relative significance.

There may be scope in future analysis to include more detailed representations of;

- storage that considers energy conversion and in situ losses,
- wind generation that includes representations of mechanical inertia and localised stochastic changes in wind conditions,
- the variability of energy prices over time and the impact of actor decision making on price.

2.8.3. Future Scenarios

The scenario has a sufficiently small number of variables for understanding, and so provided a usefully bound set of experiments to give a first pass evaluation. The initial results suggest that the boundary could be incrementally expanded future scenarios so that the problem starts to become a more realistic representation of the future energy system architecture.

STORAGE OPERATOR INVENTORY CONTROL: The analysis of future scenarios would need to consider how the storage operator maintains the energy inventory within their devices. There is currently no economically viable seasonal storage solution available to support anything but a modest penetration of renewable heat, (Lawton, 2018; Clarke, 2016).

The devices currently used for voltage imbalance and wind integration have 300 to 3,000 charge / discharge cycles per year, as presented in Section 2.2.3. This would require a storage device with a capacity below 10 MWh, as opposed to 1,300 MWh for the entire season.

The future scenarios should also consider storage devices with more appropriate power limitations. This may require developing the conceptual architecture so that ESP had other levers to address significant imbalances, (such as a predicted drop in wind) and use storage for finer control.

CONSUMER DEMAND SIDE MANAGEMENT: The scenario analysed currently assumes that the ESP has no interaction with the consumer. In other words, usage of the heating appliance is unconstrained.

A future scenario may consider Demand Side Management (DSM) of the consumer load. This can be achieved by pre-heating to charge energy and shedding to discharge energy. The limits in this case will be maintaining the temperature within comfort bounds.

The subsequent analysis can consider how this lever can be used to reduce the power capacity of the storage device.

This could be combined with work from the HESG project to understand how levers for DSM may fit into the winder energy system architecture.

IMBALANCE REPRESENTATION: The scenario assumes that the voltage stability is a function of the demand / supply averaged over a 15-minute window.

The voltage on the distribution network could be impacted by; the degree of the demand / supply imbalance, the time window, the signature of signal within this window and the location of the loads on the network topology.

The inclusion of a distribution network model is planned for future scenarios. This can help determine a metric for the ESP to adhere to that causes minimum problems on the network.

COST REPRESENTATION: The financial viability of the scenario will depend on the differential between the price of wind relative to: the spot market, gas price and storage margin.

The price will depend on the generation mix available, demand and the business operation of actors. The future scenarios may want to consider the change in price over the day and between days.

The energy prices will change in the future depending on the energy mix and demand. These can be obtained from energy transition models, such as ESME and the UCL TIMES Model, (Pye, Sabio, & Strachan, 2015).

There will be a break-even price, where the supply cost is equal to the price of purchasing all energy from the market. The break-even storage margin could be derived as a linear equation where the coefficients relating to prices, become KPIs that feed into a wider analysis.

The viable storage margin will depend on the lifecycle cost of the asset. This is a function of the utilisation of the assets, the operating cost and capital costs.

The wider analysis could consider the points in these transition scenarios, where storage becomes a significant proposition. This would in turn impact the viability of different energy mixes and therefore the price, which may iterate back into EPO analysis. This may also consider how the storage devices could be utilised for other services, such as voltage contingency to handle generation outages, considered as part of Storage and Flexibility project.

FORECAST REPRESENTATION: The analysis of perturbations in the forecast time constant suggests that a first order filter may not be an appropriate forecast representation. It gives weighting to recent past events, which is not entirely realistic.

The ESP would likely have a 'model' based on data collected, to give an understanding of the 'general shape of the profile' and key factors that impact the shape. It is unlikely they will have visibility of short term volatilities caused by the coordination of chaotic behaviours.

The ESP forecast model could be a static input, or something that the ESP learns / refines based on the data collected over a simulation, (Mirasgedis, et al., 2006).

ACTOR DECISION MAKING: The decision making by the actors (ESP, Generator and Storage Operator) is currently static. In reality the control decisions, including pricing, will be based on the information available and an incentive. The decision-making processes will have interacted, as the actor's response to constraints and prices effect the other actors in the system. This is a growing body of work and something to consider for future scenarios, (Bublitz, Genoese, & Fichtner, 2014; Behboodi, Chassin, Djilali, & Crawford, 2018; Ringler, Keles, & Fichtner, 2016).

ABNORMAL OPERATION: The analysis just considers normal operation. The impact of mechanical failures, unusual events and information communication faults may be something to consider in future scenarios.

2.9. Conclusions from Use-Case Analysis

The analysis presented has shown how EPO can be used to analyse a conceptual architecture under a given operational scenario.

2.9.1. Definition

The process has a structure for defining the problem. This included justifying the significant decisions and assumptions at increasing levels of decomposition.

This analysis process starts by taking a high-level scenario definition, '*the ability of an ESP to manage the delta between the demand for electricity and the available supply from the wind generator using storage*.'

The process then defined at high level; the actors (and their relationships), the disturbances (including the time steps and horizon) and the outputs (insights required). The process described the physical processes and business processes that need to be represented. Finally, the process then details; the KPIs to provide the insights, the physical representation of the system and appropriate modelling assumptions.

This provides a foundation for defining, the requirements of the EPO library modelling objects and the data sources to parameterise the simulation runs. Furthermore, this provides a structure for defining the analysis, such that any assumption or decision, (at any level), can be challenged and revised in subsequent iterations of the analysis. The challenge is ensuring that the definition is sufficiently comprehensive to allow this, yet has a story that is explainable to a stakeholder.

2.9.2. Execution

The analysis process then defines a methodology for conducting the analysis. Given that there is no interaction between the consumer and ESP, the demand was calculated by a separate off-line consumer model. The demand profile was fed into the on-line Conceptual Architecture model.

Given that the unknowns in the variability of the topology, a set of runs were conducted to consider the stochastic differences in appliance allocation and occupant behaviour. The 'worst', 'mid' and 'best' variant topologies were selected for a week, then evaluated over the heating season to look at performance with changing periods of weather.

2.9.3. Results

The analysis showed that the conceptual architecture improved the utilisation of renewable energy (wind generation) and reduced usage of fossil fuels. The implementation of heat pumps in the scenario causes a 25% reduction in gas usage and allows nearly 99% of the electricity to come from the wind turbine.

There were periods where it was not effective for balancing supply / demand for network stability. The distribution of imbalance over the scenario run has a long tail, where the imbalance was up to 20% of total consumption.

The analysis indicates that finer resolution of forecasts improves imbalance, but (with the metric used) increases the cost to the ESP. The architecture would need business processes between the network operator and ESP to ensure that two parties financial incentives are aligned.

The reality of the analysis is however limited by the assumption of infinite capacity, which would be economically unrealistic to supply. The energy capacity of the storage required for a part of a town is greater than the total non-pumped hydro storage currently available in the UK. The operators generally have smaller storage devices with alternative sources to top-up or empty storage.

2.9.4. Further Work

There is scope to widen the boundary of future scenarios to include the business processes that the storage operator may use to maintain inventory using devices with capacities that are economically realistic. Additionally, it may also look at other levers, such as using consumer demand side management, yet ensuring comfort is maintained. These could be included developing the analysis to compare the impact / value of introducing each handle.

The analysis of this example scenario suggests that the representation of the aggregated consumer demand is critical. The objective here should be to get an aggregated curve with a sufficiently representative shape to test the control of the architecture for the insights required. The representation of occupant behaviour is noted in literature to be difficult to define. This needs further investigation and validation and will be further complicated as there is more scope for transport, non-heating loads and behind-the-meter storage etc.

It is also affected by the local control of the heating appliances. The local control should be considered when defining and refining conceptual architecture design. Making the individual profiles less volatile will reduce the impact of co-ordinated chaotic behaviours, so will reduce volatilities in aggregated consumer profile.

The forecasting could also be reviewed to provide a more realistic representation of the prediction that an ESP could obtain with the understanding and data of their consumers.

The use of the 15-minute moving average to quantify imbalance may also want to be investigated in future analysis. This may need refinement when networks are introduced in the model to verify that it is an appropriate metric to use with respect to impact on voltage stability.

3. Appendix – Analysis Detailed Results

This section provides further detail about some components of the analysis described in section 2.

3.1. Selected Topology

The table below compares the topology chosen for the analysis:

- The topology used in the scenario. This represents an area of Bridgend with 7,484 domestic properties.
- The housing stock in England, derived from the English Housing Survey (EHS)

The rows highlighted red show where the proportion in the EHS are significantly greater. The rows highlighted green show where the portion in Bridgend are significantly greater.

	Bridgend HV560024	EHS
Property Type		
Detached	22.33%	21.67%
Semi-detached	35.90%	28.58%
Mid terrace	22.86%	18.93%
End terrace	12.19%	10.48%
New build HLR 1	0.00%	0.12%
Purpose-built flat	3.10%	16.17%
Converted flat	3.62%	4.05%
FloorAreaBand		
Floor area band 1	1.65%	50.70%
Floor area band 2	8.26%	28.08%
Floor area band 3	29.31%	11.51%
Floor area band 4	23.42%	4.71%
Floor area band 5	37.36%	5.00%
Floor area band 6	3.95%	0.22%
Floor area band 7	1.37%	0.04%
Property Age		
Pre-1914	30.18%	19.95%
1914-1944	2.95%	15.83%
1945-1964	16.92%	18.95%
1965-1979	22.02%	20.13%
1980-present	14.31%	5.18%
New Build	13.62%	19.95%
Occupancy		
1 person	20.99%	30.39%
2 people	42.61%	35.30%

3 people	12.91%	15.15%
4 people	23.49%	19.16%

Selected Topology

The region has slightly larger houses, with fewer solo occupant and fewer flats, compared to the national average. The region looks reasonably 'typical' of a 'semi-urban' neighbourhood and not significantly different to the national average.

The impact of these differences could be investigated, (if desired), by re-running the analysis using the national proportions.

3.2. Consumer Model Tuning

The heating system, building and appliance control parameters were tuned to give a 'realistic' room temperature response and energy consumption profile to heating demand.

This was done for combi-boiler and HHP. These are controlled so that the appliance switches on / off based on whether the room temperature is above/below set-point, with a hysteresis. The appliance power is defined by proportional control based on the radiator set-point. When the radiator temperature is significantly below set-point (which is usually the case when the device switches on), the appliance switches on at maximum capacity. As the radiator temperature comes close to set-point, the device power reduces in proportion to the difference, until the system approaches a steady state equilibrium. This then ends when the room is at temperature set-point, the heating appliance switches off and the cycle repeats.

In the case of the HHP, the heat pump provides the space heating demand. There is a switch-over temperature to allow the combi-gas boiler to be used instead at low temperatures, but in the analysis, this is set at a very low value so it is never activated. The combi-boiler provides the hot water heating. The control logic is configured such that both devices cannot be on together.

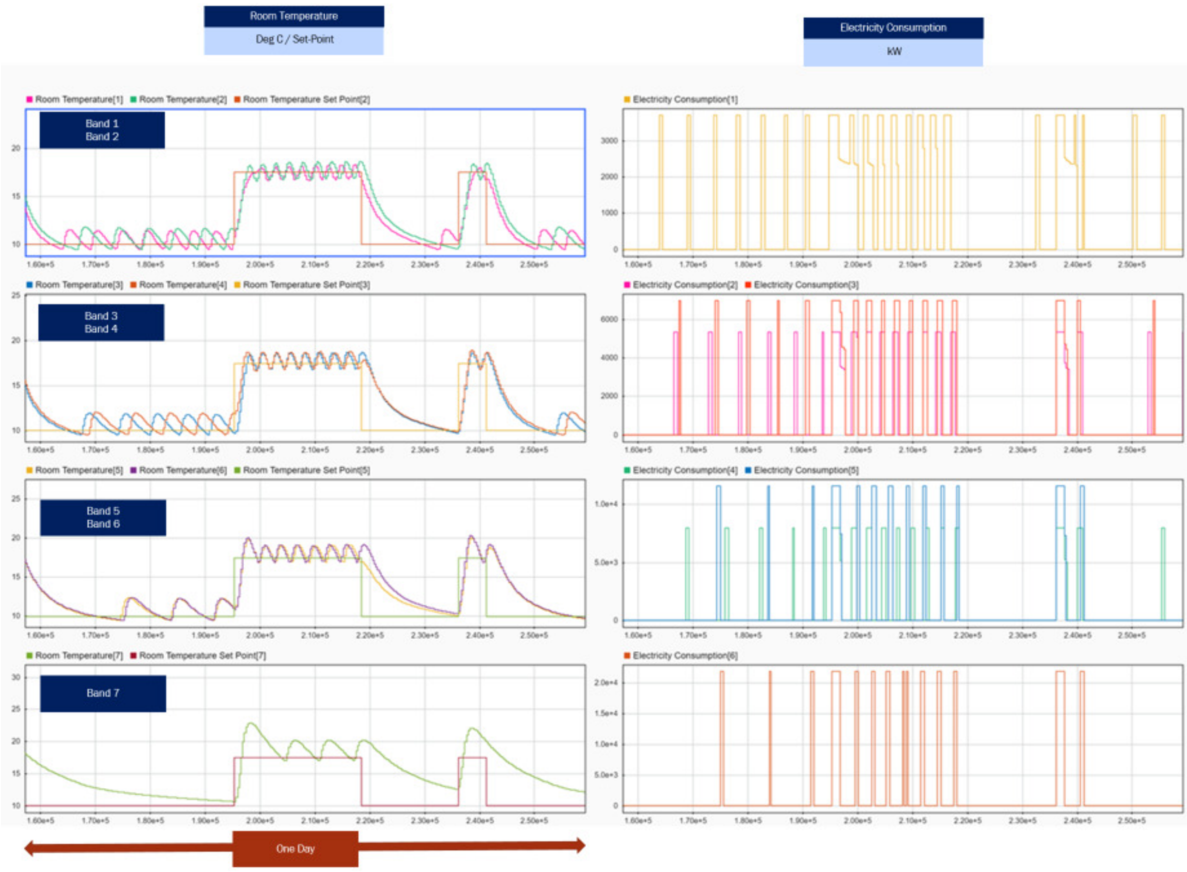
The initial tuning was based on a central archetype. This was taken to be the 1970s semi-detached house average with floor area band 3. The ambient temperature was kept constant at 5^{o}C.

The tuning was then scaled using building thermal resistance (UA) values from the Cambridge Housing model relating to the English Housing Archetypes. These are based on the Government's Standard Assessment Procedure for Energy Rating of Dwellings (SAP) calculations, (Standard Assessment Procedure (SAP 2012), 2014). The building's heat capacity was scaled based on floor area (physical dimensions), with the remainder attributed to property age – to match the spread of values defined in the SAP calculations.

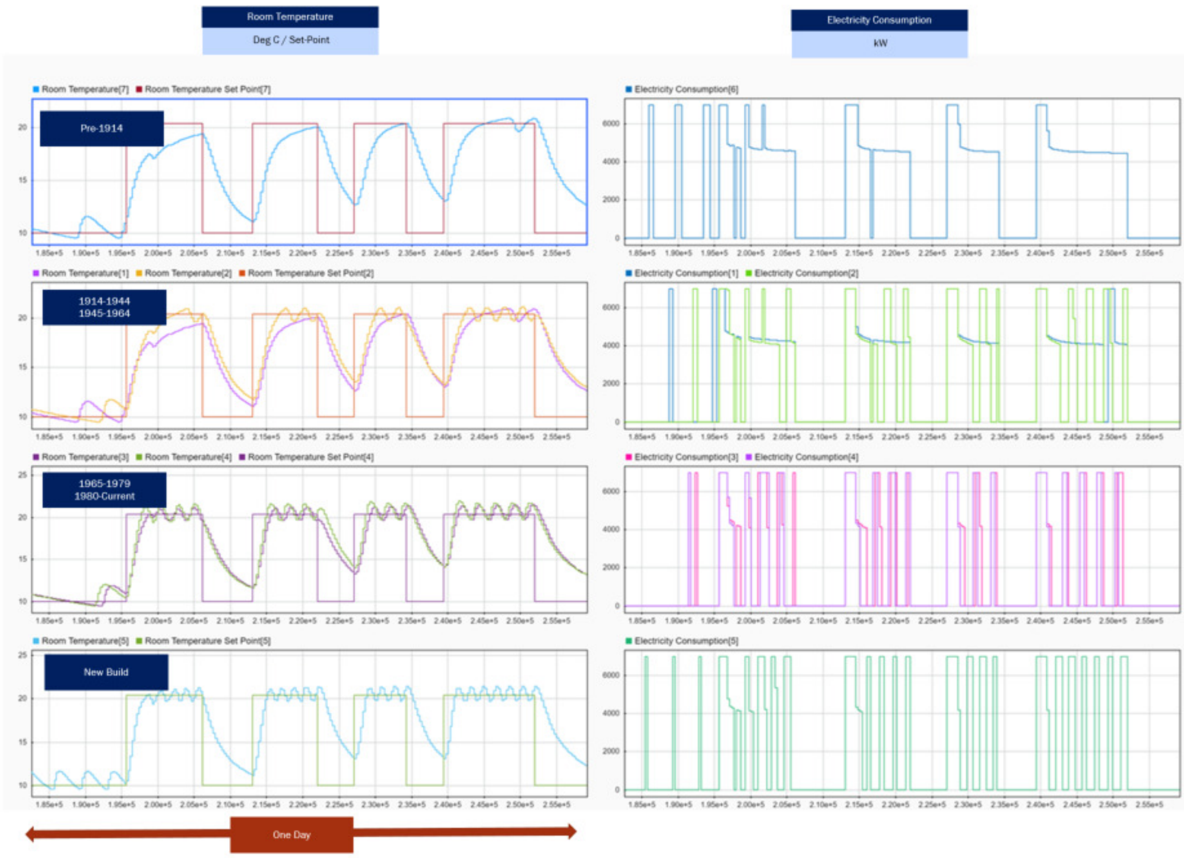
The runs suggested that the consumer model needs to be run for a minimum period of three days to allow the model to 'soak', before looking at the profiles. After this period the electricity and temperature consumption profiles do not appear to be significantly influenced by the initial conditions for the thermal states (heating system and building fabric temperatures). It may be appropriate to conduct further tests to compare the profile and internal states with daily repeating disturbance conditions, to verify this conclusion.

The figure below shows the room temperature and electricity consumption for 1970s semi-detached house with increasing floor areas.

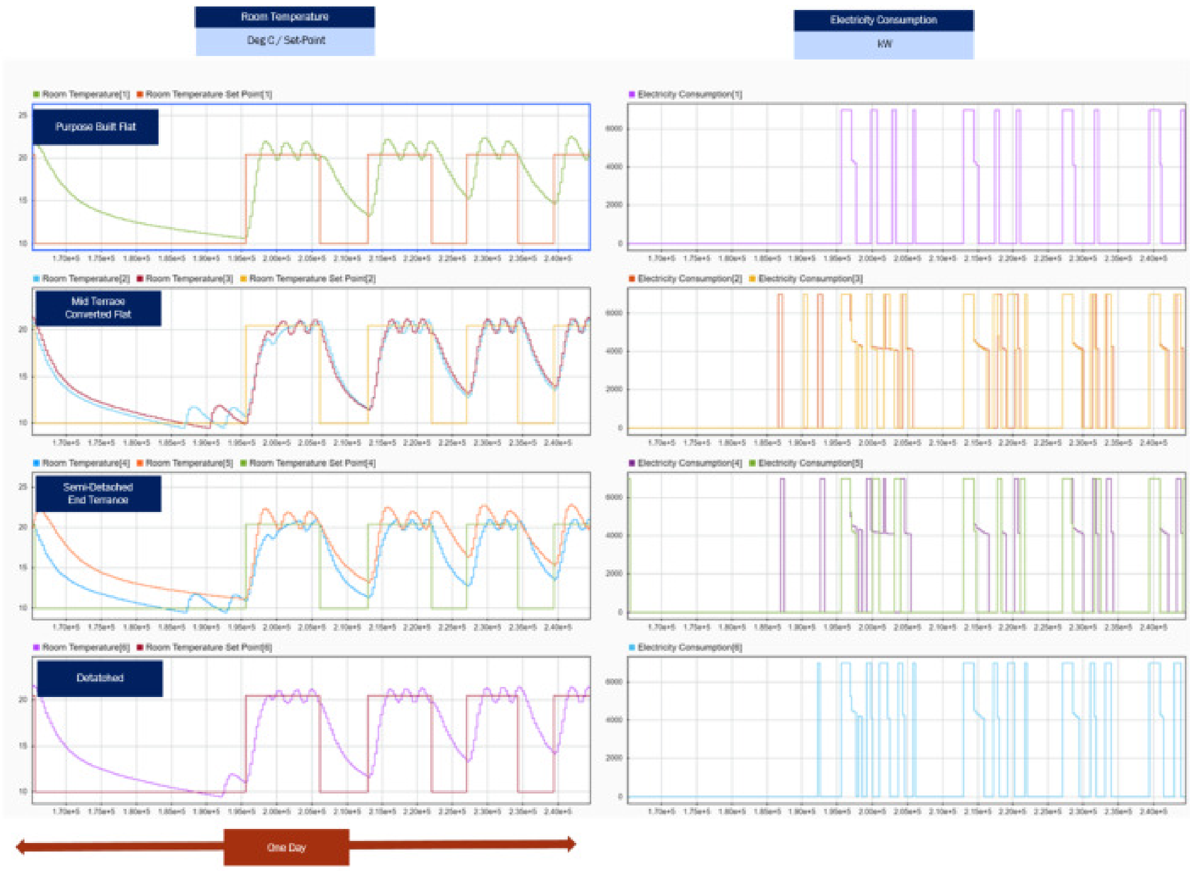
The duty of the heating appliances and the size of the radiators (defined by heating appliance resistance and thermal capacitance), were scaled in proportion to the floor area (average value of the band).



The figure below shows the room temperature and electricity consumption for semi-detached house, floor area band 3 with property age – older to newer properties.



The figure below shows the room temperature and electricity consumption for 1965 – 1979 properties, floor area band 3 for different property types.



slices of house archetypes.

The trends do however suggest the house may cool down too much when heating is switched off. This was difficult to tune at the expense of the cycling of the heating device. This suggests that the model may be over simplistic. The 'grey box' representation may not be sufficiently complex to capture the key aspects of the response required (Bacher & Madsen, 2011).

The response of the electricity consumption is potentially more volatile than expected. There are a variety of HHP control schemes. These generally use gas boiler to supplement the heat pump during the warm up period and often attempt to keep the heat pump at a steady speed below maximum. These local control schemes can be considered as part of the architecture design and evaluated in subsequent analysis.

In addition to the trends, the daily consumption (integral of the demand curve) was calculated. This was typically between 15 and 40 kWh/day, which is a realistic expectation for an ambient temperature of 5 ^{o}C. The trends were also consistent with property types, increasing with floor area, decreasing with age and detached houses using more than terraces and flats.

A similar analysis was conducted for combi-gas boilers. This is not shown because the gas consumption profile was not considered in the analysis conducted, and electricity consumption was based on input data.

The results are appropriate to demonstrate the principles of the analysis. There is however an ongoing piece of work to compare the consumer model against the Integrated Electric Heating (IEH) model (Energy Technologies Institute, n.d.), which has a more detailed representation. Initial investigations show significantly higher aggregated energy consumption of the EPO consumer model using the tuned parameter values described in this section, compared with IEH results, apparently due to significant differences in the building-to-environment thermal resistance values specified in the Cambridge Housing Model and the IEH model. Further work is required to understand the rationale behind these differences.

The method does not consider the impact of different energy efficiency measures (secondary classifications in the EHS). This would lead to a greater number of archetypes. In order to facilitate simulation with efficient run times, an approach of clustering properties based on similar thermal properties rather than exact archetype classifications would need to be considered, using a similar approach to that used on EPN.

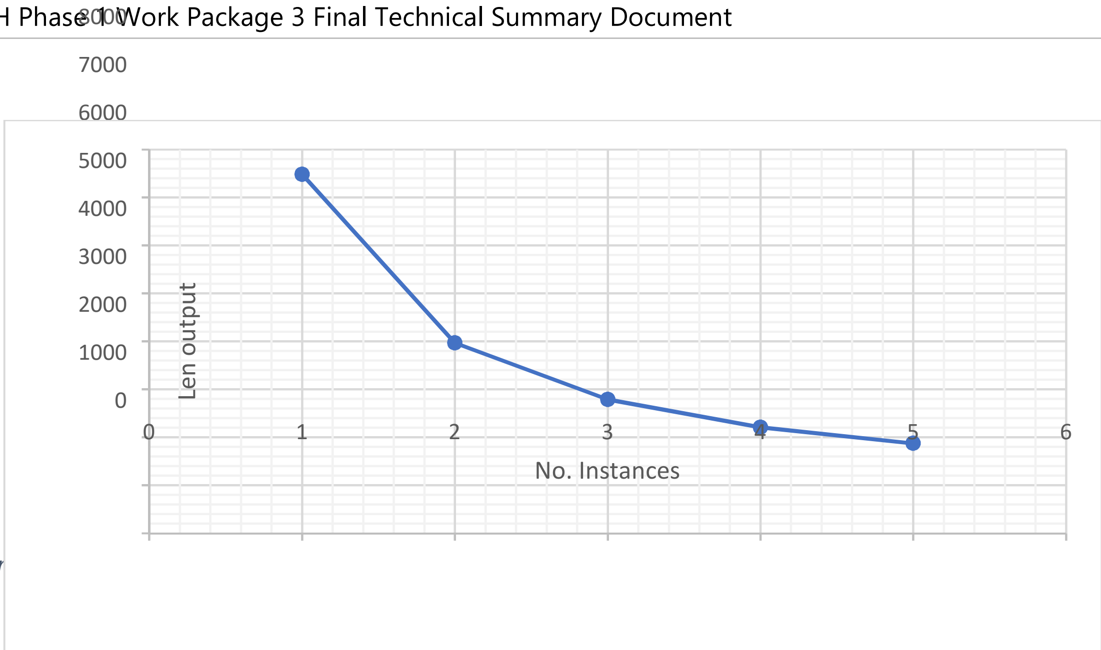
3.3. Off-Line Consumer Model Check

The off-line consumer model contains the consumer model, environment model and aggregation node. The ability of this to simulate topology (HV560024 Bridgend) with the tuned parameters was sanity checked to ensure that the model produced sensible results within a practical simulation time.

3.3.1. Grouping Instances

The analysis looked at whether the computation speed could be reduced by grouping houses of the same archetype into a common instance, defined in the allocation function Section 6.3.

The graph below show that based on the topology, grouping instances of the same archetype into groups of 5, reduces the number of consumer model instances from 7,484 (one for each house) to below 2,000. There does not appear to be significant saving going beyond 5 instances per group, as the curve approaches the minimum limit

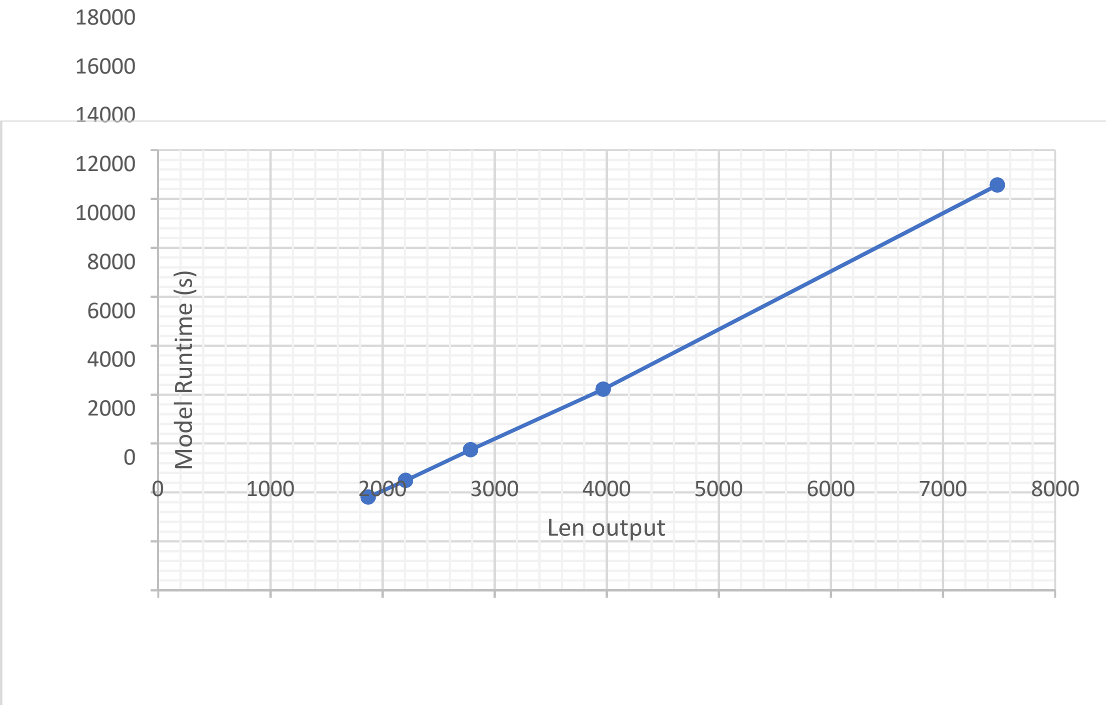


Figur

The s

based on running the model for one week on a single server core.

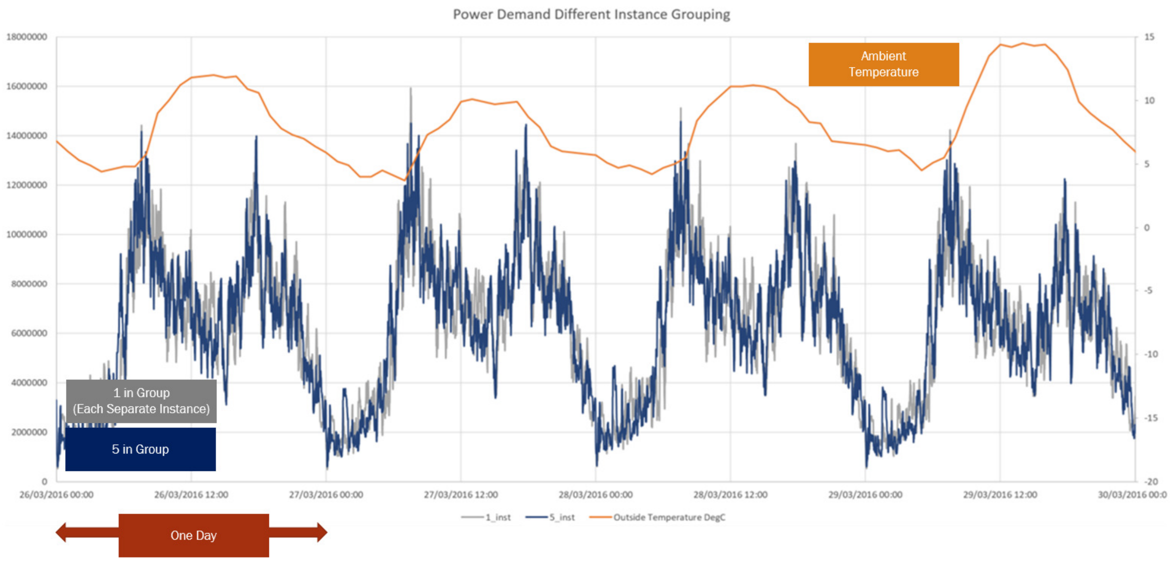
The graph shows that the run time is directly proportional to the number of instances. Therefore, grouping identical archetypes into groups of 5, will reduce the run time by a factor of four, from 16,000 seconds (6 hours) to 4,000 seconds (1.5 hours).



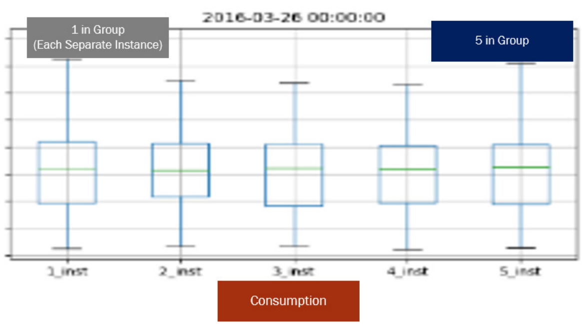
nption

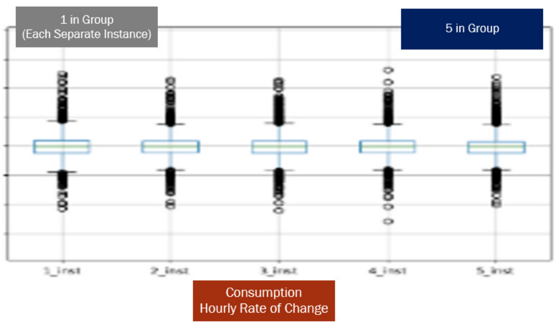
profile.

The graph below shows that the demand curves follow the same trend, when domestic properties are represented by separate instances, compared to grouping them into batches of 5.



when items are grouped together and represented by a common instance.





The grouping is considered appropriate to use in the analysis. The difference in the curves, is small relative to the fidelity of the building model and assumptions in defining the topology.

3.3.2. Comparison to Measured Data

The Consumer Lead Network Revolution (CLNR) is one of a limited number of trials that have been conducted analysing electricity consumption from installed heat pumps, (Barteczko-Hibbert, 2015; Love, et al., 2017).

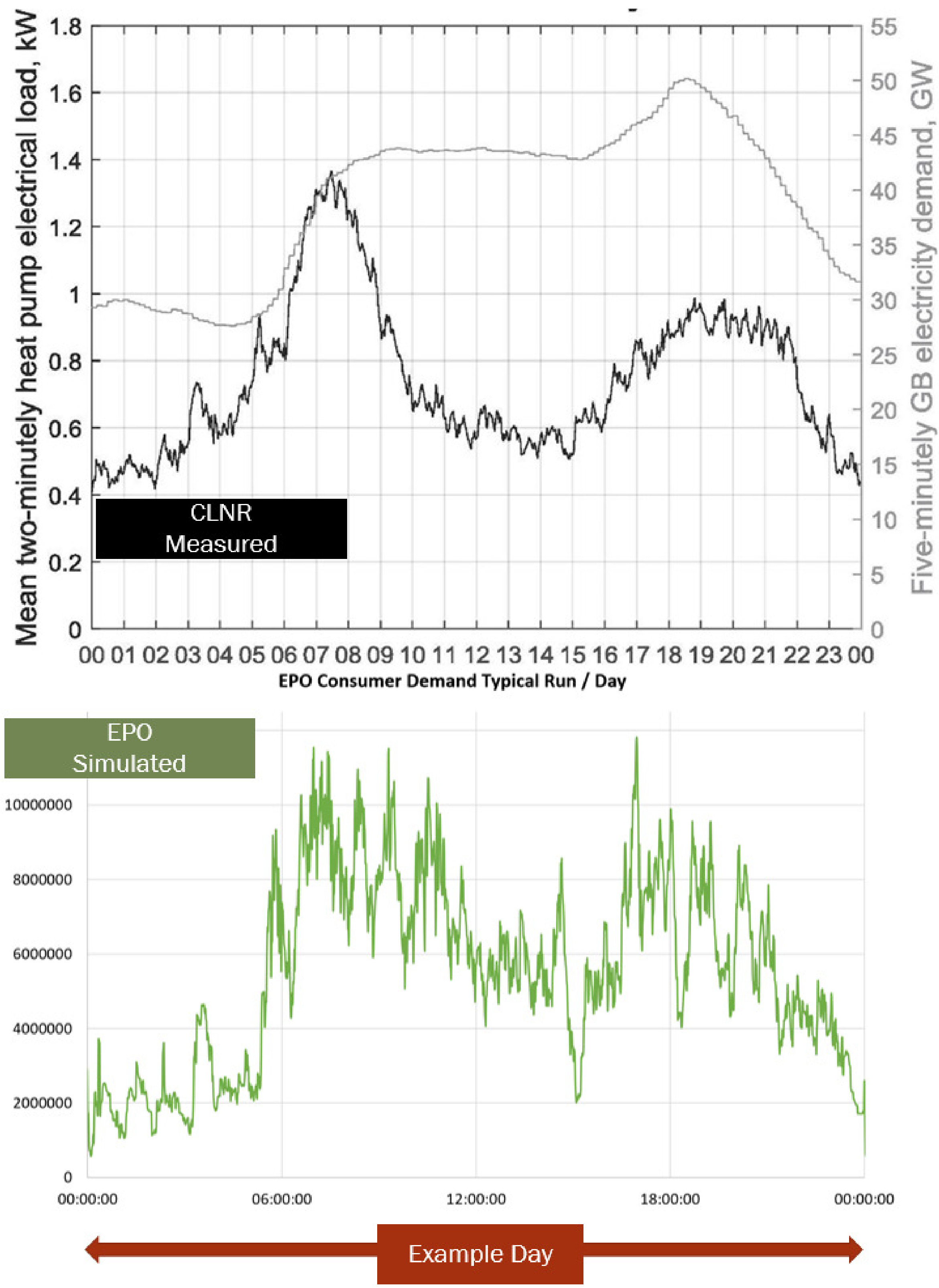
The graph overleaf shows a typical day from the CLNR project against the EPO model.

The black line on the top plot is the normalised consumption from a set of 696 heat pumps on a 'medium winters day', measured on the CLNR project.

Below this is the consumption from the medium variant topology, simulated in EPO for a 'typical day.

Comparing the graphs, both show the same general trend. The morning peak of the heat pump load profile begins just before the morning rise in load on the electricity grid, then tails to a lower value, before an evening peak.

The EPO profile has significantly greater volatility. The amplitude of the spikes is clearly greater in the EPO simulation than measured data.



Medium Typical Winter Day

3.3.3. Representation of Occupant Behaviour

The consumer demand is based on outputs from the CREST model. This is based on a small subset of (100) profiles. The same profile is therefore applied to multiple consumer instances throughout the model.

The representation of the behaviour of the occupant, (functionality of the occupant), within the model could avoid this. This would allow for separate definitions of probabilistic behaviours, including different occupant responses between each day.

There is a body of work in academia looking at different methods for representing / classifying the occupant to improve this representation, (Nijhuis, Gibescu, & Cobben, 2016; Hauser, Evora, Kremers, Hernandez, & Hernandez-Tejera, 2016; McKenna, Djapic, Weinand, Fichtner, & Strbac, 2018).

The CREST representation is based on traditional gas boiler usage. The incorporation of a HHP will cause a different behaviour usage profile. The devices have a lower capacity and therefore a warm up period, (Huebner, et al., 2013).

The incorporation of occupant decision making to conditions, (agent based behaviour), is not included, as the occupant is assumed to be passive. The has also been shown to have a significant impact on simulated consumption, (Alfakara, 2017).

There is potential scope here to build on these fields of work within academia and consumer insights relating to the HESG trial to improve this potentially critical aspect of the model.

3.3.4. Representation of Local Control

The heat pump in the EPO model switches on to full power when the room temperature falls below set-point. It falls back to a lower capacity when the heating system warms up.

This will cause a large spike as heat pumps come on-line within the morning and evening peaks. This may not be reflective of the operation of heat pumps in the trial or reality.

The IEH project is looking at the impact of control options on demand profile. This includes aspects such as, limiting the heat pump power during periods of peak demand, using storage within the property, using the gas boiler component to assist with the initial warm up period when devices come on line. There is also a growing body of work looking at how the local control of heating can fit overall smart grid control strategies, (Behboodi, Chassin, Djilali, & Crawford, 2018; Ringler, Keles, & Fichtner, 2016).

3.4. Selection of Representative Week

Selection of typical week of weather conditions is required to select representative ('worst', 'best' and 'high') curves to take forward for further analysis. The weather is taken from Cardiff which is geographically close and metrologically like Bridgend.

The week starting 21st March was chosen. This was typical with respect to; weather conditions (wind and temperature). This was evaluated by a quantitate assessment based on the statistics relative to the total period and qualitative assessment against conditions and KPI.

3.4.1. Quantitative Assessment

The values in the table below correspond to the absolute difference of the mean and standard deviation for a given week against the entire Winter period (as a measure of how 'typical' the values are). Weeks were ranked for each measure based on their distance to 0, and Overall rank was derived by giving equal weighting to each measure's rank.

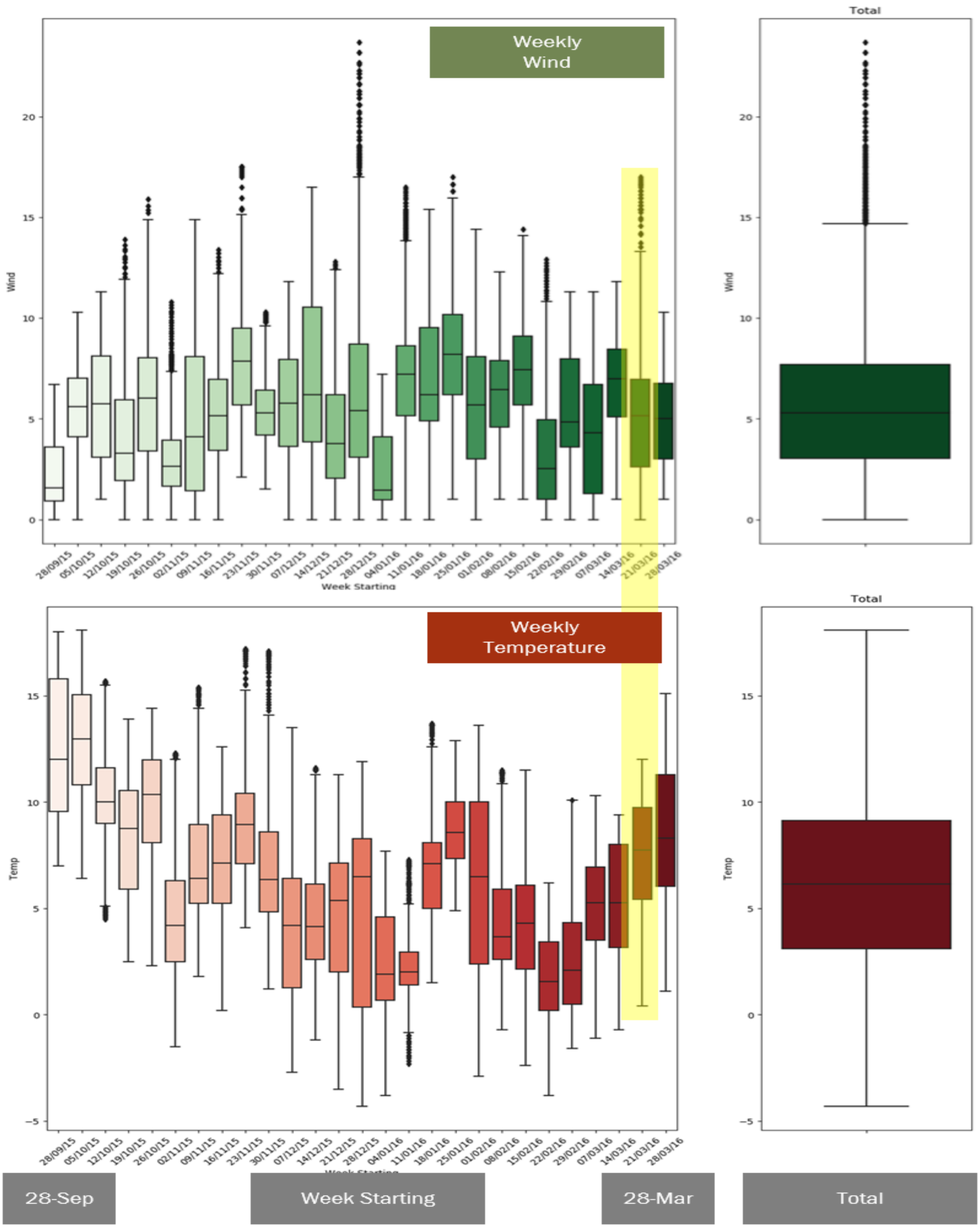
Week starting	Temp μ	Wind μ	ΔTemp μ	ΔWind μ	Temp σ	Wind σ	ΔTemp σ	ΔWind σ	**Overall rank**
23/11/2015	0.579	**0.009**	**0.001**	0.015	1.259	0.323	0.081	0.345	**1**
21/03/2016	1.344	1.192	0.017	**0.003**	1.388	0.388	**0.032**	0.097	**2**
04/01/2016	2.464	0.441	0.037	0.018	0.109	0.501	0.114	**0.029**	**3**
08/02/2016	1.125	0.296	0.044	0.032	0.401	0.189	0.043	0.113	**4**
07/12/2015	**0.067**	0.197	0.007	0.005	1.739	1.784	0.061	0.223	**5**

Weather Week Ranked Closest to Average

Key: Δ - per hour change in value / μ - mean / σ – standard deviation

3.4.2. Qualitative Assessment

The qualitative assessment looked at deviations of weather variations and KPI (based on background demand for electricity (from Elexon and CREST curves). These figures below show wind speed and temperature distributions over each week of the Winter season. The right-hand boxplot in each is the total distribution over the entire period; the typical week should be reasonably close to this in its profile.


Weekly
Wind
Total
Wind
Week Starting
Weekly
Temperature
Total
Temp
28-Sep
Week Starting
28-Mar
Total

The figures below show the graphs for the demand and KPI's for each week. The KPIs were calculated by running the weather profiles through the On-line Conceptual Architecture model, with consumer demand populated by the CREST data (for background load used in the allocation function) and Elexon profiles.

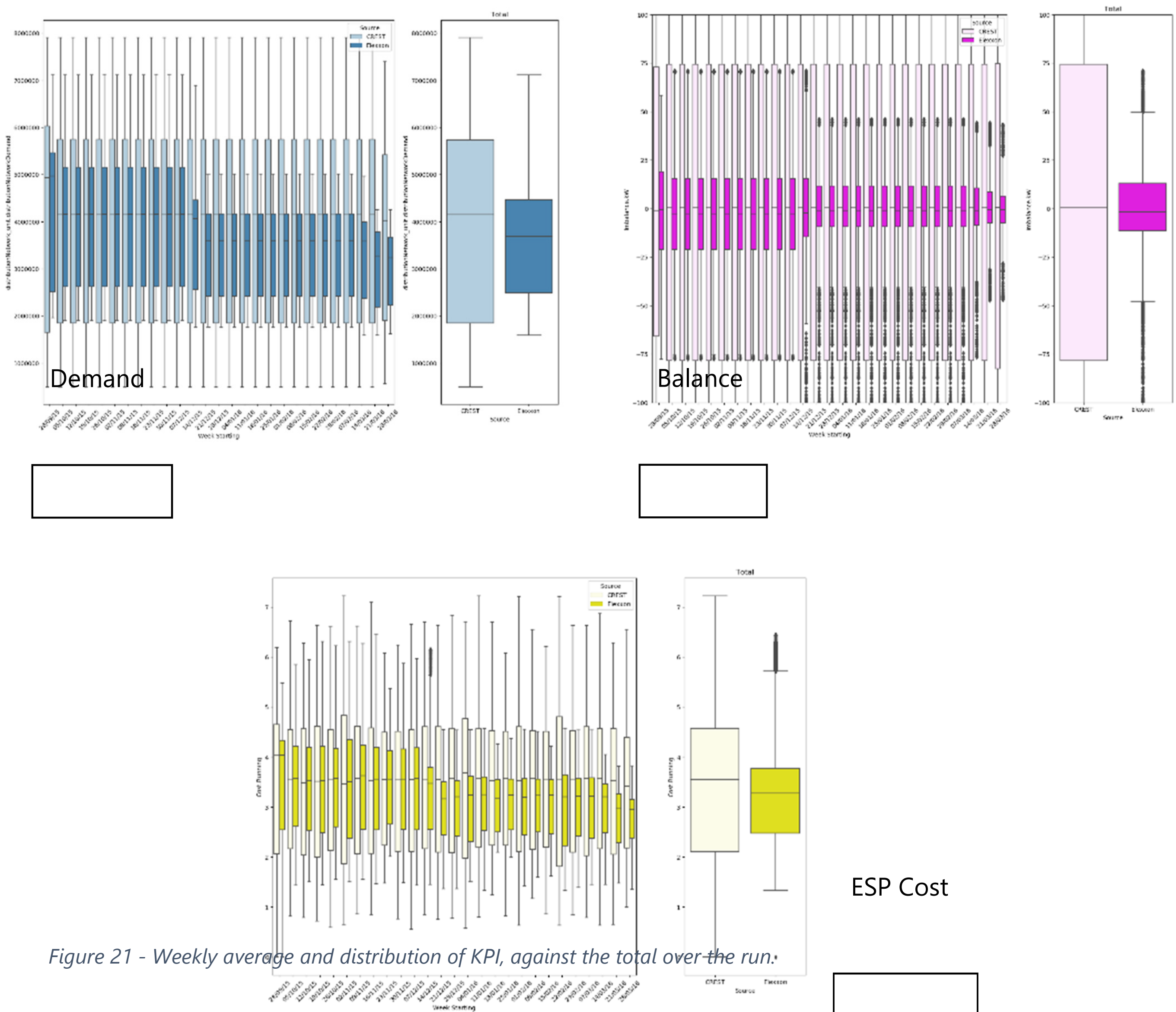


Figure 21 - Weekly average and distribution of KPI, against the total over the run.

It was found there was no strong correlation between the KPIs over the we s and that act of similarities was considered below that of weather for typical week selection. The second rank (21-March) with respect to weather was chosen as it was closer to the middle than the first choice.

3.5. Selection of Mid / Best / Worst Topology

The best, mid and worst profiles from the set of 132 variant topologies were selected by considering daily quantiles of demand and various KPIs. These were roughly taken to be the 95th, 50th and 5th percentiles, respectively.

The left subplot below shows daily aggregated demand for all simulated profiles over the selected week, while the right subplot shows the same data centred around the median value for each day (for display purposes). The three chosen profiles are overlaid.

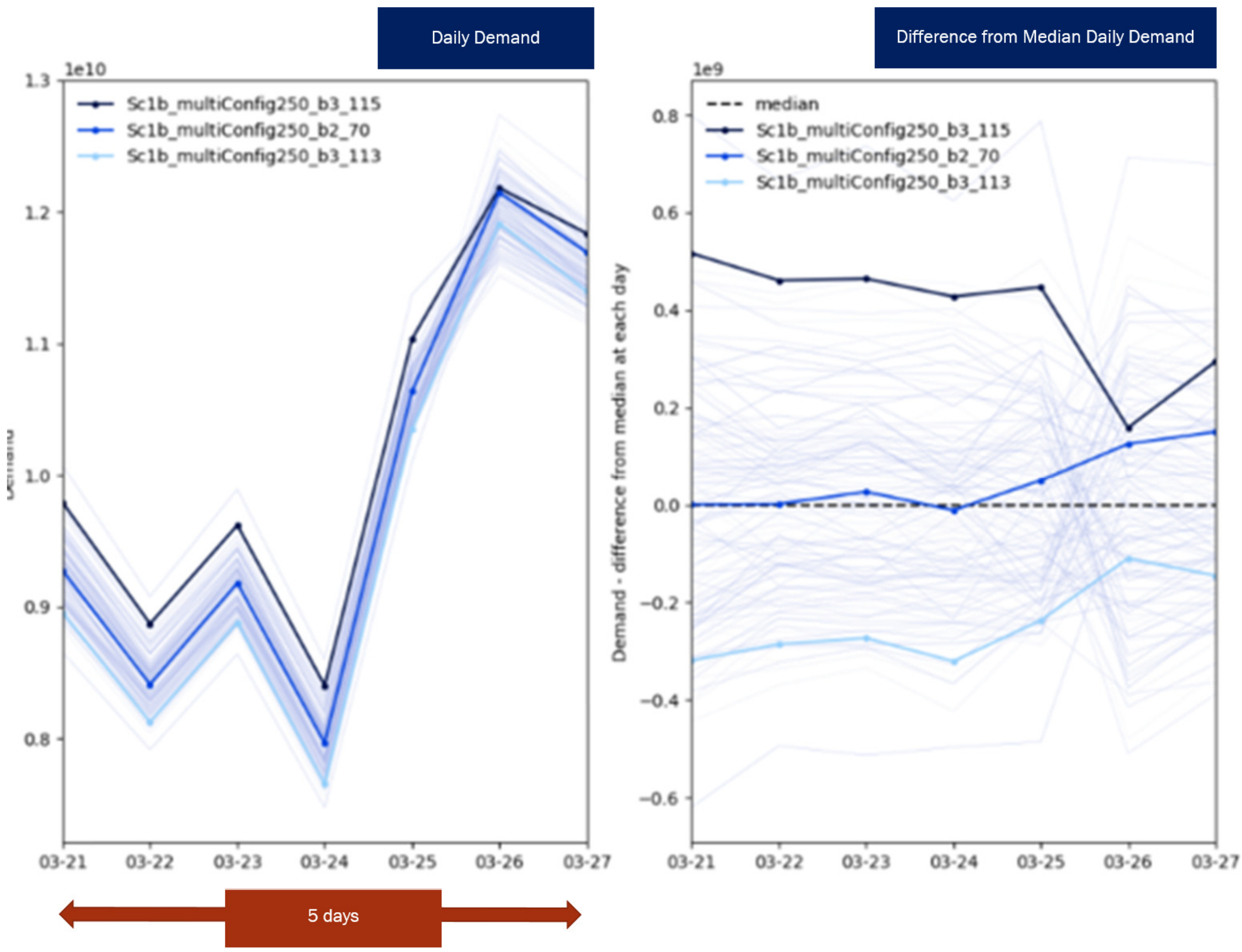


Figure 22 - Weekly average and distribution of demand for variant topologies, showing the 'Worst', 'Mid' and 'Best'.

The table below shows the ranking of the ranking of the variant topologies against the KPIs.

Topology	ESP Cost (percentile)	Aggregated storage (percentile)	Imbalance (mavg) σ (percentile)	**Overall percentile μ**
Worst	0.053	0.061	0.091	**0.068**
Mid	0.477	0.432	0.523	**0.477**
Best	0.962	0.939	0.962	**0.955**

KPI Ranking for Variant Topologies

The method selected the profiles that matched the 5th, 50th and 95th across all KPIs closely. A better approach may have been to review the correlations in the KPIs before this analysis to consider negative correlations, (such as the slight correlation with imbalance and storage).

3.6. Results

This section shows the visualisation of trends performed to understand both that, the EPO model is behaving as expected, and relationships between variables.

The graphs presented in this section relate to the worst, mid and best topologies in the case 2b base run, (30% HHP with 10 MW power limitation). Three types of plots are shown:

- The daily trend, the variation in the hourly average within each day during the heating season.
- The seasonal trend, the variation in the daily average within each day, over the entire run.
- The final plot is a correlation between key variables (average over hour).

Comparing the daily and seasonal trends in variables, there is confidence that the model behaves as expected, showing the trends defined in Section 2.5.4.

The trends are less clear in the correlation plot. There are correlations between temperature, demand and cost, plus wind and temperature. This however suggests that the scenario is highly influenced by daily and seasonal patterns.

The analysis of key trends Section 2.7.2, picks out some of the relationships between variables. The full range of plots are presented for reference, so that the reader may wish to draw further conclusions between relationships.

3.6.1. Temperature and Wind

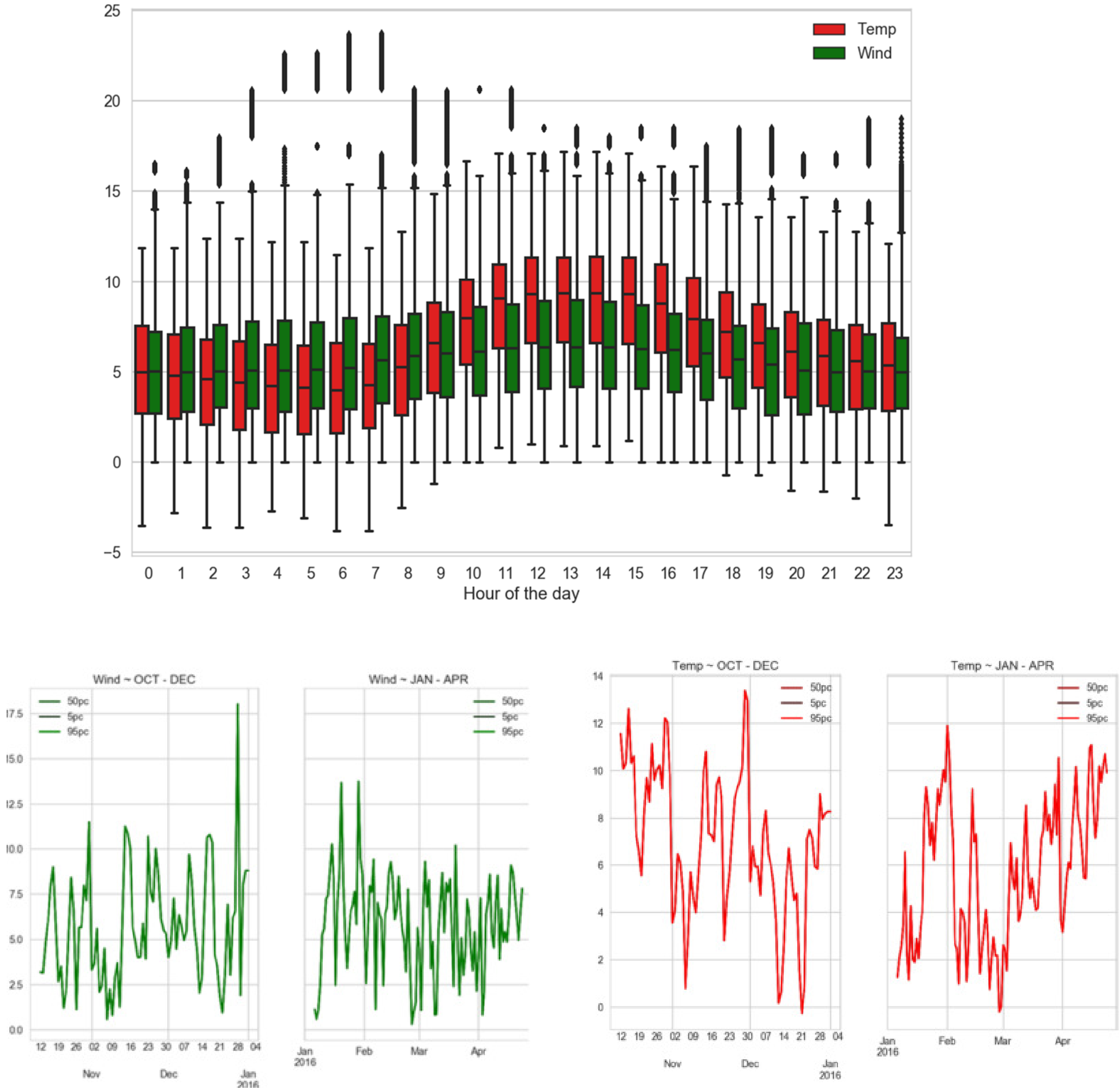


Figure 23 - Daily and Seasonal Variation in Weather Conditions (Temperature and Wind)

3.6.2. Demand

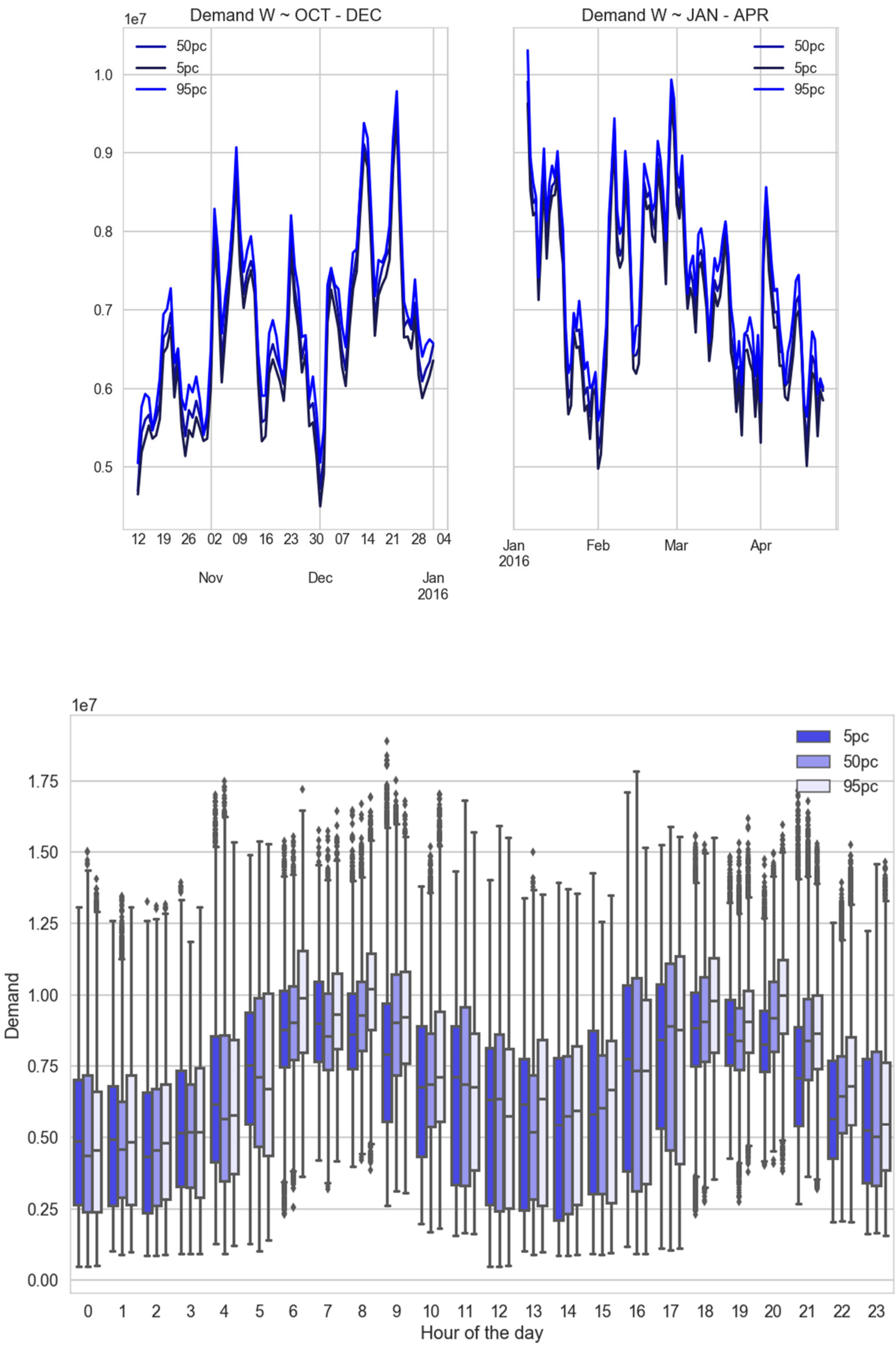


Figure 24 - Daily and Seasonal Variation in Simulated Demand

3.6.3. ESP Cost

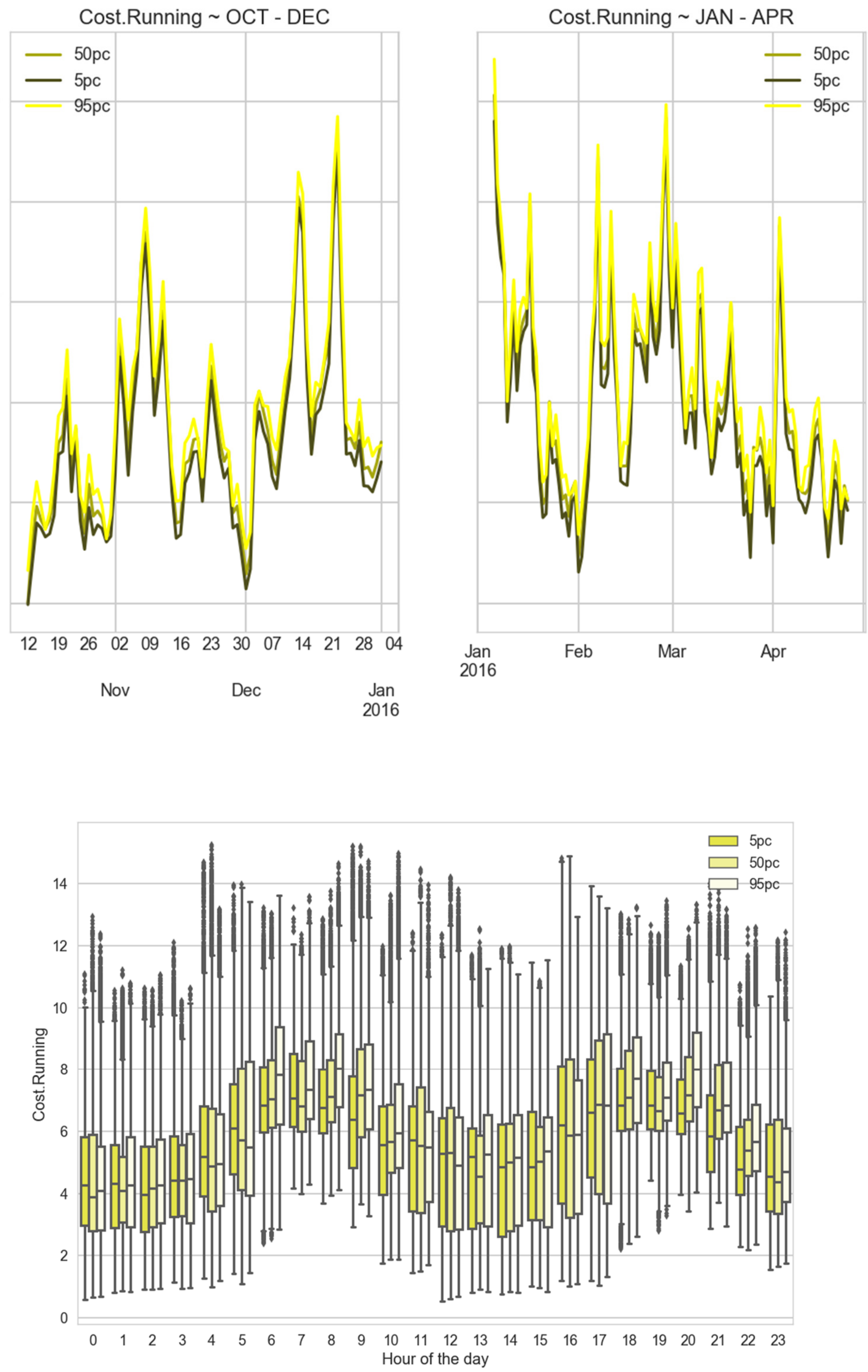


Figure 25 - Daily and Seasonal Variation in ESP Cost

3.6.4. Imbalance

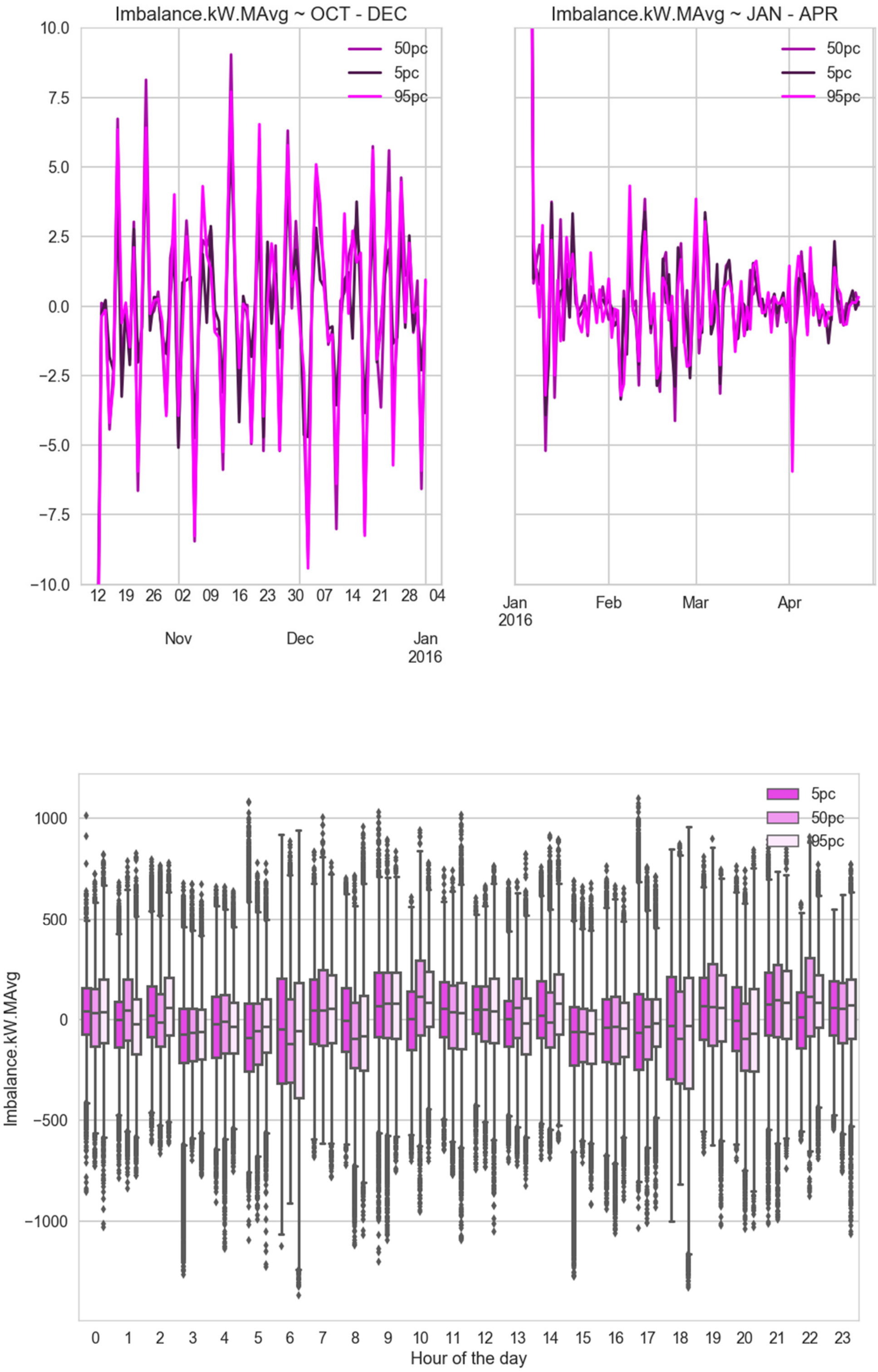


Figure 26 - Daily and Seasonal Variation in Imbalance

3.6.5. Storage Power Supply

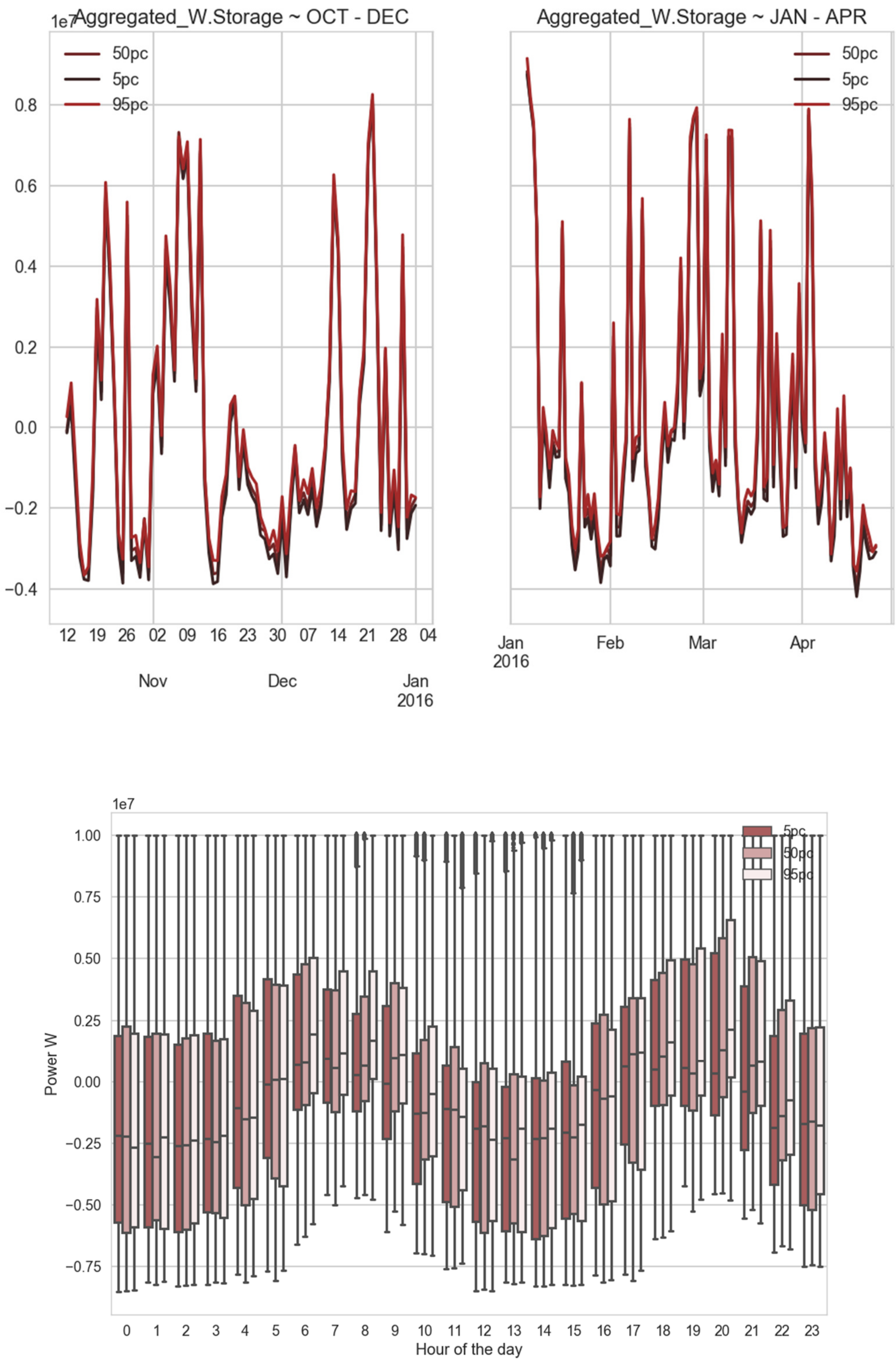


Figure 27 - Daily and Seasonal Variation in Storage Power Supply

3.6.6. Aggregated Storage

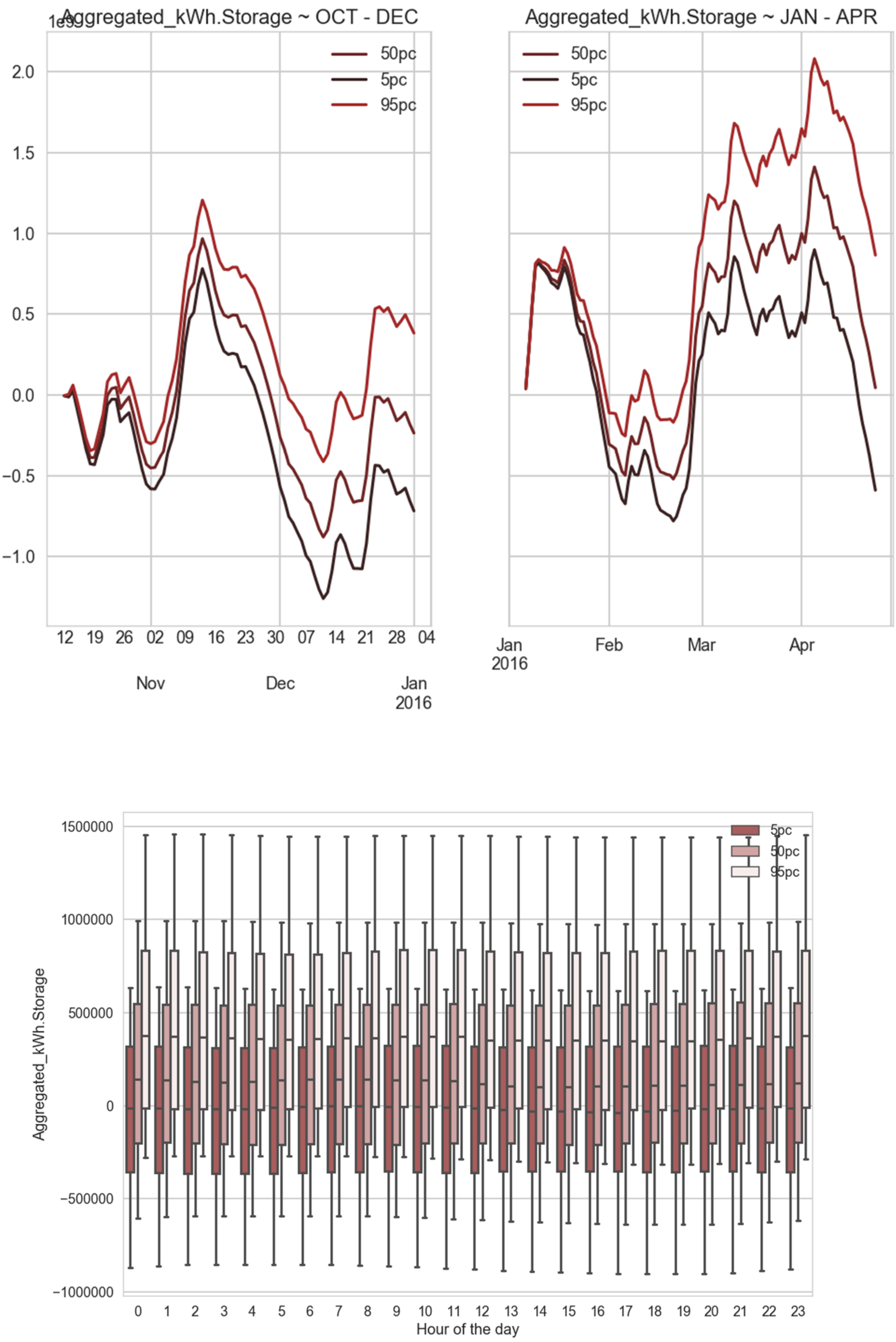


Figure 28 - Daily and Seasonal Variation in Aggregated Storage (Energy Inventory)

3.6.7. Spot Market Generation

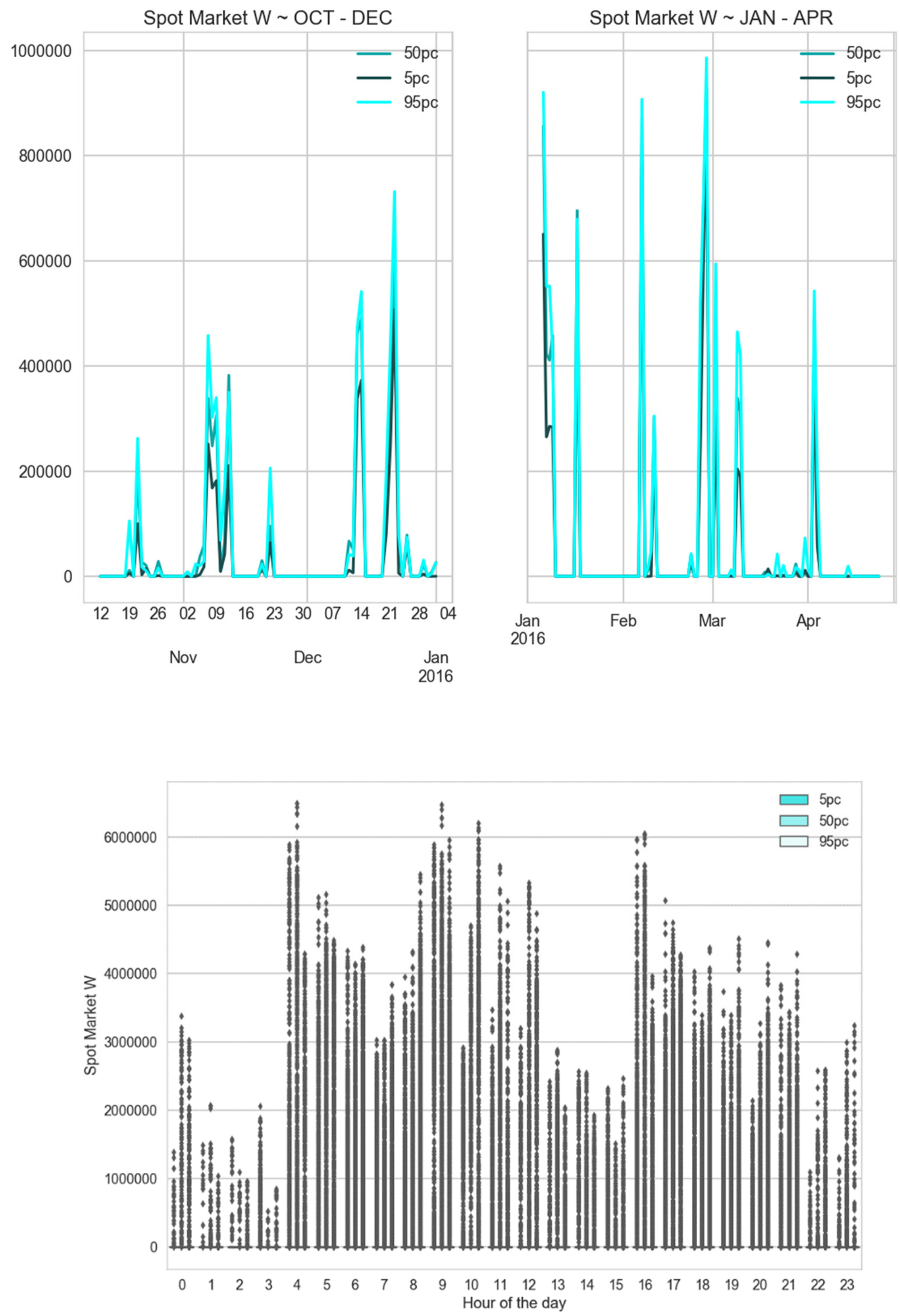


Figure 29 - Daily and Seasonal Variation in Energy from Spot Market

3.6.8. Correlation Plot

The graphs below show the correlation of the daily average in key variables.

There is a clear relationship between daily demand and ESP cost.

There is no obvious relationship between other variables, from looking at this data. This suggests that the shape of the curves over the day need to be considered for other variables.

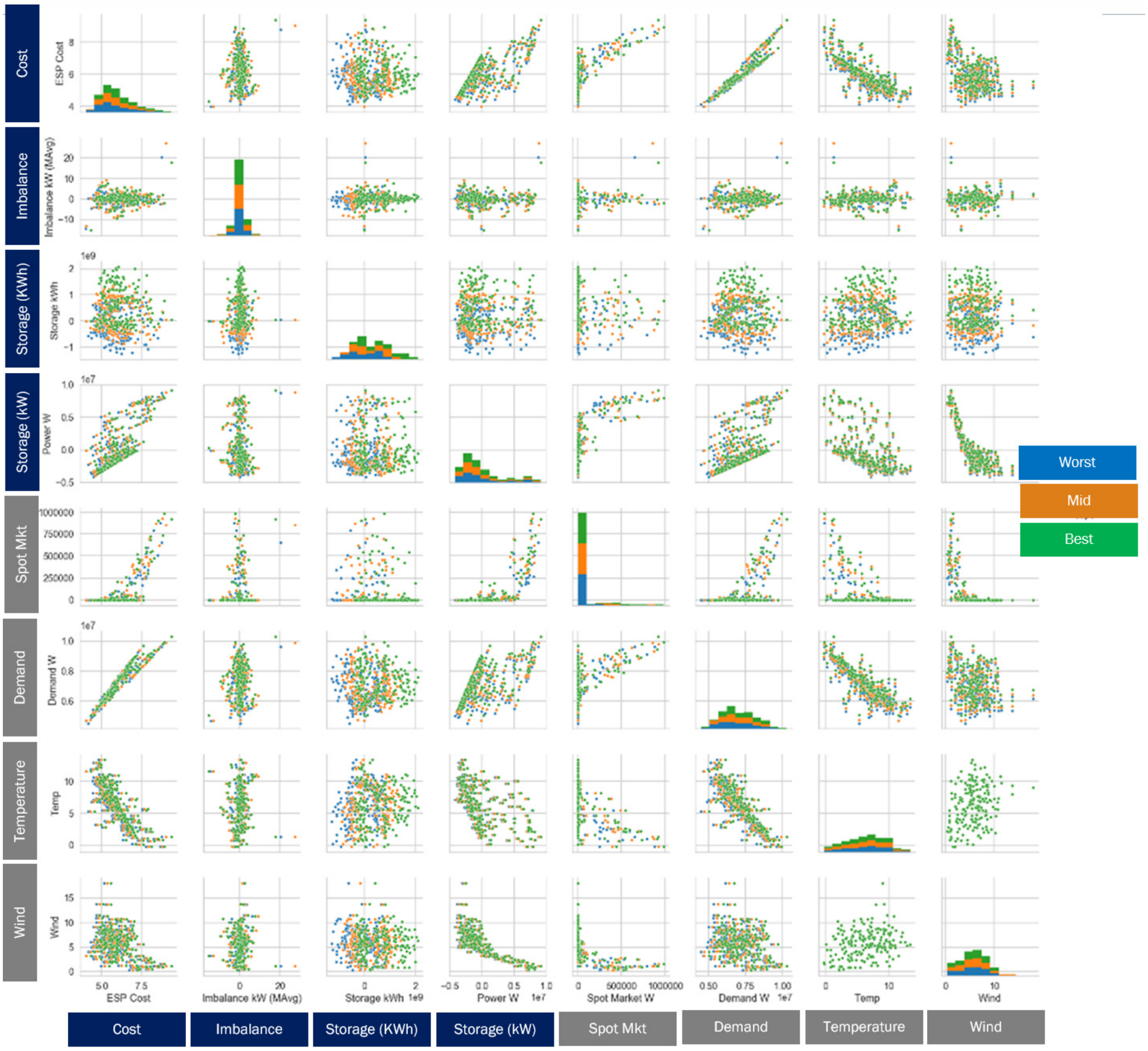


Figure 30 - Correlation between hourly averaged variables