

Article

Design, Valuation and Comparison of Demand Response Strategies for Congestion Management

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Abstract: Decarbonisation of heat and transport will cause congestion issues in distribution networks. To avoid expensive network investments, demand flexibility is necessary to move loads from peak to off-peak periods. We provide a method and metric for assessing and selecting the optimal demand response strategy for a given network congestion scenario and applied it to a case study network in Coleraine, Northern Ireland. We proposed a Price Approximation/Mean Grouping strategy to deal with the issue of congestions occurring at the lowest-price period in real-time pricing schemes. The Mean Grouping strategy increased the average lowest-price hours from 1.32 to 3.76. We show that a three-cluster tariff is effective in solving medium congestion issues in Northern Ireland and could save consumers an average of £117/year on their heating bill. However, for networks with low headroom suffering from serious congestion issues, a smart control strategy is needed.

Keywords: tariff design; congestions in distribution networks; reducing peaks caused by dynamic pricing; heat pumps and heat battery; pv and battery; social housing in Northern Ireland

1. Introduction

There is a global call for decarbonisation to prevent the global temperature rising more than 1.5 °C from preindustrial times, which would cause an irreversible change in the climate [1]. Electrification of heat and transport is the most promising method of decarbonisation, and the falling cost of renewables such as wind and solar generation presents the opportunity to decarbonise electricity generation. Low-carbon technologies such as heat pumps, thermal storage and electric vehicles provide the means for consumers to switch from fossil fuel technologies.

The UK is leading the climate action and has passed a series of legislation to cut down CO₂ emissions. First, it has legislated for a 2050 net-zero greenhouse gas target [1]. Second, it has banned new homes from connecting to gas heating by 2025 [2]. It has also proposed a ban on petrol and diesel car sales by 2030 [3].

However, the existing electrical grid was not built to handle the expected new demand for heat and transport. Furthermore, the intermittent nature of renewables, coupled with the fact that electrical demand and supply must match at any time for the grid to operate safely, creates much complexity in this new system that was not experienced in the conventional grid system [4]. The power system has not undergone this kind of change since it was invented. The result is that the existing grid infrastructure would need to be upgraded to cope with the new demand and complexities. The cost of this network upgrade and the additional complexity caused by managing renewable generation would eventually be passed down to the consumers.

Social housing is provided for people on low incomes or with particular needs by government agencies or non-profit organisations. Hence, it is easier for the government to implement policies

such as low-carbon heating in social housing than in private accommodations. In Northern Ireland (NI), such government investment in energy efficiency and building fabric upgrade with fuel poverty schemes such as the Northern Ireland Housing Executive Grant, Affordable Warmth Scheme, Boiler Replacement Allowance and NISEP have been the key instrument in bringing down fuel poverty levels from 42% in 2011 to 22% in 2016 [5,6]. However, oil and gas boilers are still installed in these houses because of their low cost, making such government schemes against current government legislation for Net-Zero and the ban of fossil fuel heating.

Hence, such fuel poverty schemes need to be modified to install low-carbon heating in these vulnerable households. However, this will mean fewer interventions can be made under the current budget since the capital cost of installing low-carbon heating such as heat pumps and thermal storage doubles that of an oil or gas boiler. Secondly, vulnerable consumers must be protected against high electricity prices that could result from the cost of network reinforcement needed to support heat electrification. Hence, by installing flexible low-carbon heating in fuel-poor homes and prioritising their use in providing system services, the government could reduce fuel poverty, CO₂ emissions while preventing expensive network upgrades.

System operators have traditionally invested in grid reinforcement to reduce congestion during peak times or worst-case scenario, thus the rule for which they size the grid. Typically, these peak times occur a few hours in the day. There are periods, especially at night, during which the grid is under-used. The load factor of a network is the ratio of the average load to the peak load. A higher load factor is needed to ensure that the existing grid is efficiently utilised before any consideration for upgrading it. Hence, the need for flexibility to move consumers demand away from peak periods to off-peak periods.

Whenever the demand on a feeder exceeds the local generations, voltage drops along the feeder. To prevent under-voltage at the end of a feeder, the system operator usually set the secondary side of the MV/LV transformer at 1.01–1.05 p.u [7]. Congestion occurs in MV/LV transformers whenever the transformer loading exceeds its thermal rating. Whenever local generation at the feeder exceeds the demand, the voltage along the feeder rises. The power system was designed for unidirectional power flow, but when generation exceeds demand at the low voltage network, there is reverse power flow to the transformer. By increasing demand during times of excess wind or solar generation, the system operator could reduce voltage rise as well as backflows. Meanwhile, by increasing local generation during peak times or by shifting or reducing demand during these peak times, under-voltage or overloading can be reduced.

Heat pumps can provide flexibility using the thermal inertia of the building, as investigated in [8]. However, this is not energy efficient, especially in buildings with low thermal inertia, as it increases overall energy consumption and could result in discomfort for the consumers [9]. Another method is to use thermal storage: Typically, a hot water buffer tank or heat batteries that make use of phase change materials, to shift demand from peak to off-peak period [10]. Lastly, heat pumps could be installed in combination with an existing oil or gas boiler in a hybrid configuration, switching to the oil or gas boiler whenever there is network constraint or when it is inefficient to run the heat pump such as when the external temperature is very low.

While several demand response optimisation strategies in the literature such as [11,12] did not consider the grid's capacity constraint, [13] developed a methodology to assess the long-term demand response benefits from a systems perspective. The conclusion from the study is that an efficient demand response strategy should be market-based while respecting grid capacity constraint [14]. This will ensure that new congestions do not arise as a result of conflicting demand response programs [15,16]. Various methods of ensuring cost-reflective pricing in distribution networks were reviewed in [17,18]. A method to assess the cost-reflectiveness of network tariffs is developed in [19]. The study also discusses how tariffs could be adjusted to better align consumer bills with their contribution to network peak. Such cost-reflective tariff is vital for a sustainable electricity grid [20]. To improve efficient price formulation, [21] proposed that each consumer establish a contract-based baseline before

joining a demand response program. The issue of congestions from microgrids is investigated in [22]; the recommendation is that capacity billing should be favoured over volumetric billing to incentivise microgrid operators to balance their load and generation.

Consumers behaviour and acceptance to demand-based tariffs is investigated in [23–26]. The challenges of achieving effective voluntary demand reduction for residential consumers is investigated in [27,28]. The study shows that a significant number of consumers are unresponsive to price. However, low-income households and households that use electricity for space heating are more responsive. The impact of time of use pricing on network peak is investigated in [29]. The study concluded that the success of a demand response program depends on the flexible nature of the consumer devices and customer education about the tariff structure and implications. The study in [30] developed a methodology for grid operators to decide whether to implement demand response by comparing the cost of curtailing demand or distributed generation with the cost of additional network investment. It further develops a dynamic pricing model for it. A reinforcement learning algorithm to solve the uncertainty in real-time pricing faced by consumers and energy suppliers is developed in [31].

An agent-based demand response mechanism for real-time congestion management in low voltage networks is developed in [32]. The work assumes the day-ahead market price as the price of flexibility but suggested further research to properly quantify and value available flexibility. The authors of [33] developed a data-driven approach to explore the flexibility from a cluster of buildings. The response of a pool of heat pump responding to direct load control via the Smart-Grid-Ready interface is analysed in [34]. The paper concluded that flexibility is highly dependent on the ambient temperature and the use of an electric back-up heater. The Freedom project trialled the use of hybrid air-source heat pumps and gas boiler to provide flexibility in the south-wales distribution networks. From the research, it was investigated that, with 100% penetration of air-source heat pumps (ASHP), consumers will pay an average of £50/year for network upgrade, while, with the smart hybrid system, this would be reduced to about £5/year [35].

An issue with dynamic pricing is demand response concentration at lowest-price periods, leading to new network peaks. To solve this problem, [36] suggested a restriction in the maximum power drawn from each device. In another paper, the authors later proposed penalising the extent of flexibility utilised by the consumers' load [37]. Both the restriction or penalisation strategies are not desirable by the consumers and presents another set of problems for demand response implementation, including limiting the maximum amount of response that can be gotten from a pool of assets and hence reducing the business case. We propose a Price Approximation/Mean Grouping strategy to solve this problem and demonstrate its use and effectiveness in real-time tariff design.

Assessment and comparison of demand response strategies in the literature are limited to considering only different types of dynamic pricing. For example, [38] attempts to compare tariff business models. However, its scope is limited to dynamic pricing. Furthermore, it only considers the economic incentive for consumers; the effectiveness to reduce peaks is not addressed. The study in [39] is limited to comparing a flat tariff with a generic peak-shaving tariff. The research conducted in [40] is limited to time-of-use tariff. Often, the choice is between the three main class of demand response strategies. Only after that choice is made, before details of the specific design of the tariff type is discussed. Determining how effective these strategies are in relieving congestions, how these various strategies can be combined or which strategy is best for a given network scenario, is vital for efficient and economical smart network design.

We simulate each demand response strategy on a case study network using real measurement data. We assess their effectiveness in reducing congestions using metrics such as the total hours of loading violations and the number of nodes with voltage violations.

2. Methodology

2.1. Data Processing and Selection

In this work, thermal flexibility is provided solely by using thermal storage (Heat battery) while the consumers heat demand timing (comfort) is respected. A heat battery is a type of thermal storage that uses phase change materials (PCM). The PCM melts from solid to liquid when heated beyond a specific temperature (58 °C in our case), absorbing heat energy. The PCM cools from liquid back to solid whenever cold water is passed through it; this way the energy stored is released, and hot water is produced. The advantage of the heat battery is its low heat loss and smaller size compared to the use of a hot water tank. Hence, it can be fitted into compact spaces, which is very suitable for social housing. The Sunamp Uniq Dual 12 battery was used for modelling the heat battery. It is capable of replacing a 284 L hot water cylinder. It uses 32W standby power, maximum and minimum flow temperatures of 85 °C and 65 °C, respectively, and hot water outlet temperature of 55 °C. It has a heat loss rate of 0.809 kWh/24 h. The UNIQ 12 heat battery with immersion heater cost £2641.6. We assumed each house had two heat batteries (a total of 20 kW of heat storage) powered by a heat pump [41].

Heat pump load profiles were sourced from the datasets of the Renewable Heat Premium Payment (RHPP) trial, which monitored heat pump loads in about 700 homes [42]. The time-series data in watt-hour for both space heating and domestic hot water was recorded at two-minute resolution. The dataset includes metadata describing the kind of heat pump and type of dwelling of each site. Some filters were applied to the processed sample to remove sites that either had technical issues such as incorrect sensor installations or when a significant amount of data streams was missing from the data. Only the best 12 months period of the data was selected for each site. The results were uploaded as Sample B2, which contains 418 sites [43]. However, the Sample B2 also contains lots of missing rows; hence, further cleaning was done to fill up these missing rows by setting them to the previous value if the missing time-step was not more than 10 minutes; otherwise, the values are set to zero. This was done to make each site data the same size and allow for further calculations to be done on the data.

One hundred social housing profiles with ASHP capacity between 7–14 kW and radiator heating (reflecting typical Northern Irish social housing of 90 m² floor area) were selected from the RHPP dataset. Details of the selection process is shown in Figure 1. The selected profiles were used to simulate the default individual heat pump profile (without storage) in this work. The data contained both the electricity drawn by each heat pump and the amount of heat generated. This is used in the simulation. However, when simulating charging of the heat battery with the heat pump, we use the hourly average coefficient of performance (COP) of the heat pump to determine the amount of heat stored per kWh of electricity drawn, since the actual COP for that hour is unknown.

Time series data from a 2 kW SolarEdge PV panel installed at the Ulster University test house and monitored using the SolarEdge monitoring platform were used in the simulation to represent the PV generation profiles for the portfolio. SonnenBatterie ECO 8.4 with 6 kW capacity, 2.5 kW inverter charging and discharging power and a round-trip efficiency of 83% was used to model the battery [44]. By using real heat pumps, PV and Network data, this methodology guarantees that the results are as close to a real-life situation as possible since the simulation was considered for a full year, which caters for seasonal and diurnal changes. The uncertainty in this work stems from a lack of Northern Ireland specific heat pump dataset since the RHPP trial was limited to British households. Hence, we call for a large-scale heat monitoring trial to give a detailed picture of how Northern Irish consumers would use heat pumps and other low-carbon heating solutions.

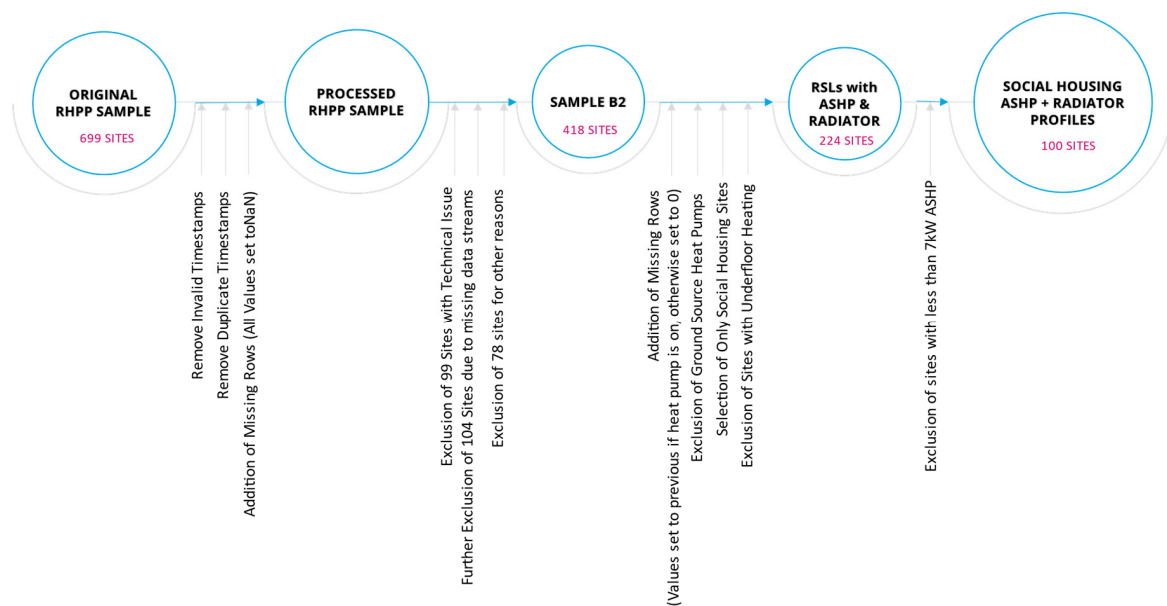


Figure 1. Social housing heat pump time series data cleaning and selection process for use in simulation.

2.2. Case Study

We investigate the value of demand flexibility from several social housing estates connected to Loguestown Substation, a constrained network in Coleraine, Northern Ireland. There are two 7.5 MW, 33/11 kV transformers (TX3 and TX4), making a usable capacity of 9.75 MW (with 65% thermal intervention threshold). The maximum demand is 7.4 MW. The demand is only above 5.25 MW 4% of the time. However, a new data centre at an Enterprise Zone connected to Loguestown substation has reduced the demand headroom at the substation. This means that future loads such as heat pumps and electric vehicles cannot be accommodated without reinforcement. The network was modelled on NEPLAN Software. Table 1 gives a breakdown of the various estates connected to Loguestown.

Table 1. Breakdown of number of social housing per feeder.

Social Housing Estates	11/0.4 kV Transformer	Rating	No of Houses Per Feeder	
			79/94	79/87
BALLYSALLY ESTATE	Glenvara Drive	500 kVA	217	-
	Rochester Court	300 kVA	91	-
	Sprucefield Drive	500 kVA	-	135
	Elms Park	315 kVA	-	70
	Ballygallin Park	500 kVA	-	161
MILLBURN ESTATE	Rosemary Place	315 kVA	166	-
	Willow Drive	500 kVA	160	-
Total (1000)			634	366

Figure 2 shows the 33 kV, 11 kV, 415 V model on NEPLAN. Measurement devices were placed at various points on the network to record the power flows on the network from January to December 2018. These measurements were then uploaded to NEPLAN for the load flow analysis.

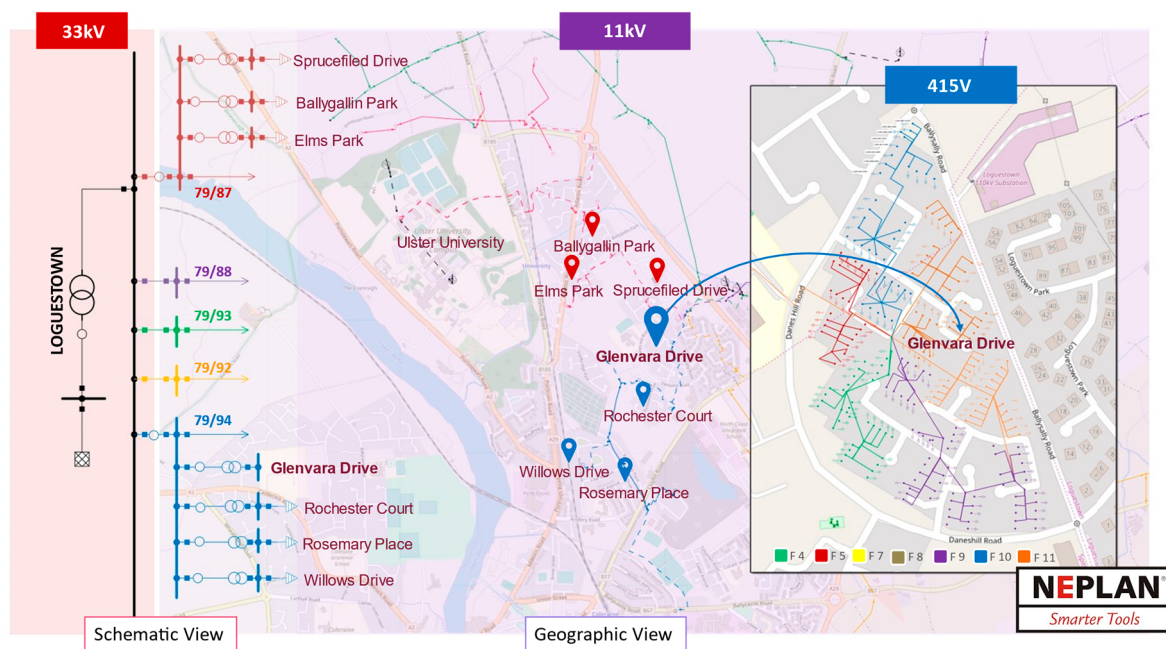


Figure 2. Technical model of the network on NEPLAN software.

2.3. Demand Response Strategies

There are two main demand response strategies: Tariff-based and incentive-based demand response. Among the tariff-based strategies, we consider the real-time tariff (RT) in which consumers respond to the price of electricity in real-time and the Time of use tariff (TOU), which has a fixed price for certain periods of the day, week or year. We also considered the incentive-based scheme using a smart network. In this section, we present a detailed design of these three strategies for managing congestion.

2.3.1. Real-Time Tariff Design

Figure 3 shows the retail tariff make-up for October 2019 of PowerNI, the largest electricity supplier in Northern Ireland. The retail electricity cost was 17.85 p/kWh [45]. While most of the components are relatively fixed, the wholesale cost and the use of system (UoS) charge depends on the time of day and other factors. NIRO is the Northern Ireland renewable obligation, and its cost is used to subsidise investments in renewable generation. Levies include system support services as well as public service obligations. The day-ahead market (DAM) price is included in the energy component in the pie-chart along with balancing market, premiums and hedging costs. Between October 2018–September 2019, the DAM price varied from −9 p/kWh to 32.9 p/kWh, with an average of 5.03 p/kWh. Details on the other component of the wholesale cost can be found in [46].

The UoS charge is issued by the system operators to suppliers for transmitting and distributing electricity to their customers (homes and business). The UoS charge is higher at peak demand times and lower at off-peak times. It comprises TUoS (transmission use of system charge) and DUoS (distribution use of system charge). There are different rate types for domestic DUoS: Standard, Economy 7 and 4-Rate time banded tariff. The 4-Rate time-banded charge is more reflective of the loading on the distribution networks with a peak charge between 4 pm–7 pm. However, it does not yet cover the morning heat peaks expected between 6 am–8 am. Hence, the 4Rate time-banded DUoS charges and TUoS charges were adjusted to cover the 6 am–8 am peak in the tariff development. We compute the average hourly 4 Rate DUoS charge and the TUoS charges using the network operator data [47,48]. The other charges were sourced from the supplier (PowerNI).

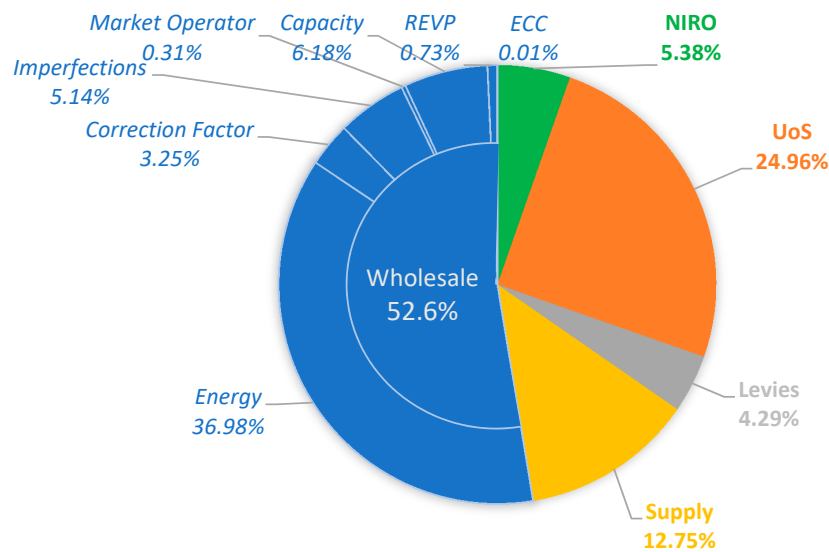


Figure 3. Breakdown of PowerNI retail tariff for October 2019.

Figure 4 shows a plot of the maximum demand for the year with and without the 1000 Heat pumps on Loguestown primary transformer vs. the average hourly DAM price as well as the UoS charge. While the peak time for the transformer is 4 pm–7 pm, which correlates with the UoS charge, the day-ahead market price peaks at 7 pm–9 pm. An effective tariff should incentivise the shifting of demand away from spot market peak times as well as network peak-usage time.

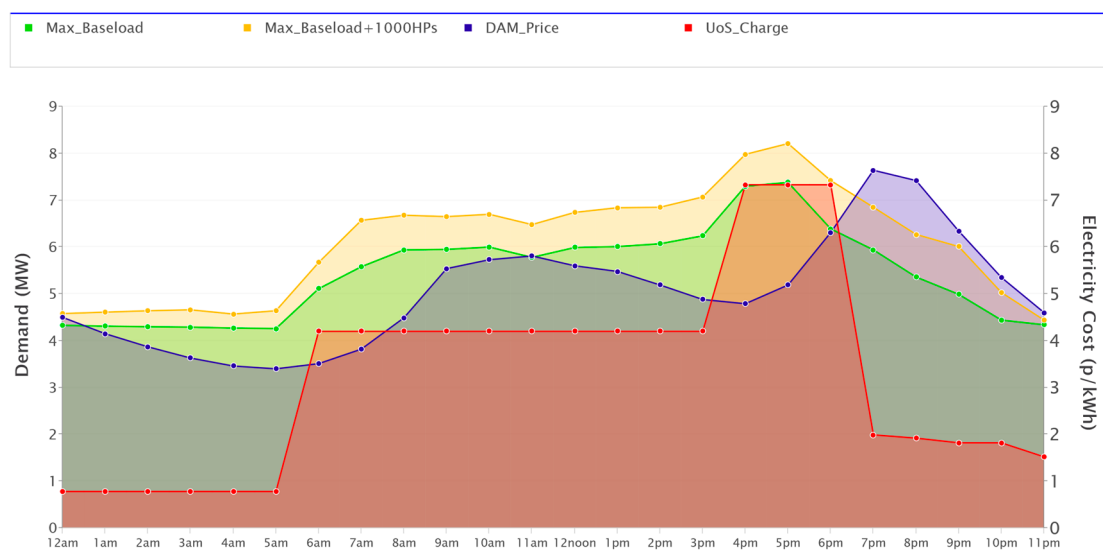


Figure 4. Loguestown hourly demand (with and without the heat pump) vs. day-ahead price.

The real-time price for any given time (R_t) can then be calculated using Equation (1)

$$R_t = D_t + O_t + U_t + NIRO + Levies + Supplier \quad (1)$$

where D_t is the DAM price, O_t is other wholesale cost and U_t is the UoS charge at time t .

Figure 5 shows the breakdown of the average hourly price for each component. Real-time prices are usually capped to protect consumers against very high spikes in the spot price. For example, Octopus Agile tariff is capped at 35 p/kWh [49]. When the day-ahead market price spiked to 32.9 p/kWh as happened on 2nd February 2019 7:00 pm, the total real-time price would have been 42.39 p/kWh. The spot price might spike higher in the future; hence, a price cap is needed.

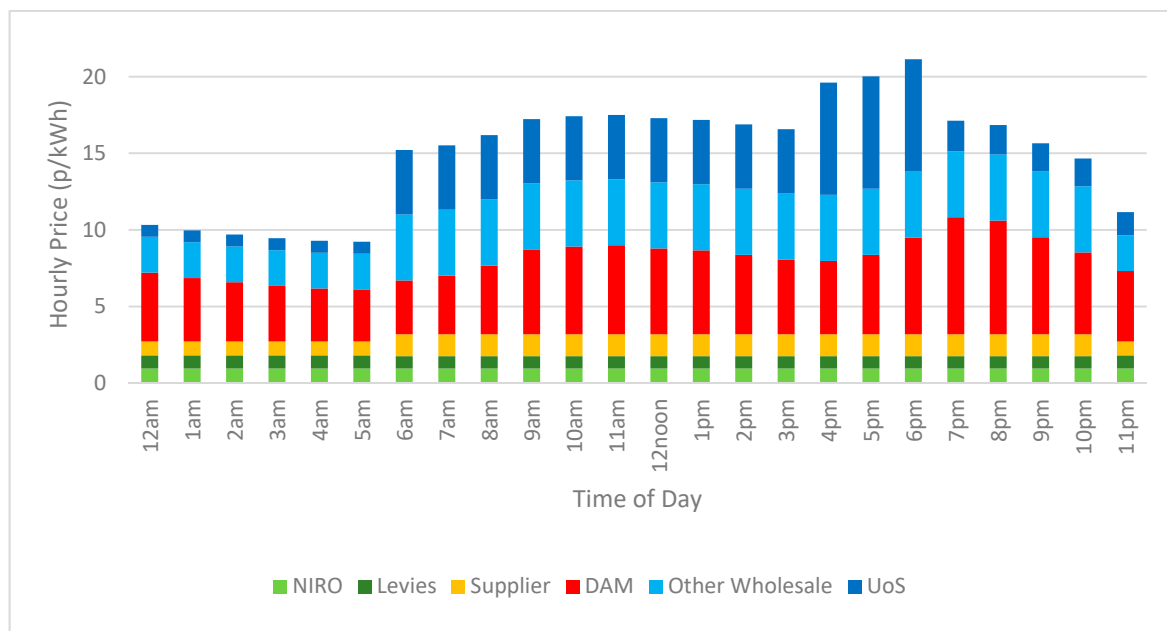


Figure 5. Breakdown of average real-time hourly price.

As mentioned earlier, care should be taken when implementing real-time pricing to avoid creating a new network peak. Research by [50] recommended 3 am for starting night charge due to the highest curtailed wind or cheapest real-time price between 3 am–5 pm. It also recommended 2 pm for the starting day charge due to the higher ambient temperature between 2 pm–4 pm and hence the expected higher coefficient of performance of the heat pump. However, while this is true, the difference in the average ambient temperature between 2 pm and 12 pm is less than 0.5 °C, and the difference in the average real-time price between 12 am and 3 am as seen in Figure 5 is less than 1p. Automated devices that have been optimised to charge at the cheapest hours could cause a demand surge at those cheapest hours.

We propose a price approximation/mean grouping strategy. For example, approximating tariff prices to the nearest 0.5 p or to the nearest 1 p. We also considered a mean grouping strategy, where tariff prices within each 0.5 p band or 1 p band are grouped together with a representative mean price. An example is given in Table 2 for illustration purpose only. In this example, without the grouping strategy, the incentive would be for all devices to turn on at exactly 1 am. However, with the grouping strategy, there would be six lowest-price hours (falling within the 12.25 p–12.75 p band), four highest consecutive lowest-price hours (1 am–4 am) and two lowest price periods ((1 am–4 am) and (10 am–11 am)). Hence, the incentive would be spread across multiple hours in the day.

Table 2. Illustration of grouping strategies for nearest 0.5 p band.

Time	1 am	2 am	3 am	4 am	5 am	6 am	7 am	8 am	9 am	10 am	11 am	12 am
RT_Actual (p)	12.42	12.61	12.73	12.55	13.47	14.49	18.77	19.50	16.32	12.55	12.45	13.71
RT_Approx (p) (nearest 0.5 p)	12.50	12.50	12.50	12.50	13.50	14.50	19.00	19.50	16.50	12.50	12.50	13.50
RT_Mean (p) (nearest 0.5 p)	12.55	12.55	12.55	12.55	13.59	14.49	18.77	19.50	16.32	12.55	12.55	13.59

We applied the approximation and mean strategy for both the 0.5 p grouping and 1 p grouping. The mean percentage error (MPE) and the mean absolute percentage error (MAPE) from the grouping were calculated using Equations (2) and (3). We also compute the average daily lowest-price hours (ALH), the average daily consecutive lowest-price hours (ACLH) and the average number of lowest-price periods (ANLP) per day. The values are presented in Table 3.

Table 3. Comparison of the various price grouping strategies.

	RT_Actual	RT_Approx (nearest 0.5 <i>p</i>)	RT_Approx (nearest 1 <i>p</i>)	RT_Mean (nearest 0.5 <i>p</i>)	RT_Mean (nearest 1 <i>p</i>)
MPE	-	0.0%	0.1%	0.0%	0.0%
MAPE	-	0.9%	1.8%	0.4%	1.1%
ALH	1.32	2.93	3.76	2.93	3.76
ACLH	1.31	2.83	3.66	2.83	3.66
ANLP	1.01	1.08	1.10	1.08	1.10

$$MAPE = 100 \times \frac{1}{n} \times \sum_{i=1}^n \frac{|O_i - P_i|}{O_i} \quad (2)$$

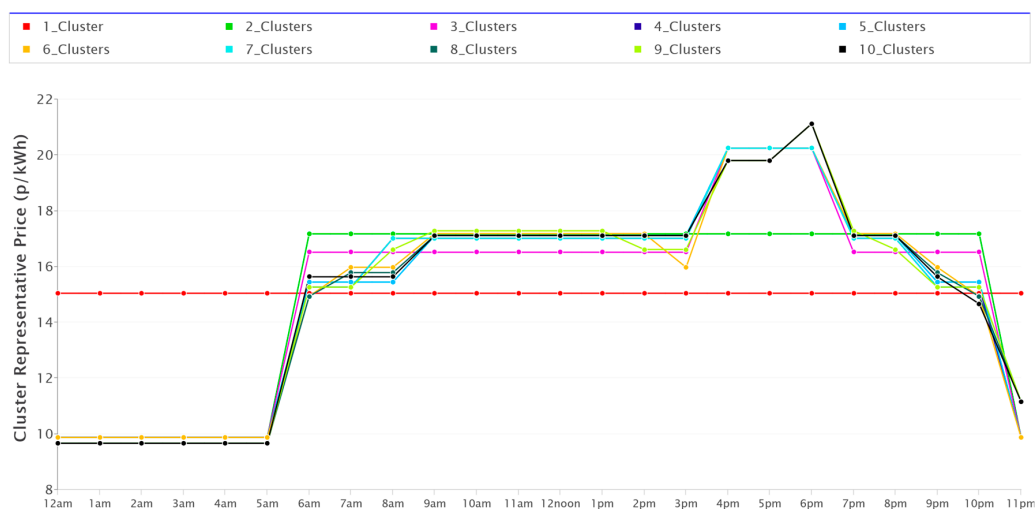
$$MPE = 100 \times \frac{1}{n} \times \sum_{i=1}^n \frac{O_i - P_i}{O_i} \quad (3)$$

where O_i is the actual price and P_i is the approximated or mean price, $n = 8760$, the number of hours in a year.

Though there were very little absolute error for all the grouping strategies as indicated by the MAPE value, these errors offset each other, giving an MPE of 0% for the mean and the 0.5 *p* approximation strategy. The MPE increases to 0.1% when approximated to the nearest 1 *p*. Hence, to improve accuracy, the mean strategy is recommended. Furthermore, by increasing the grouping from 0.5 *p* to 1 *p*, the ALH has increased from 2.93 h to 3.76 h. In this work, the mean strategy with 1p band is used to simulate the real-time pricing. The drawbacks of real-time pricing include the administrative and communication cost [29], and the burden on consumers constantly monitoring electricity prices to take advantage of the lowest-price periods [51]. In this regard, a time of use tariff is easier to implement and for consumers to get accustomed to.

2.3.2. Time of Use (ToU) Tariff Design

The objective of the ToU tariff is to group hours of similar prices. These prices are then fixed for a longer period of time and do not change based on the daily energy market prices. K-Means is a simple unsupervised machine learning algorithm used to group datasets into several clusters (k) [52]. We use K-means to cluster the average hourly real-time price into different clusters: From 1–10 clusters. Each cluster has its representative price, which is the cluster centroid. Figure 6 shows the representative prices for different clusters.

**Figure 6.** K-Means clustering of average hourly retail prices.

One method of validating the optimum number of clusters is the elbow method [53]. This is done by calculating the sum of squared errors for each value of k . Then, if the plot of the sum of squared errors vs. the number of clusters looks like an arm, the “elbow” on the arm is the optimal number of clusters. Figure 7 shows the sum of squared errors for the various cluster numbering. From the chart, we see an elbow on the three-cluster. Hence, this is the optimal number of clusters. Furthermore, the three-cluster pricing is not difficult for consumers to get accustomed to and reflects the true state of the spot market price as well as the network loading.

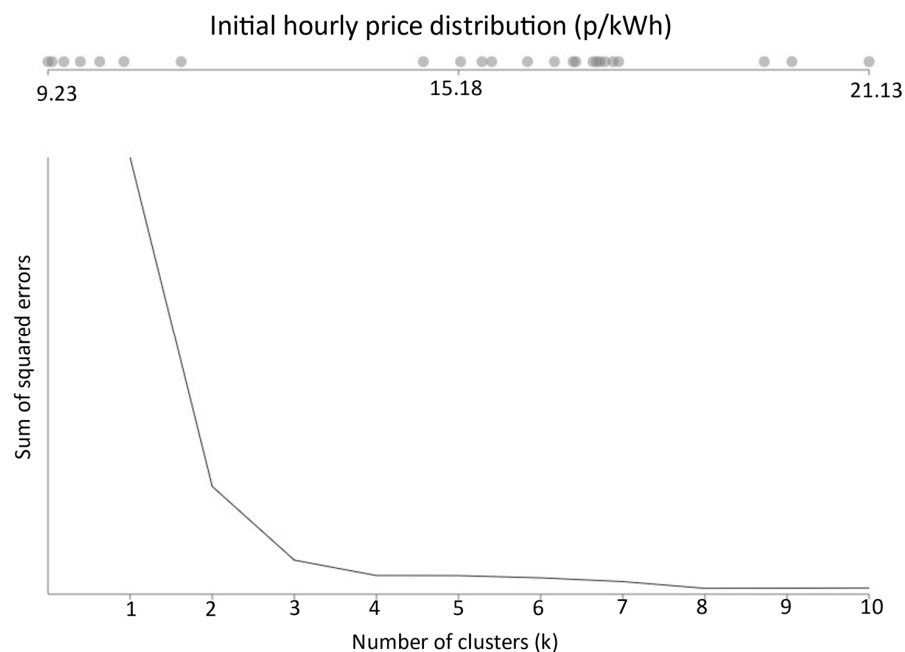


Figure 7. Elbow chart (sum of squared errors vs. number of clusters).

Figure 8 shows a graph of the optimal three-cluster pricing. The peak period coincides with the peak period of Logvestown substation. This optimum pricing has effectively defined a value for flexibility of demand for congestion management.

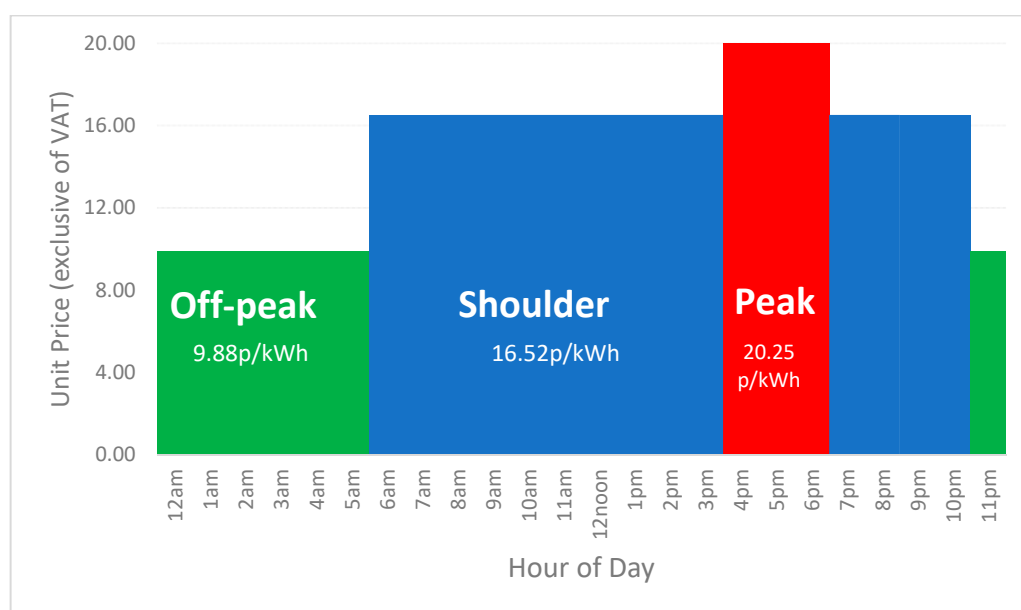


Figure 8. Optimum time of use pricing (three Clusters).

Figures 9 and 10 shows the control logic for simulating the time of use and real-time demand response. For the time of use response, the storage is charged during the off-peak period (night) to be used for meeting heat demand during the day. It might also be topped up later in the afternoon to reduce evening peaks effectively. For real-time response, the prices for different hours are usually released daily after the clearing of the day-ahead market. The charging time is based on the cheapest hours leading up to the next heat demand.

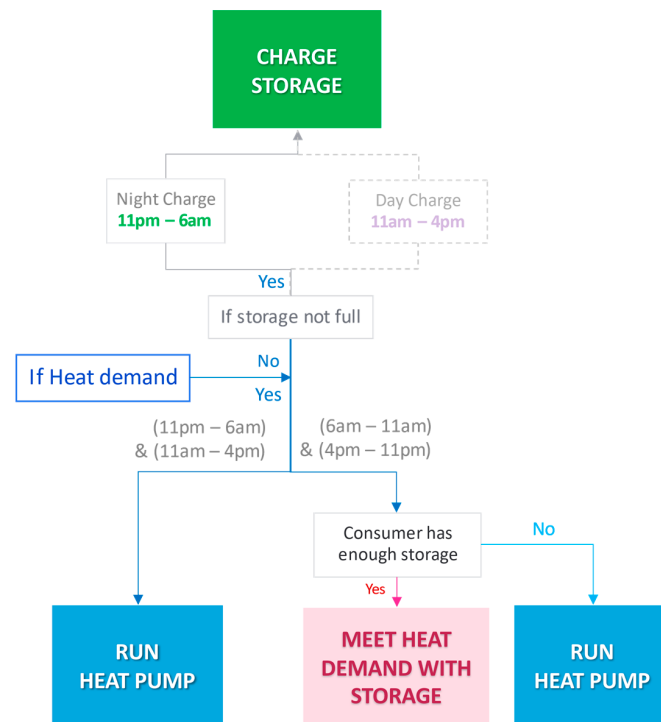


Figure 9. Control Logic for Simulating Time of Use Demand Response.

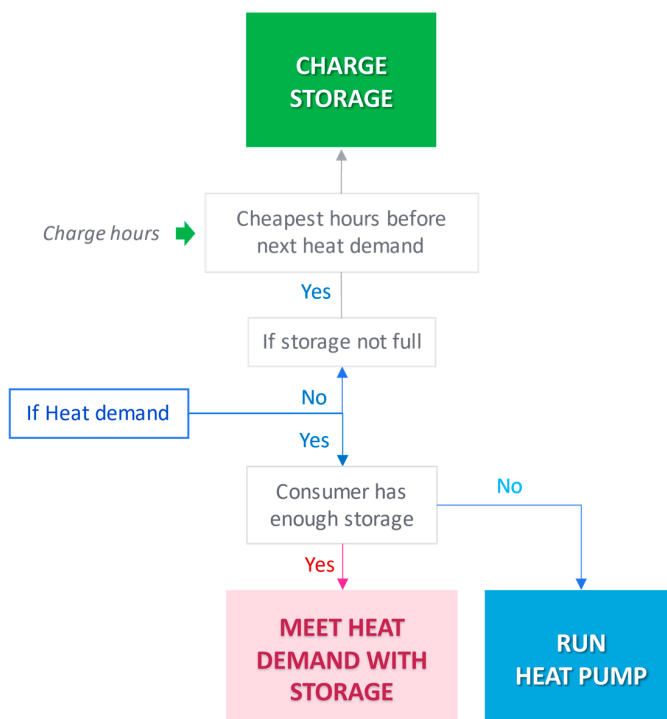


Figure 10. Control logic for simulating real-time demand response.

2.3.3. Smart Control via Distribution Network Monitoring

Smart distribution grids make use of a smart fuse—a special low voltage fuse with a current and voltage transformers, sensors, an integrated electronic card (similar to three-phase smart meters) for measurement of current, voltage and a remote terminal unit (RTU) or Gateway for processing and real-time communication with the DSO control centre [54]. The smart fuse is usually installed at secondary substation feeders or pole-mounted transformers to replace the basic fuse. Smart fuse has previously been tried for monitoring, fault location and management (the Smart fuse project [55]), for voltage management and active network meshing (the smart street project [56]).

By monitoring the voltage and current, network conditions can be communicated to devices, which can respond appropriately. Furthermore, platforms such as if this then that (IFTTT) offers options to connect smart thermostat, inverters and smart plugs for electric vehicles and other home appliances while allowing the control of these devices through conditional statements that could be triggered via an application programmable interface (API) [57]. By connecting a SCADA or distribution management systems (DMS) with such API, the DSO could provide accurate demand response signals for management of network congestions and take-up of new business models. Figure 11 gives an overview of the smart control strategy. The OpenLV project investigated how secure sharing of low voltage network data could open up new business models [58]. Furthermore, such an API could also be integrated with the TSO ancillary services platform, allowing proper TSO-DSO co-ordination. Modern heat pumps can now respond to control signals from the smart grid, more recently using the SG-Ready specification [59].

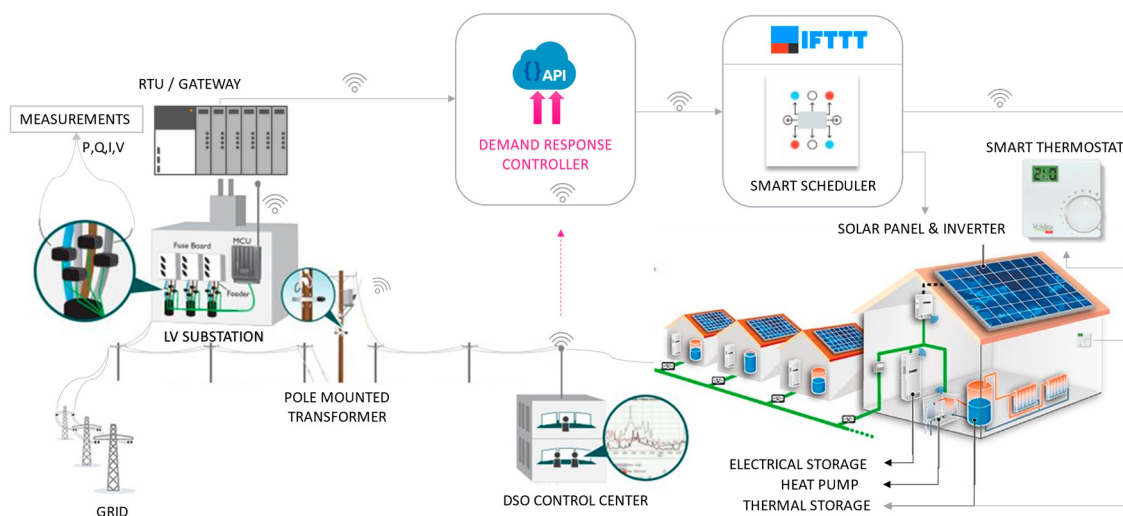


Figure 11. Overview of demand response with smart control.

In addition to using storage for providing flexibility, we use a hybrid heat pump such that whenever there are loading or congestion issues, the previously installed oil boiler is utilised. Depending on the use case and connected system, the control logic would involve several layers. The thermal intervention threshold for 33/11 kV primary transformer is 65%, and that for the 11 kV feeders is 60%. For the secondary substation, the thermal intervention threshold for 11/0.415 kV transformer is 130%, and that for the low-voltage feeders is 100% [60]. However, to reserve capacity for future loads such as the adoption of electric vehicles we have set the maximum loading limit of the secondary transformer to 90% and that for the low voltage feeders to 70% and the 11kV feeders to 50% in the simulation. Furthermore, to provide capacity for the Enterprise Zone with the data centre, we limit the loading on the primary substation to 5.25 MW (35%), leaving about 4.5 MW for the data centre and other future loads before the thermal intervention threshold would be exceeded.

Each device sends a connection request to the API and receives a Boolean response: True (connect) or false (do not connect), and the connection request is repeated in 30 min interval for the duration

of the heat demand to seek connection. Furthermore, whenever there is an overload in any of the control layers, the API sends a disconnect request to several devices that could bring it back within the loading limit. Hence, such API should be capable of tracking each connected device with an ID. This is further explained by the API control logic in Figure 12. In this work, connection and disconnection requests are issued through the first-in-first-out (FIFO) order. However, for aggregators with business models such as heat as a service, in which the consumers heat demand profile is known beforehand, the decision on which load to put on first when the network has limited capacity would depend on the consumers start time on their heating contracts, the internal temperature of the houses, historical heat profiles, if they have thermal storage and the state of charge of such storage. Figure 13 shows the control logic for simulating the demand response of the heat loads via the DSO smart controller.

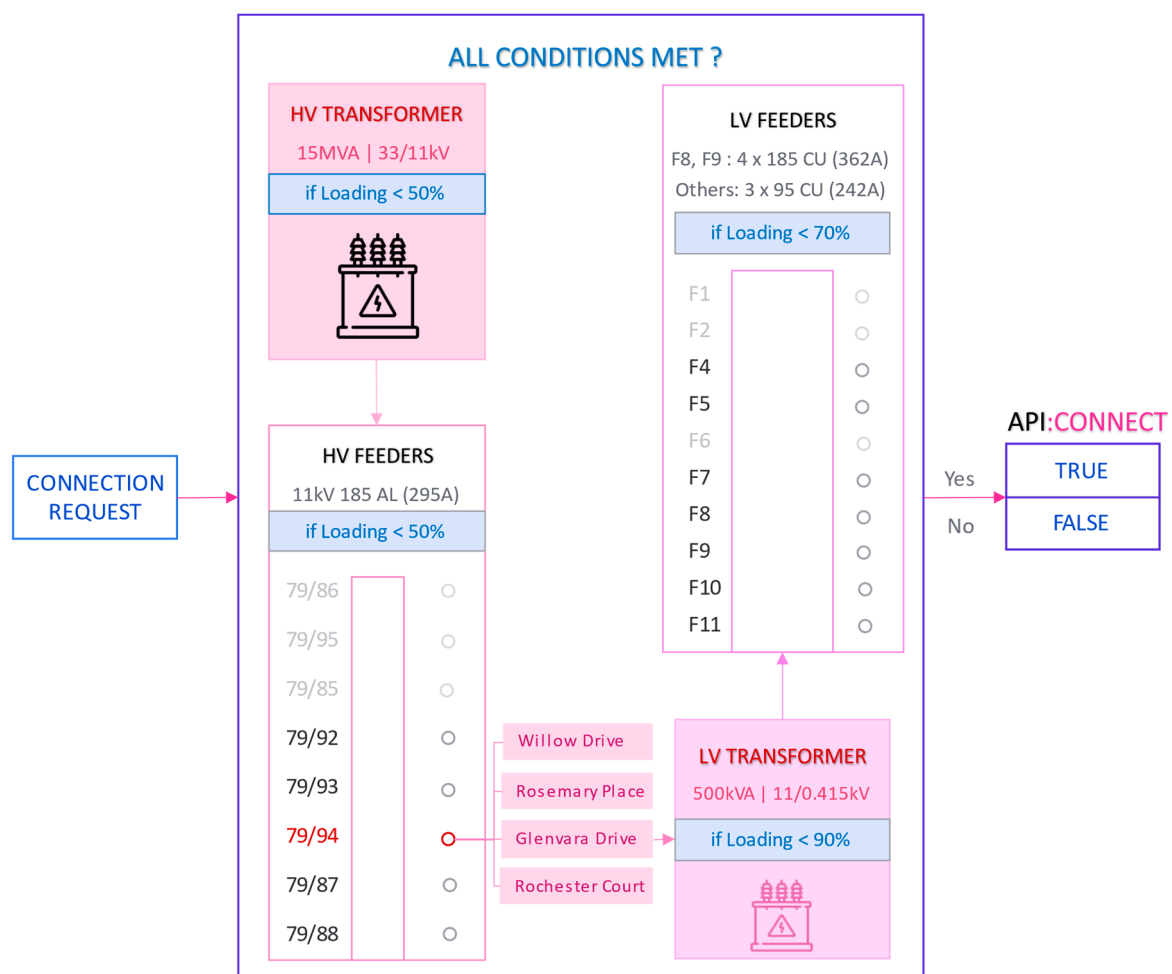


Figure 12. Application programmable interface (API) control logic for responding to a connection request.

Smart LV control could help in opening up other markets or business models such as the sale or matching of excess generation from wind farms or from companies or industries looking to install renewable generation but might not have enough night-time load. Such market signals can be organised within the API controller. Furthermore, the end of the feed-in-tariff (FIT) and renewable obligation certificates (ROCs) have stalled the development of community energy projects and threatens the sustainability of existing ones [61]. Smart matching of community generation, with community demand made possible with smart control strategy, will open up new income streams for such community energy projects. The UNIQ ID of each connected device in the controller could also allow accurate billing and settlements for such projects.

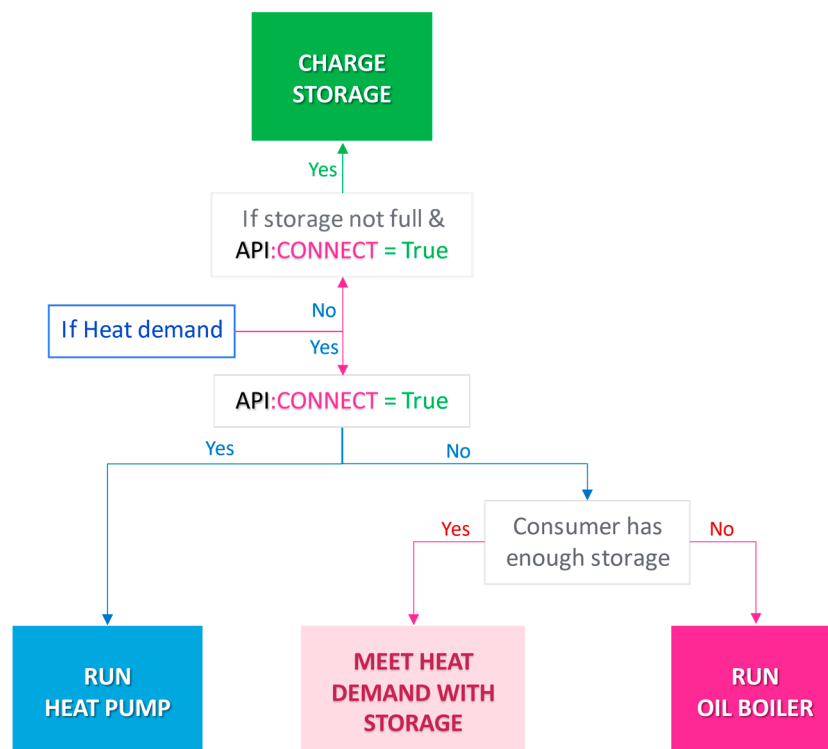


Figure 13. Control logic for simulating demand response via smart control.

The limited budget of the DSO, coupled with some technical constraint, limits the number of Smart fuses/RTU's to be installed. Previous authors [62] developed a multi-objective GA and TOPSIS approach for optimal siting of RTU's in distribution grids. A recommendation for manufacturers of low-carbon technologies such as solar panels, batteries and heat pumps/ heat batteries is to setup interface to platforms such as IFTTT, as such integration is vital to utilising the flexibilities from these devices. Standardisation of components is also vital, for example, using SunSpec open communication protocol for interoperability between distributed energy resource components and smart grid applications [63].

Care must be taken when heat pumps are responding to a time of use tariffs or network availability from the smart control, to ensure multiple heat pumps do not start at the same time. This is to prevent a voltage dip on the system, which would be felt by other consumers connected to the same phase on that feeder. Even with a soft start feature, heat pumps usually draw twice as much current on starting than when running. This is worse with a direct-online starting, in which case it draws 4–7 times more current on start. This problem is more noticeable in weak networks, e.g., rural networks with small pole-mounted transformers (25 kVA). This is because of the higher source impedance from the transformer to the heat pumps, hence causing a higher voltage dip. The size of the voltage dip will drop on heat pumps connected to bigger transformers and lines [64]. Hence, the DSO should regulate for manufacture and installations of only soft-start and inverter connected heat pumps, especially in rural or weak networks.

2.3.4. Managing Congestion Using Solar Panels and Batteries

As seen in Figure 4, without the heating loads, the demand at the substation exceeds 5.25 MW during the day. Hence, the substation will face some loading issues, particularly during the daytime and evenings. This indicates that local generation from solar panels and batteries could relieve some of the constraints. Excess PV generation within the day is used to charge the battery. Under time-based demand response, the incentive would be for the consumer to make use of the charged battery during peak times (mainly 4–7 pm and onwards). While for the smart control, in addition to reducing consumer

demand during the daytime, the smart control API would send requests to houses to discharge their battery during network congestion.

We simulated the effect of installing solar panels and batteries on each of the 1000 houses. In addition to storing up excess solar generation using the batteries, we also simulated a separate case for arbitrage (where the battery charges up with cheap electricity at night to relieve some of the morning loads). Using batteries for arbitrage purposes improves the utilisation factor of the battery and could help complement low solar generation experienced in the winter months. Figure 14 shows the control logic for simulating the PV and battery operation under the time of use pricing, while Figure 15 shows the control logic under Smart Control.

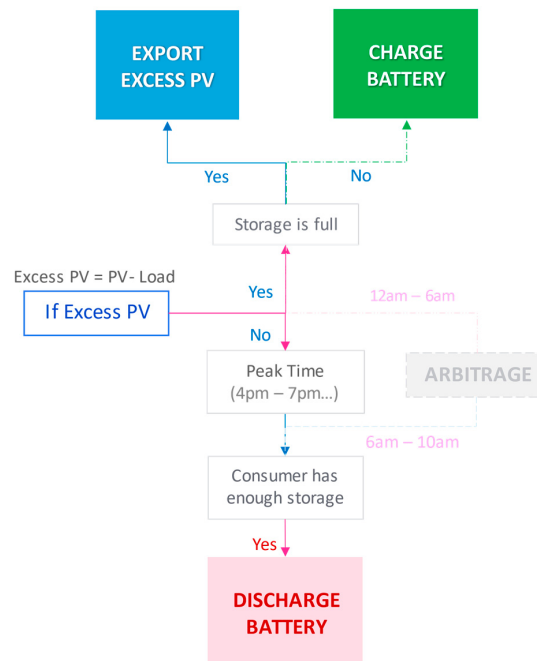


Figure 14. Control logic for simulating PV/battery operation under time of use pricing.

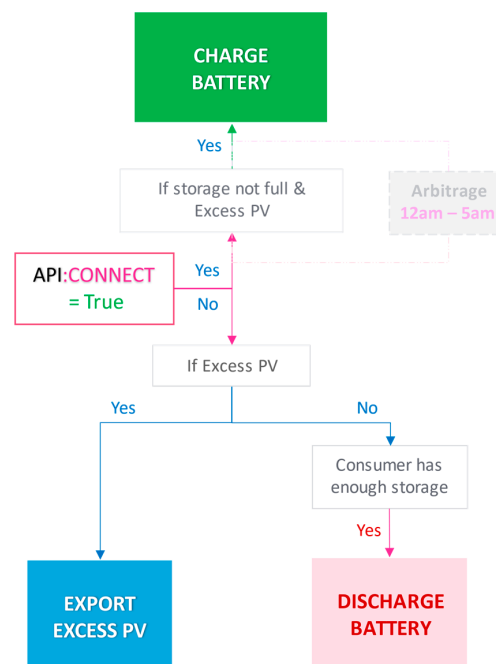


Figure 15. Control logic for simulating PV/battery operation under smart control.

3. Results

3.1. Impact of LCTs on Secondary Substation

Figure 16 shows the average hourly electricity demand of the various heating scenarios for the secondary substation (Glenvara Drive). To better understand the impact of time of use pricing on network peaks, we simulated three ToU scenarios.

- HP_ToU_Full signifies the scenario where 100% of the consumers adhere to the time of use signals, charging their heat battery at night between 11 pm–6 am and at daytime between 11 am–4 pm.
- HP_ToU_Half signifies the scenario where only half of the consumers adhere to the time of use tariff or if all consumers are responding half of the time.
- HP_ToU_1_Charge signifies the scenario where half of the consumers respond to the time of use tariff, but only charge their heat battery at night (no day charge), and the charged battery is used only to meet the evening demand.

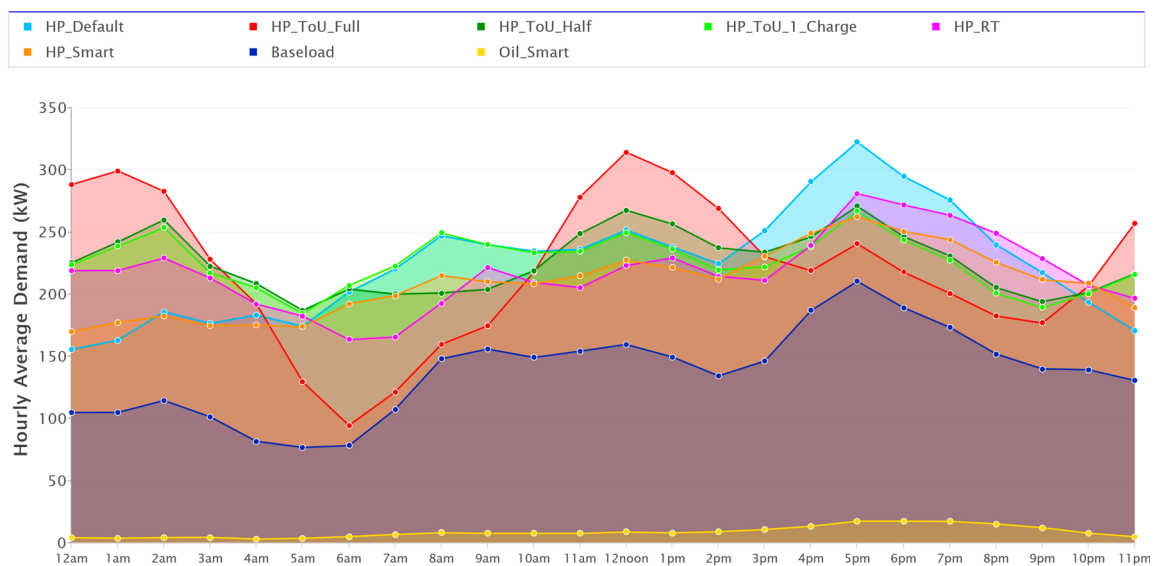


Figure 16. Secondary substation average hourly demand for the various scenarios.

As stated earlier, the smart control is operated in a hybrid setup, making use of the oil boiler during times of congestion and when the storage is used up, hence the graph also shows the heat demand (in kWh of electricity) that is passed to the oil boiler. The oil boiler delivers 5.3% of the total heat demand, and this usually happens between 4 pm–10 pm.

Figure 17 shows the total yearly hours of violations experienced in each hour of the day. As seen from the graph, while the HP_ToU_Full scenario reduces the total hours of violation experienced in the evenings, it creates significant violations in the night and afternoon periods. When only half of the consumers are responding to the time of use pricing (HP_ToU_Half), the demand profile is flatter, and the number of violations is reduced from 481 h in HP_ToU_Full to 153 h (Figure 18). Furthermore, by charging only at night (HP_ToU_1_Charge), more violations occurring in the afternoon are reduced, leading to just 116 h. There is no economic advantage of the night and day charging over the night only charging. The optimal plan will be to use the off-peak electricity rate to offset the peak rate. The heat battery has a very low heat loss, so it serves this purpose well, ensuring significant reduction of congestions. Hence, we recommend and utilise the single charge strategy for time-of-use simulation for the rest of the work, hereafter referred to as HP_ToU.

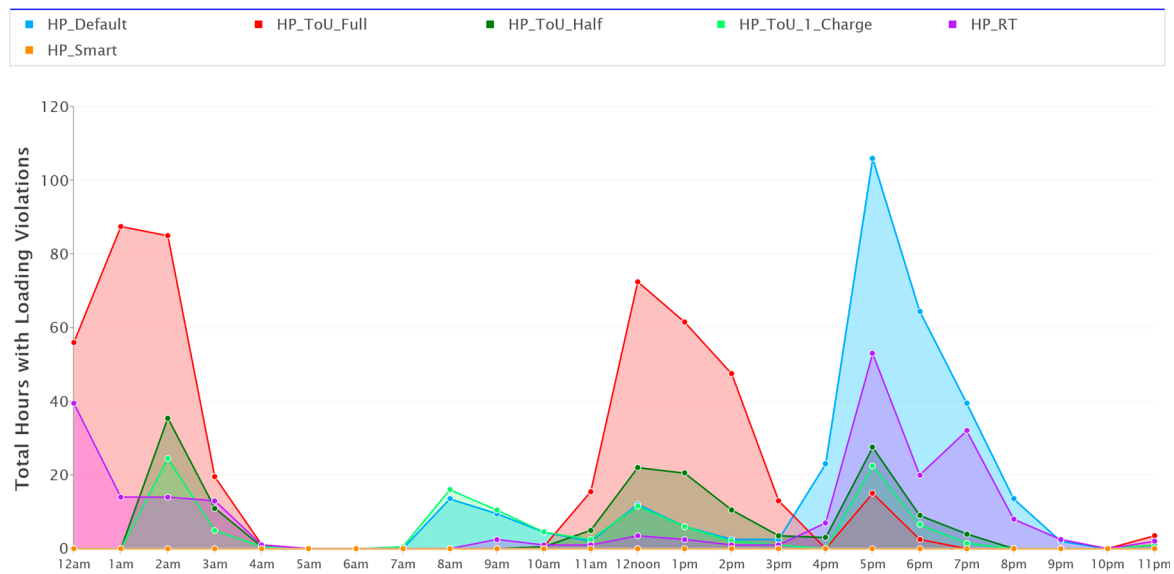


Figure 17. Total hours with loading violations for the various scenarios for each hour of the day.

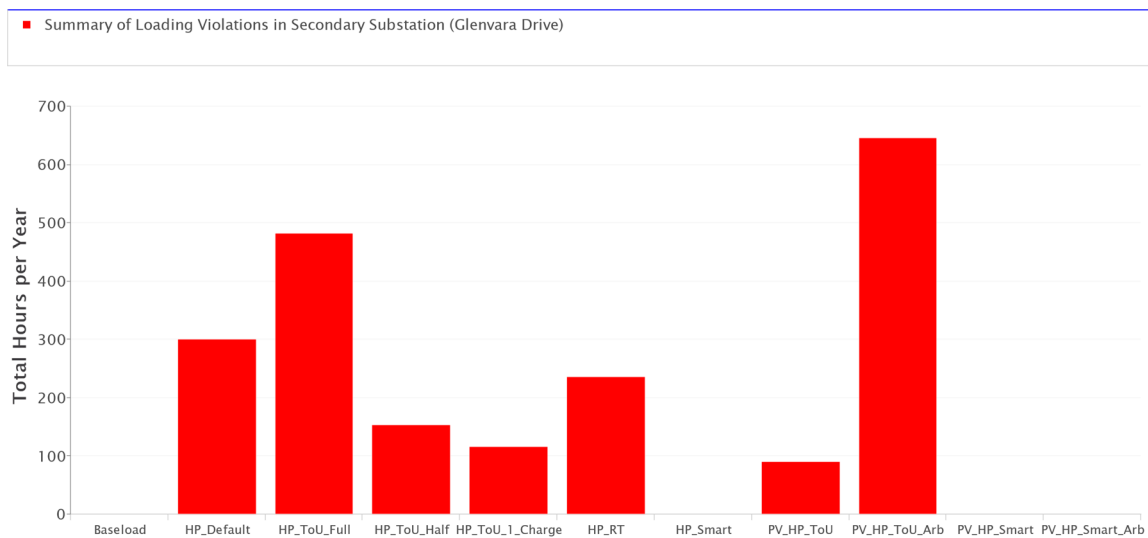


Figure 18. Summary of loading violations of the secondary transformer under the various scenario.

As seen in Figure 18, there is not much difference in the number of congested hours between the default scenario (301 h) and the real-time demand response scenario (236 h). Under the smart control scenario, there is no congestion.

Most of the loading issues on the primary transformer (Load greater than 5.25 MW), as seen in Figure 4, happens in the afternoon and evening period. Hence, the adoption of solar panels and batteries could be useful in reducing these congestions. We first investigate the impact of adopting solar panels and batteries on the secondary substation. We considered two scenarios: When the PV system is operating normally under the time of use and smart control scenarios and when it is also performing arbitrage.

Figure 19 shows the new average demand profile for the PV cases compared to the HP_ToU scenario. As seen from the graph, while the afternoon congestions have been reduced for all the scenarios, there is a new peak at night for the PV time of use with arbitrage (PV_HP_ToU_Arbitrage). Figure 20 shows the hourly loading violations for the PV cases. The total number of violations increases greatly under the PV_HP_ToU_Arbitrage scenario to 646 h (shown in Figure 18). This happened during the night due to the network capacity already being exhausted by charging of the heat batteries.

Without arbitrage, the number of violations under the time of use scenario drops to just 90 h. No violations are recorded for the PV smart control scenario with or without arbitrage. Hence, the use of arbitrage should be restricted to the smart control scenario, which can confirm that there is spare network capacity before allowing the batteries to charge.

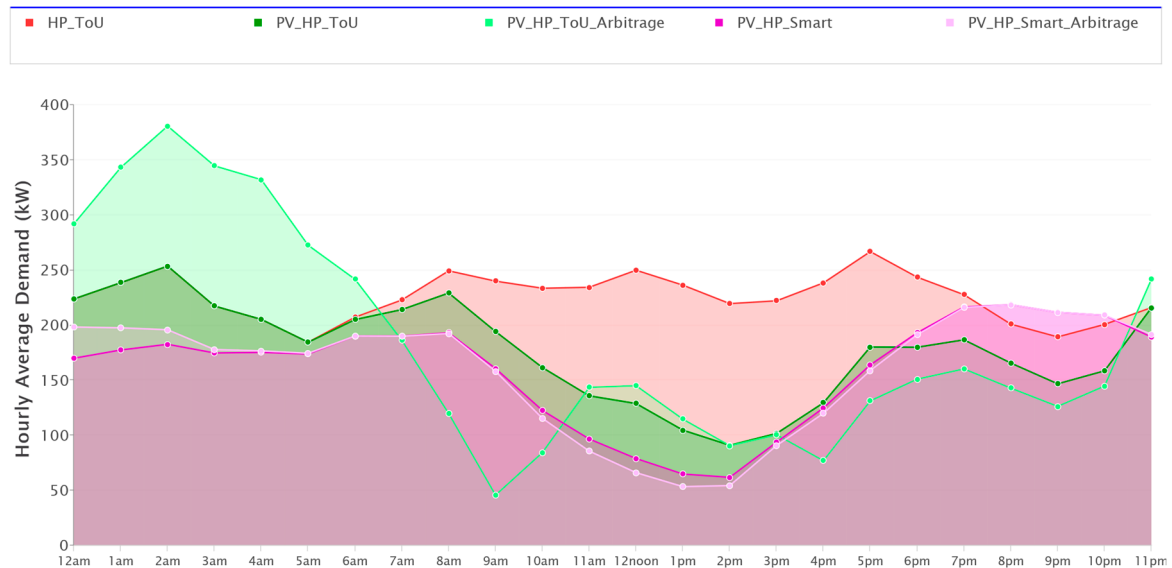


Figure 19. Secondary substation average hourly demand for the PV scenarios.

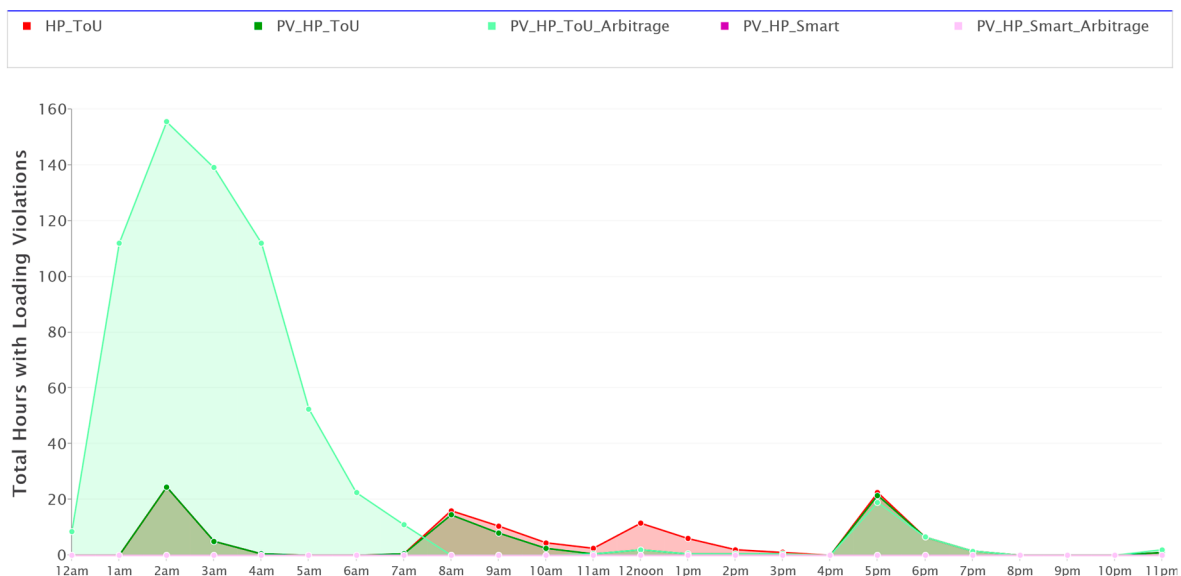


Figure 20. Total hours with loading violations at secondary substation for the PV scenarios.

3.2. Load Flow Results

The heat pump consumption data from RHPP does not include the reactive power measurement, however, for the sake of the load flow analysis, we have assumed a power factor of 0.95 (typical of modern inverter heat pumps) [65]. We also assumed the PV system is operated in normal operation and hence only injecting active power to the grid without any reactive power. The statutory voltage limit for low-voltage supply is 94% to 110% of the nominal value [66]. Table 4 shows a summary of the measurement values used for the load flow study.

Table 4. Measurement data used in load flow.

Date	Scenarios	Logestown Primary		Feeder 79/94		Glenvara Drive	
		kW	kVAr	kW	kVAr	kW	kVAr
Winter Peak 22/01/2018 17:00:00	Base Load	6639.68	735.68	1338.84	72.30	390.37	124.92
	HP_Default	7713.98	1018.49	2019.94	297.06	623.50	201.85
	PV_HP_Smart	5249.68	735.68	457.58	72.30	88.74	124.92
	PV_HP_ToU	7234.48	789.38	1715.94	72.30	519.44	124.92
Summer Min 19/05/2018 14:00:00	Base Load	568.54	499.17	473.73	73.33	105.20	33.66
	Base Load + PV	−1190.47	499.17	−641.47	73.33	−276.51	33.66
	PV_HP_Smart	−1038.47	546.07	−533.00	107.06	−235.07	46.63
	PV_HP_ToU	−1041.80	535.80	−547.22	96.56	−244.24	41.61

In Figure 21, we show the voltages at houses connected to the low voltage feeders of Glenvara drive on a peak winter day under the various scenarios. As seen on the graph, under the baseload scenario, all houses are at an acceptable voltage level ($>95\%$). However, for the HP_Default scenario, there are 34 nodes with undervoltage issues. Under the smart control scenario, the voltages are improved (all $> 97.5\%$) due to the restriction of heating loads and the target support from the PV system. For the time of use scenario, the voltages are just within the acceptable limit.

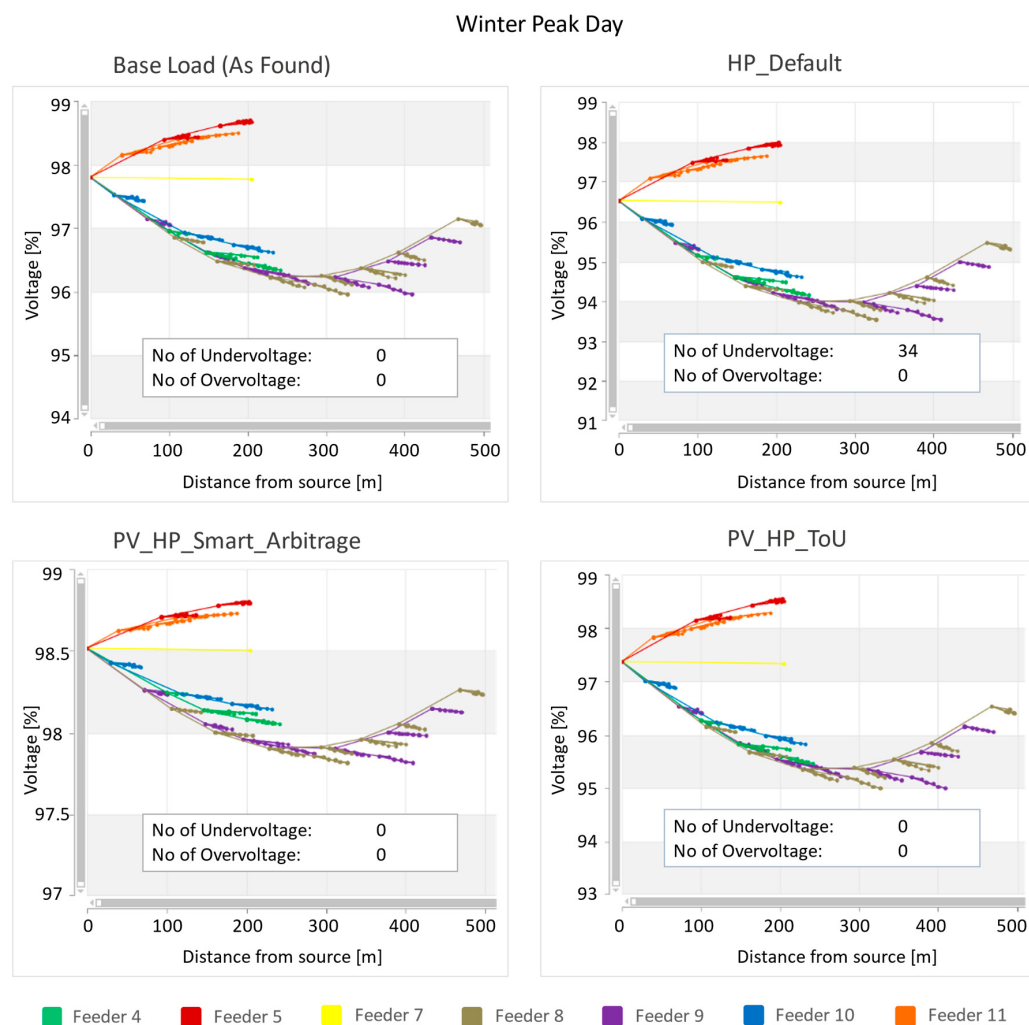


Figure 21. Voltages at the low-voltage feeders for winter peak load scenario.

In Figure 22, we show the voltages on a summer day with very low demand and excess solar generation. We also compare the scenario where there is no heat pump (Base + PV). As seen from the graph, the excess generation causes the voltage to rise, but all within the acceptable limit (<110%). The +1 MW excess generation at Loguestown should disappear with the addition of the data centre load.

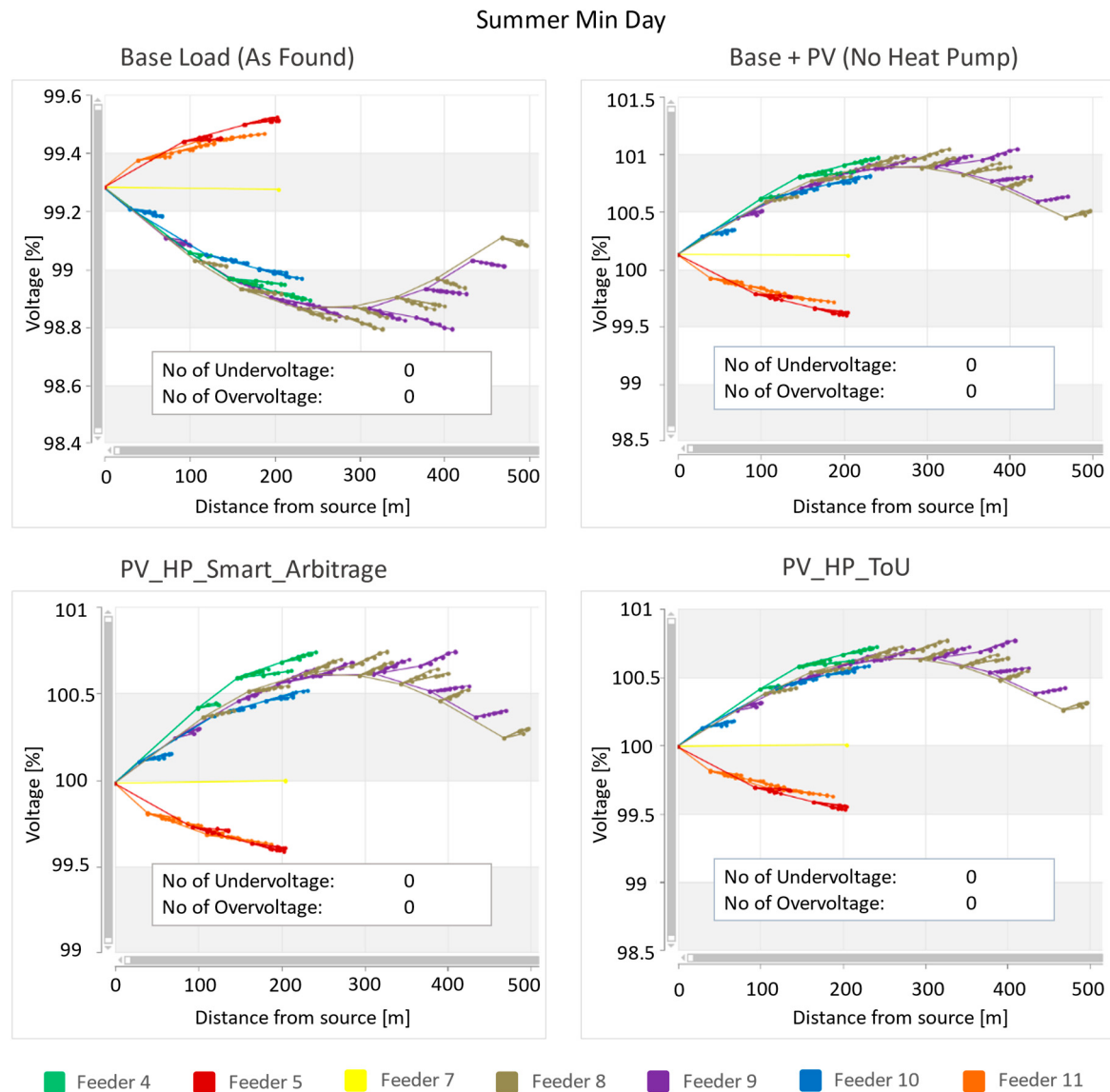


Figure 22. Voltages at the low-voltage feeders for summer min load and excess PV.

3.3. Impact of LCTs on Primary Substation

With these results, we proceed to investigate the impact of these LCT in relieving the congestion on the primary substation (Loguestown) and its feeders. In Figure 23, we show the maximum hourly demand profiles of the Loguestown substation under the various scenarios. The addition of 1000 heat pumps without a proper demand response program could increase the load above 8.2 MW, which is about 3 MW greater than the 5.25 MW limit set for the study. The new data centre is a relatively flat load with capacity up to 4.5 MW. Hence, there is very little room for flexibility there. The time of use strategy does not show a significant reduction in maximum demand, even with the employment of PV systems. There is a greater reduction in the maximum demand for the smart control scenario, while with arbitrage, the maximum demand is almost entirely within the set limit.

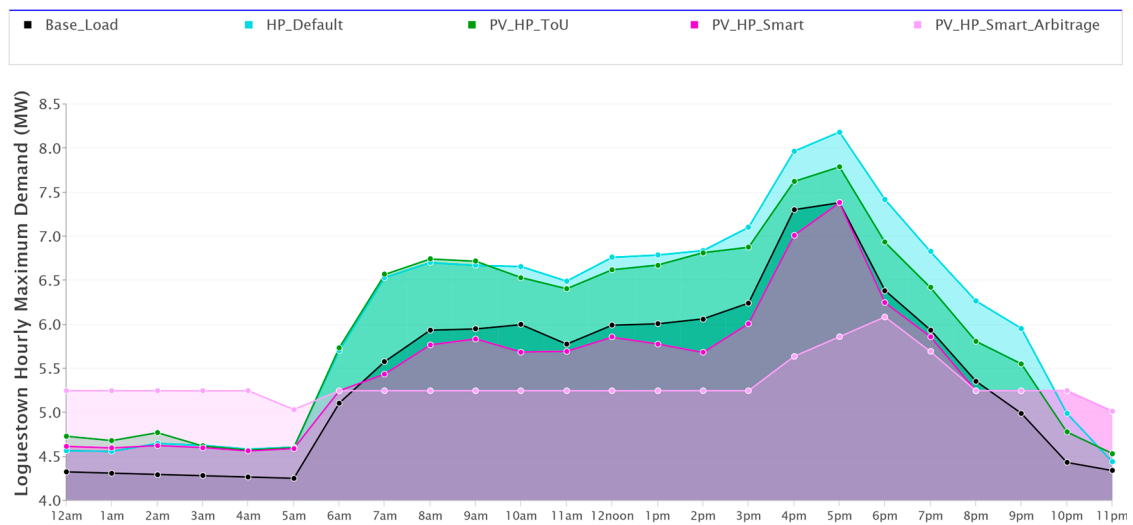


Figure 23. Hourly maximum demand for primary substation under each scenario.

In Figure 24, we show the distribution of violation hours, while in Figure 25, we show the summary of loading violations for the primary substation for all the considered scenarios. As seen from the graphs, violations are lowest under the smart control scenarios, with violations almost completely removed in the PV smart control with arbitrage scenario.

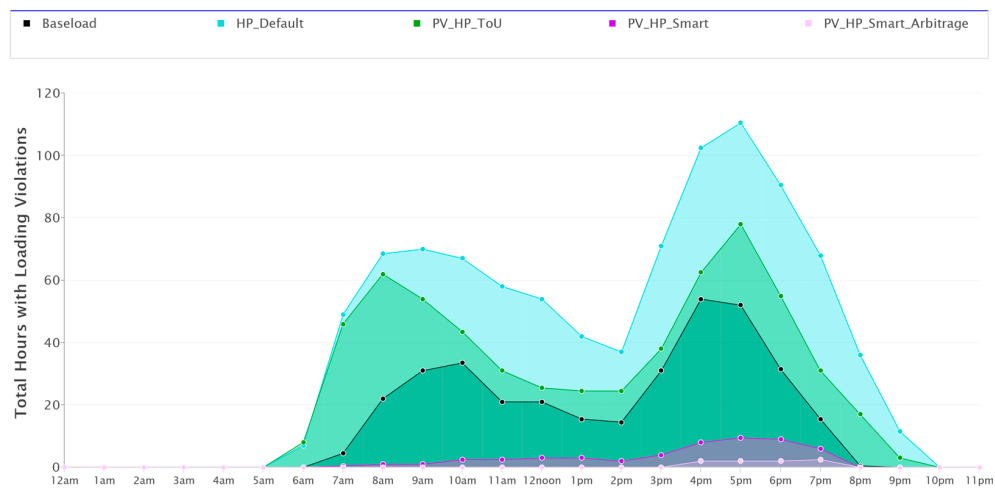


Figure 24. Hourly profile of the total hours with loading violations for primary substation.

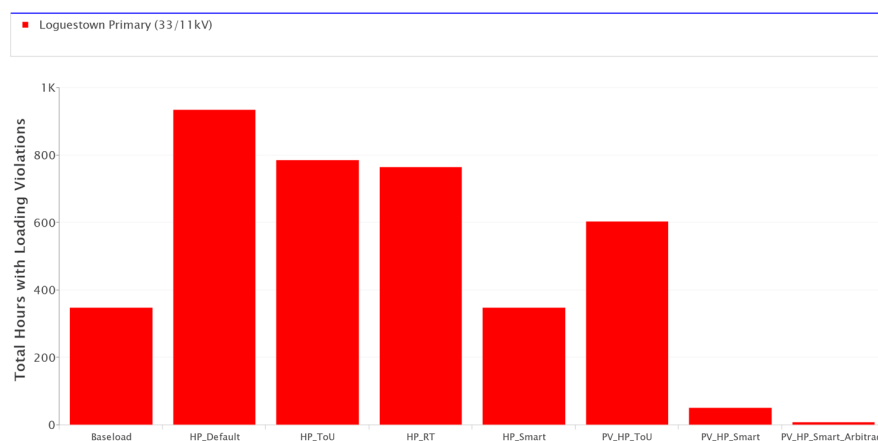


Figure 25. Summary of total hours with loading violations for primary substation.

3.4. Managing Backflows and Excess Generation

Downstream Feeder 79/87 is the University of Ulster (UU) Coleraine campus. The campus has two wind turbines each 800 kW and exports excess wind energy back to the grid, which results in backflows from the feeder to the transformer up to 600 kW, as shown in Figure 26. This excess generation could be used to charge up thermal storage in some of the 366 social housing connected on the same feeder (79/87) and prevent backflows; while the storage could be used as the first source for space heating/ hot water in the morning, reducing the expected early morning peaks.

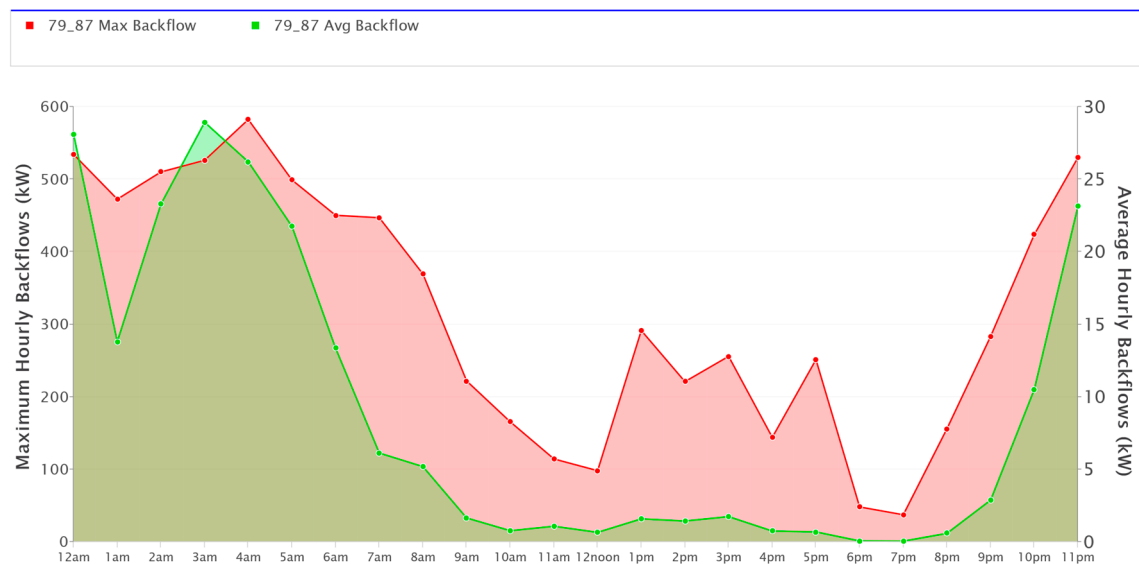


Figure 26. Maximum and average hourly backflows for feeder 79_87.

Figure 27 shows the backflows from feeder 79/87 with wind turbines from Ulster University under the various demand response signals. The smart control provides more precise matching of the excess generation. As explained earlier, implementation of the smart control would open up business models such as matching of excess wind from commercial or community projects for domestic heating.

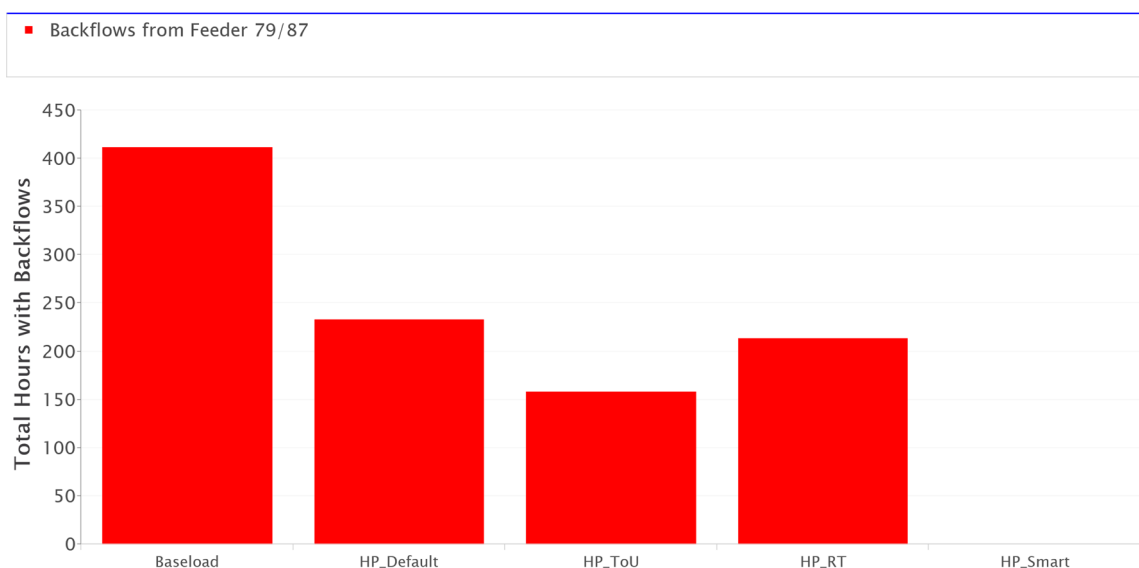


Figure 27. Maximum and average hourly backflows for feeder 79_87.

3.5. CO₂ Emissions

Using a time-series of the CO₂ intensity in the All-Island grid available from Eirgrid Smart grid Dashboard [67], we calculate the savings in CO₂ emissions under the various heating scenarios as opposed to oil heating, which is currently used. The CO₂ intensity of oil was assumed as 0.3 kgCO₂/kWh. The monthly CO₂ emissions of an average social housing for the various scenarios are shown in Figure 28.

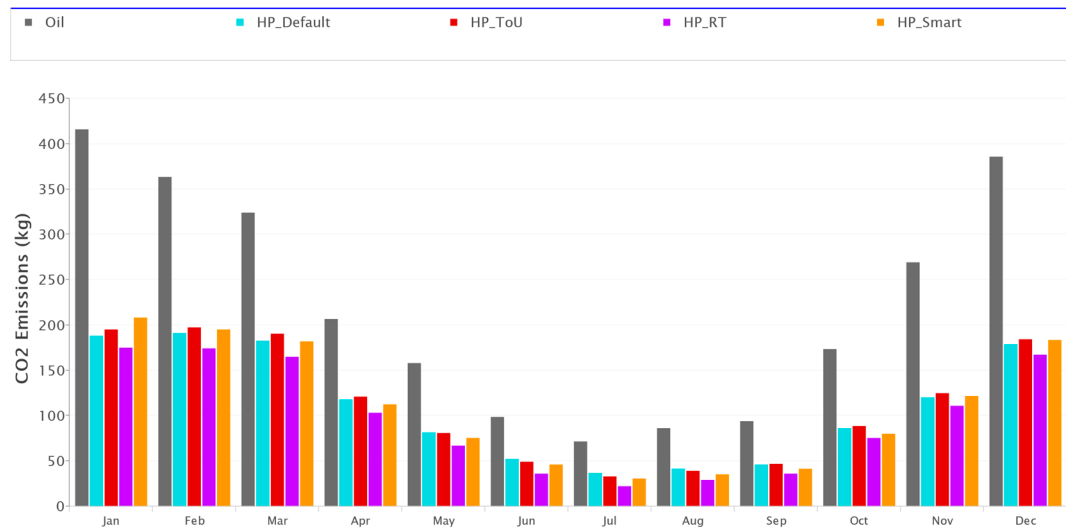


Figure 28. Monthly average CO₂ emissions per house for the various heating scenarios.

Table 5 shows a summary of the reduction in CO₂ emissions under the various scenarios when compared with oil heating. There is a saving of about 50% with the move from oil to heat pump due to the higher efficiency/coefficient of performance of the heat pump for the default, time of use and real-time scenarios. The savings in the smart control scenario is reduced to 46% due to the few times when the oil boiler is used.

Table 5. Reduction in CO₂ emissions per house for the various scenarios compared to oil heating.

	Oil	HP_Default	HP_ToU	HP_RT	HP_Smart
CO ₂ Emissions (Kg)	2648.45	1342.57	1369.38	1365.52	1427.00
% Reduced		49.31%	48.29%	48.44%	46.12%

However, with the move to 70% renewable electricity and 95% system non-synchronous penetration (SNSP) limit by 2030 [68], existing fossil fuel generators are expected to be decommissioned, and the CO₂ intensity of the grid is expected to be considerably lower, as shown in the system operators future energy scenarios (Figure 29a,b). Furthermore, there will be more saving from the time of use and real-time scenarios because most of the heat loads will be moved to times of high wind penetration when the CO₂ intensity of the grid is lower.

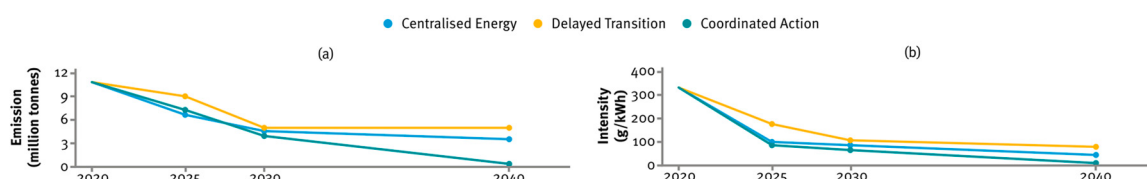


Figure 29. CO₂ emissions and intensity (Eirgrid's Tomorrow Energy Scenarios (a) Emission and (b) Intensity [68]).

3.6. Price of Flexibility

Table 6 shows the annual heat bill savings under various scenarios. The calculations do not include the cost of implementing each of these strategies. Using the current electricity price (17.85 p/kWh), consumers will be paying an extra £9.3/year for moving their heating loads to off-peak periods due to the lower COP at night. This clearly shows that the current system discourages consumers response. However, with the three-Cluster pricing, they will save £117/year, and for the real-time pricing, they will save £107/year.

Table 6. Annual savings in electricity price for consumers under the time of use and real-time pricing.

	HP_Default	HP_ToU (Flat Tariff)	HP_ToU (3 Cluster)	HP_RT
Total Annual Heat Electricity cost for Portfolio (1000 HPs)	£630,331	£639,670	£513,342	£522,900
Savings/Consumer/Year		−£9.3	£117.0	£107.4

While time-based demand response strategies create a system by which the existing market pays for the flexibility, the smart control strategy requires the DSO to purchase flexibility at a certain price either via direct bilateral agreement or in a local flexibility market [69]. In this case, flexibility may be procured to avoid or delay network investments in distribution lines or transformers.

Overloading of transformers does not immediately result in a blackout but leads to an increased internal temperature, which eventually reduces the lifetime of the transformer for insulation hotspot temperatures up to 140 °C with an attached cost. Higher temperatures can cause permanent damage to the transformer. This cost of lifetime reduction together with the risk of an outage as proposed in [70] can be used to determine the price the DSO may be willing to pay for flexibility. Furthermore, it is usually in the DSO's interest to delay a decision on network upgrade until future load pattern becomes clear. Previous authors [71] developed a real-option framework to value demand response strategies against conventional solutions.

Without smart management, the conventional solution would be to install a new primary transformer to serve the feeders going to the data centre as well as other future loads in that area. The cost of a 33/11 kV transformer (up to 12.5 MVA) is £228.7 K [72] with an annual OPEX of £1.158 [60], while installing a new secondary transformer would cost £20 K, and other costs would also be incurred for upgrading constrained lines. Some of the cost associated with setting up a smart control scheme such as IT cost is usually shared among several constraint managed zones, hence the specific setup cost for a particular constraint zone would be limited to installation of smart fuses, RTUs and sensors, as well as the cost for flexibility setup, procurements and contracts. By adopting the smart control strategy, the DSO can save in cost for managing congestion while supporting the energy transition [73].

4. Conclusions

In this work, we assess the performance of various demand response strategies in relieving network congestions using two metrics: The number of hours of loading violations and the number of houses experiencing under voltage. Our results show that time-of-use tariffs that incentivise charging at afternoon periods could cause new congestions at those periods. Hence, tariff developers must implement such tariffs only in cases where the load profile of the network show significant low demand in the afternoon. Otherwise, tariffs should incentivise only night charging. As a result, thermal storage, which can shift demand over long hours (above 16 h) such as heat batteries, are preferred over hot water tanks for mitigating congestions.

Secondly, if too many people adhere to the time of use pricing, there would be a new network peak. This result also agrees with the studies in [74,75]. In our case study, a price responsiveness of 50% was adequate in mitigating the peaks. Hence, system operator must consider the price responsiveness of the consumers in a network while selecting a demand response strategy. For example, low-income neighbourhoods might be more responsive than affluent neighbourhoods, as indicated in [28]. They may

consider deploying the smart control strategy if the amount of consumer response predicted is contrary to the amount desired. Further research should be done to develop detailed prediction methodologies to help system operators make better choices.

Naive real-time pricing methodologies could cause congestions at the lowest-price periods. The mean grouping strategy proposed in this work was able to increase the average lowest-priced hours from 1.32 to 3.76. While it has been more demanding for the consumers and might require automation, real-time pricing does not have much advantage over well-designed time-of-use pricing in terms of reducing congestion. Furthermore, [76] shows that risk-averse consumers do not have an incentive to switch to real-time pricing. However, real-time pricing is particularly useful when the main objective of the demand response program is to improve the performance of the day-ahead market or in networks dealing with a high amount of intermittent renewable generation.

Therefore, we recommend that the optimal (three-cluster) time of use pricing be implemented for Northern Irish networks in general to improve the load factors of the distribution networks. On average, the consumer saves £117 per year for the three-cluster time of use pricing, and £107 per year for the real-time pricing on their electric heating bill when compared to a flat tariff rate.

For networks at risk of congestion or with lower headroom, in addition to the time of use pricing, implementation of the smart control strategy would be necessary. There could be congestions upstream at the primary substation (as in the case of Loguestown) or its feeders. Loads at the low-voltage network might be needed to respond to resolve the congestion at the primary substation. The result from this work shows that though the time-of-use strategy was able to reduce the number of hours of congestion at the primary transformer by 35%, there were still about 600 h of congestion. With the smart control strategy, this is reduced to just 8 h in the year (99% reduction) and even then, the level of congestion in those hours was significantly reduced.

Utilities usually have a connection request for low-carbon technologies. To safely accommodate heat pumps and electric vehicles in existing networks, such connection request might need to be updated to include a proof that such a heat pump can respond to grid challenges. As stated earlier, the German SGReady label can also be adopted while each heat pump is registered to the DSO's API as part of the connection process. By following this process, the DSO could quickly set up the smart control whenever it requires, since consumers would already have flexible resources ready to be activated.

Adoption of solar panels and batteries should be encouraged in networks with existing congestion issues. While business models such as using batteries for arbitraging could complement low solar output in winter periods, its use is severely limited by the capacity of the low-voltage network; it could cause new congestion issues. We recommend that arbitrage be used with the smart control strategy and not with the time-of-use strategy.

While thermal storage can handle the heat demand during periods of congestions, there are times (5.3% of the demand in this study) where the storage is exhausted and turning on the heat pumps would lead to congestions. Hence, oil heaters must be left in place to handle the heat demand at these times using a hybrid setup. However, where the consumers heating is completely managed by a smart scheduler, which can forecast congestion on the grid and preheat the house, reliance on oil heating as a back-up might not be needed. Further research is needed to confirm how probable this is.

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