Intelligent Community Control using Digital Twin Model Prediction

Kate Naughton[1], Catherine Conaghan[1], Dr. Michael Bennet[1], Dr. Mike Oates[1]
Integrated Environmental Solutions, Glasgow G20 0SP, UK

Abstract

As the requirement to decarbonize the power sector increases globally, community based renewable energy sources (RES) is increasing, creating an urgency for grid modernization. However, facilitating control of RES with traditional top-down methodologies is challenging due to insufficient visibility on the distribution network.

The Intelligent Community Control (ICC) uses digital twin prediction with network level forecasting to recommend control strategies from the bottom-up, accounting for all grid interconnected components. This has been virtually tested on a model of an existing network in Eday, Scotland, where benefitting from existing RES was challenging due to operating on an already constrained network.

The ICC approach increases the economic benefit to end-users, while simultaneously improving local load balancing to improve grid stability and reduce network costs.

Introduction

Distributed RES penetration is a key pillar in creating a competitive low-carbon economy (European Commission, 2013). Current RES penetration has surpassed 18% (Eurostat, 2020) in the European Union (EU), and 26% globally (REN21, 2019). This growth is expected to continue with EU targets for 2030 set at 32% (European Union, 2018), in addition to worldwide targets of individual countries of up to 100% RES by 2050 (REN21, 2019). The majority of RES integration to date has been at a large-scale and installed far from existing infrastructure, where installations require grid connections and infrastructure reinforcement, which result in higher transmission costs (Giordano et al., 2011). Added to this, renewable electricity production, particularly from solar photovoltaic (PV) and onshore wind turbines, continues its trend to become an increasingly affordable and competitive source for electricity generation at community and building level.

Although diversification of the energy network is essential to ensure a secure, economically efficient and sustainable power system (Leal-Arcas et al., 2018), replacing fossil fuels with RES is not a like-for-like exchange. RES such as Wind Turbines or PV rely on variable weather and are inherently less reliable and consistent than traditional generation systems. Without adequate energy storage on the grid (European Commission, 2017; Renewable Energy Agency, 2018) the power produced must equal power demand at all times, which is becoming an increasingly complex task for grid operators.

These changes to the grid environment are driving the traditional energy market into large-scale transition. Traditionally transmission system operators (TSOs) have been responsible for balancing and distributing load at high voltage levels to the distribution system operators (DSOs). As such, metering was required down to substation level only, making sections of the distribution network effectively unobservable by the grid (Strachan et al., 2018). The decentralised nature of RES places the DSO at the heart of the transition, and drives the requirement for better visibility and control of all grid connected assets (Leal-Arcas et al., 2018). Although significant efforts and investments are continuing, grid modernisation is very much in a transition phase. Barriers currently exist such as; lack of decentralised management and control of DER's, lack of optimisation of decentralised assets, and a lack of mutually beneficial solutions (Yoldaş et al., 2017).

In parallel to these changes there have been significant advances in other areas including; evolving information and communication technology infrastructures (ICT), the emergence of smart devices, and the increase of cost-effective storage technologies. This yields optimum conditions to facilitate Demand Response (DR) as a viable energy and grid management strategy (Ghaemi & Schneider, 2013). These advances create an opportunity for consumers to actively engage with the grid through small-scale generation, energy storage, and offering flexibility to better align with the increasingly variable energy supply.

By 2050 it is estimated that 83% of European households could become active participants in the energy market, producing 45% of European energy demand (Kampman et al., 2016). At a global level, DER is also expected to increase from 2% in 2017 to 21% by 2050 (Renewable Energy Agency, 2018). Installing RES and energy storage closer to the point of connection offers a more economical means of facilitating additional decentralised RES (Worthmann et al., 2015) in the energy system, while reducing issues associated with grid stability and power quality disturbances (Mohd et al., 2008).

One of the greatest technical barriers to network management at distribution level is the lack of visibility of the connected assets. Although many countries are rolling-out smart metering at building level, this data is often aggregated or does not offer sufficient granularity for real-time optimisation (Strachan et al., 2018). Without adequate knowledge of the connected buildings, it is difficult to use the collected data to adequately predict demand for DSO's to enable real-time network management (Poursharif et al., 2017). In addition, although the integration of DR is advancing in industrial applications, DR for domestic consumers is particularly challenging due do similar data availability issues and the inability to make predictions on their available load flexibilities (Giordano et al., 2011).

The ICC addresses these challenges with a bottom-up approach in place of traditional top-down network control methodologies. The ICC achieves this through dynamic energy building simulations to create a "digital twin" of each connected building. In this instance, a "Digital Twin" refers to a model, calibrated in line with ASHRAE Guideline 14's (ASHRAE, 2014) targets for Coefficient of Variation of Root-Mean Squared Error (CVRMSE) and Normalised Mean Bias Error (NMBE). The ICC uses the Intelligent Virtual Network (iVN), the Virtual Environment (IESVE) and Intelligent Control and Analysis (iSCAN) software packages to create the digital twin building and network models (Integrated Environmental Solutions Limited, 2020). In combination with measured data, the ICC uses information around building construction, occupancy patterns, heating schedules, and others, in conjunction with geometry (typically imported from Open Street Maps) to generate energy models using the IESVE simulation engine. These digital models are mapped to virtual distribution networks with integrated physics-based models of distributed energy resources within the IVN. Although there has been much research in the area of Virtual Power Plants (VPP) (Saboori et al., 2011), which solve for the optimum dispatch of DER's for a known set of demand and generators, the ICC approach has the added ability to include dynamic energy models of individual buildings for building thermal analysis. The ICC uses this combination of digital building prediction and network forecasting with optimisation algorithms to predict both individual building demand and available generation from local DER to identify available load flexibilities, and facilitate more effective management of all grid connected assets.

Method

The ICC was tested on a virtual network model of Eday, an islanded community within the Orkney Islands, Scotland. The Orkney islands are located in the North East of Scotland's mainland, with a single grid connection to Scotland (Scottish and Southern Energy Distribution, 2013). This isolated connection in combination with a high penetration of wind generation has led to constraints and restrictions on the distribution network. The challenges experienced on Eday are the same challenges that grid modernisation needs to address, and will become increasingly relevant as decentralised generation increases globally. Eday and the wider Orkney islands have become an area of interest for many studies to improve grid balancing at community level (Innovate UK, 2019). The intermittent nature of RES creates a highly variable and unpredictable load profile in the absence of optimisation. For a small group of buildings, the sudden peaks and troughs in demand would go unnoticed by the grid, but at a larger scale create a risk of grid instability. This is due to poor network visibility in conjunction with traditional power generator's inability to respond to unpredicted changes in energy demand.

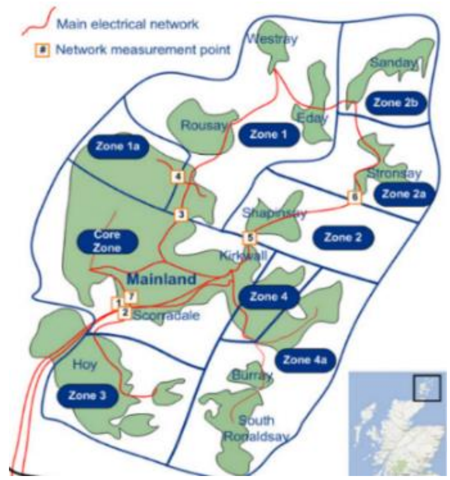

Figure 1: Orkney Island Transmission Network (Scottish and Southern Energy Distribution, 2013)

Eday currently has 150kW of small-scale domestic wind turbines installed on the islands low-voltage network. The initial digital twin and network model was created as part of the CEDISON project (Innovate UK, 2018), which was funded by the Innovate UK programme. As an initial step surveys were carried out on the island to obtain detail on building construction, energy consumption, occupancy patterns, etc. This information was used to create the digital twins and integrated network model.

This study uses the ICC to create a virtual model of Edays' electricity infrastructure and its interconnected components. The network is optimised virtually by testing control strategies for buildings with the use of thermal analysis, and energy storage at network level. This study aims to identify the strategies which could potentially be adopted by the Eday community to reduce grid imports and improve grid stability of the wider network.

The network control strategies analysed are based on the approach of optimising performance from the bottom up i.e. building demand up to network level, as opposed to the traditional top down approach. This was accomplished using the digital twin building and integrated electricity network model. The initial model indicated an annual electricity demand of 615MWh, heat demand of 1552MWh, and total wind generation of 665MWh, with 28MWh of excess generation based on data obtained for 2019. Wind turbines were modelled in the IVN, using the turbines power curves and Edays' weather file for the actual meteorological year (Martinez, 2001), and buildings were simulated in the IESVE with a 1-hour timestep. The error between monthly simulated and measured data was minimised to meet ASHRAE-14 guidelines to ensure the model corresponded to actual energy demands reported in Eday (Figure 2).

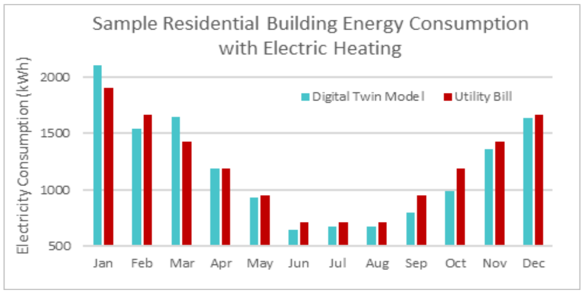

Figure 2: Monthly comparison of Digital Twin vs. measured data with CVRMSE of 14% and NMBE of 1% in line with ASHRAE-14 targets of 15% and 5%, respectively)

Network layouts and cable information were obtained from Scottish and Southern Electricity Networks to create the integrated bus-branch network model within the IVN. This used the Classical DC Power Flow modelling method, which is a linear approximation to the general AC power flow. The network model was not validated as part of this study due to lack of network level data.

The initial model indicated high building energy consumption, with the average home consuming 17,438kWh for heating, 35% higher than the average on mainland Scotland (The Scottish Parliament, 2017). This was found to be as a result of poor thermal performance due to an older building stock with inadequate insulation.

Before the electricity network may be optimised for self-consumption, building energy demand needs to be significantly reduced to increase the available excess generation. This was achieved by applying interventions in sequence using the digital twin model through the IESVE building energy simulation. The sequence of interventions applied is shown below, with the results summarised in Table 1. Wind generation was excluded from this analysis, focusing on total building electricity and heat fossil fuel (i.e. gas, oil and peat) consumption only.

A. Baseline Scenario + 200mm Roof Insulation
B. A + 50mm Cavity Insulation
C. B + Hot water tank and piping insulation
D. C + LED lighting
E. D + 10kW air-source heat pump with COP 3.75

Table 1: Total demand of retrofit scenarios

Scenario	Energy		Savings			EUI
	Fuel	Elec	Fuel	Elec	Total	
	MWh	*MWh*	*%*	*%*	*%*	*kWh/m2*
Initial	1522	615	0%	0%	0%	161.1
A	1339	575	12%	7%	10%	144.3
B	1154	504.3	24%	18%	22%	125
C	604	368	60%	40%	55%	73.3
D	646	269	58%	56%	57%	69
E	0	523	100%	15%	76%	**39.4**

Results from the integrated digital twin community model indicate that total savings of 76% could be achieved through retrofit measures, reducing the average building Energy Use Intensity (EUI) from 161kWh/m^2 to 39.4kWh/m^2 and increasing excess wind generation from 28MWh to 249MWh. These results were the output of the CEDISON project, and will be referred as the Baseline Model for the purpose of this virtual study. As the aim of this study is to demonstrate building and network control, the costs of the renovation measures were not the focus of the analysis.

The following control strategies were applied to the Baseline model of the Eday community, using brute force computation to explore the feasibility of the ICC concept:

- Active demand response using digital twin prediction
- Passive battery storage (combined with active demand response strategies)
- Active battery storage during peak hours (combined with active demand response strategies)
- Active battery storage throughout day (combined with active demand response strategies)

Active Demand Response using Digital Twin Prediction

Demand response creates an opportunity for energy users to actively engage in response to times of grid congestion or loss of load. Time of Use (ToU) tariffs were used to identify times of grid congestion. For this study the 3-rate ToU Tariff offered by Bulb for Northern Scotland was assumed for the analysis (Figure 4), This tariff was applied to all weekdays. Weekend tariffs consisted of the overnight and off-peak rate only. Although the driver of the control strategies and the cost savings achievable in this study are specific to this tariff, the ICC concept may be adapted for use with other tariffs or be driven by other parameters as required.

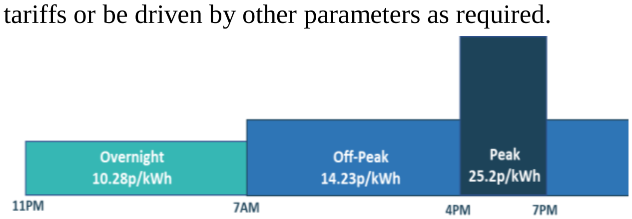

Figure 3: Northern Scotland time of use tariffs (Bulb, 2020)

Two methods of active demand response were applied to the buildings within the Eday community;

- Active heat pumps
- Active plug loads

Buildings were categorised into three groups, based on their hourly operation profile;

- P1: Buildings with 24hr occupancy.
- P2: Buildings with 12am-6am & 5pm-12am occupancy.
- P3: Buildings with 9am-5pm occupancy.

The digital twin model uses the IESVE simulation engine to determine the available load for demand response for both heat pumps and small plug loads in each building.

Active Heat Pumps

Three scenarios were investigated for utilising heat pumps as a demand response strategy;

- HP1: Heat pump off from 4pm – 7pm
- HP2: Heat pump off from 5pm – 7pm
- HP3: Heat pump off from 6pm – 7pm

For buildings occupied from 12am-6am & 5pm-12am occupancy (P2), a fourth scenario (HP4) was investigated, pre-heating the building from 3pm-4pm, prior to occupancy and outside of peak hours.

Using the occupancy profiles of the buildings and the scenarios for peak load reduction, the following combinations were applied to each group;

- P1: HP1, HP2 & HP3
- P2: HP2, HP3 & HP4
- P3: HP1

The IESVE was used to model the impact of each scenario on the indoor air temperature. For this study, a temperature drop of less than 2℃ over the demand response period was assumed acceptable.

Digital twin prediction was used to determine the maximum level of DR available in each building, based on indoor temperatures remaining within +-2℃ of the indoor set-point temperature, to maintain comfort levels during occupied hours. Before each peak-demand period, the model runs an algorithm to forecast the indoor conditions at the maximum demand response scenario (HP1). If the temperature drop during that period is less than 2℃, that scenario is applied. If the temperature drop exceeds this limit, the model evaluates the following scenario (HP2, and following that, HP3, etc). If indoor constraints are not maintained in any of the scenarios simulated, no demand response is applied for that period.

Active Plug Loads

Active plug loads can be used as a DR strategy through shifting the load of flexible household appliances from peak to off-peak hours. A study on the potential for residential demand response (Bilton et al., 2014) determined that peak-load saving of up to 10% could be achieved through active demand side management of washing machines, dishwashers and tumble dryers. A similar study (Ghaemi & Schneider, 2013) indicated a 10-23% potential for demand response during peak hours through active load management of appliances and heat pumps.

For this analysis, 10% was assumed as the potential for peak-load shaving through plug loads across all buildings in Eday. The peak load was reduced by 10% for all buildings during the peak-period (4pm-7pm), and the energy shaved off peak-times was then applied to the overnight rate. The outcome of this scenario analysis will determine the maximum peak-load reductions achievable through flexible load shifting on the island.

Passive Battery Storage (in combination with the Demand Response strategies)

Due to the variable nature of wind powered generators, there will be times when there is either excess or insufficient wind to meet the network demand. Load mismatch is one of the most common challenges that electricity grids will face with increasing integration of RES (Yoldaş et al., 2017). The baseline model indicates an excess generation of 249MWh. This is problematic for the already highly-constraint Orkney network, though it does create the opportunity for energy storage to maximise self-consumption.

This scenario applied community storage to the island's network to reduce grid congestion through local management of the existing DERs. Lithium-ion batteries were used as the method for energy storage. The battery operates in passive control strategy, where the battery stores excess RES generation when available, and discharges in the absence of renewable generation (Reimuth et al., 2019; Worthmann et al., 2015). The aim of this scenario is to minimise grid imports, maximise self-consumption and reduce local energy costs.

Active Battery Storage During Peak Hours (combined with active Demand Response strategies)

The previous scenario uses a passive battery to store excess generation for use during times of low wind to meet demand. Although this can be a successful strategy in minimising grid imports and exports, it cannot eliminate fluctuations in demand at times when wind energy drops.

The focus of this scenario is to minimise local energy demand during peak times to relieve congestion on the network. This will be done through active battery management, charging the battery from the grid at times of low congestion (i.e. overnight, at the cheapest rate), and discharging during peak hours to relieve congestion. This strategy will be implemented by;

- Using the digital twin model to predict grid imports over peak period (4pm-7pm) each day.
- Using digital twin model to predict generation from domestic wind turbines over peak period each day.
- If wind generation > demand, apply passive control
- If wind generation < demand, apply active control
- The battery will charge only what demand is needed to match demand during peak hours, to minimise costs.
- The battery charging will be limited by the battery capacity, charging flux, and discharging flux.

Active Battery Storage Throughout Day (combined with active Demand Response strategies)

Although minimising grid imports during peak hours is effective for reducing energy costs and peak load, this is not a sustainable solution at a larger scale. To ensure a balanced, secure and robust electricity system it is necessary to match power generation with demand for all times, across the entire grid. This involves equalising fluctuations in demand not just during peak hours, but throughout the entire day (Reimuth et al., 2019; Worthmann et al., 2015).

For this scenario, the balancing period is driven by the ToU, where costs are at a minimum overnight. During this period, it is essential to produce a balanced load profile as seen by the grid. This will be achieved by;

- Using the digital twin model to predict demand during the day from hours 7am-11pm.
- Using the digital twin model to predict demand overnight from hours 11pm-7am.
- Balancing grid imports overnight, to ensure overnight demand is met and sufficient energy is stored to be discharged to meet demand during day.
- The battery will charge only what demand is needed to match demand during daytime hours (7am-11pm).
- The battery charging will be limited by the battery capacity, charging flux, and discharging flux.

Results

Active Demand Response using Digital Twin Prediction

Two methods of demand response were investigated; active heat pumps and active plug loads, applying the ToU tariff (Figure 3). The impact of existing wind generation was considered for both the Baseline model and DR scenarios.

Active Heat Pumps

The ICC determined the potential for adjusting heat pump operation as a DR strategy without compromising comfort of the occupants. The algorithms defined in the model aimed to maximise the demand response period, while maintaining indoor air temperature within 2℃ of the setpoint.

It was found that when using heat pumps as a DR strategy, the electricity demand "spikes" once the heat pump is switched back on (Figure 4). This is caused by the heat pump working to meet the setpoint temperature following a drop in indoor air temperature. The impact of the "spike" increases with longer durations of demand response.

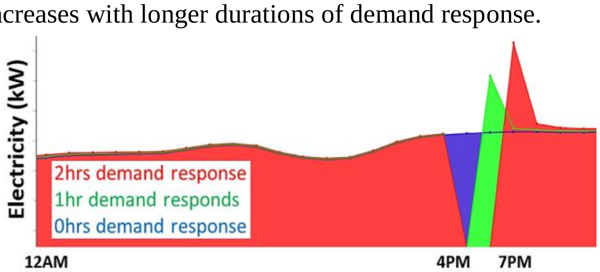

Figure 4: Example spike in heat pump electricity consumption following demand response

Although the energy savings outweigh the energy increase, it is important to ensure this spike occurs outside of peak hours to minimise grid congestion. The chosen DR scenarios prevent this occurring through only reheating the space outside of the peak period, without significantly impacting thermal comfort.

Figure 5 shows the optimum demand response scenarios for each building group. As shown, the potential duration of DR increases in the summer months when outside air temperature is higher.

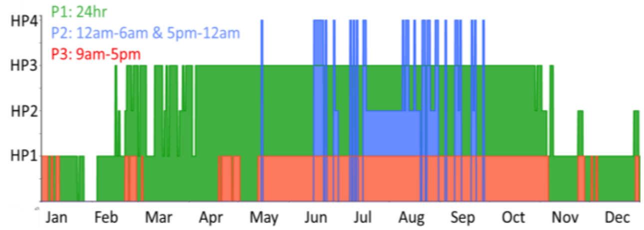

Figure 5: Optimum daily DR scenarios with Active Heat Pumps

As heat pumps were not operational during the DR events, energy savings were made. The results of this scenario are summarised in Table 2. Although overall energy savings were low (2%), peak load was reduced by 13% annually, with cost savings of 5%.

Utilising digital twin prediction when engaging heat sources as a DR strategy ensures that the peak load reduction is achieved without compromising the indoor comfort levels of the occupants, or risking a spike in heating energy consumption during peak hours.

Active Plug Loads

Implementing a demand response strategy with flexible plug loads enables the shifting of demand from times of high network congestion to off-peak times. Although peak load and energy costs were reduced, this scenario did not result in any additional reduction in energy consumption. Figure 6 shows the impact of a sample daily load profile with and without flexible plug loads as a demand response strategy.

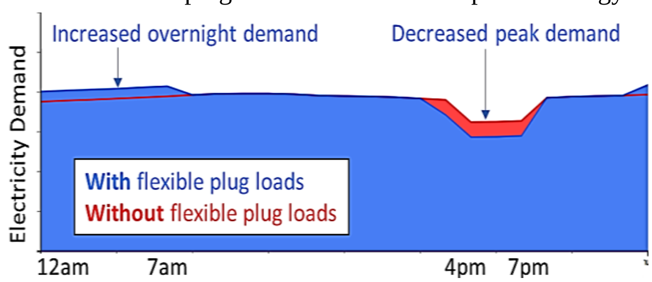

Figure 6: Impact of flexible plug loads on hourly vs, total daily electricity demand

Flexible loads were applied to each building, in combination with active heat pumps. The results for this scenario are summarised in **Error! Reference source not found.**

Table 2: Active Heat Pump (HP) DR results vs. Active Heat Pump with Flexible Plug Loads (HP&PL) DR results, where energy costs are based on aggregated community grid imports

Scenario	Total Demand	Grid Imports	Peak Load	Energy Costs
	MWh	*MWh*	*MWh*	*£x10^3*
Baseline	523.0	140.3	22.5	20.15
HP DR	512.0	135.2	19.5	19.18
HP&PL DR	512.0	135.2	15.0	18.3
HP Saving	2%	4%	13%	5%
HP&PL Saving	2%	4%	33%	9%

Using flexible loads for DR has the potential to reduce peak load by a further 20% compared to active heat pumps as the sole DR strategy, reducing peak loads by up to 33%. Energy costs were also reduced by an average of 9% across the community, with excess wind increasing to 289MWh.

The results indicate that engaging with ToU tariffs and using active DR management can benefit the end-user through cost savings, but also the grid through reduced peak load.

Passive Battery Storage (in combination with the Demand Response strategies)

Following the implementation of the DR strategies described, grid imports are reduced to 135.2MWh and excess wind energy increased to 289MWh.

To address this increase in unutilised wind generation, a community battery energy storage system was investigated to minimise grid exports and maximise self-consumption within the community. A 2MWh community battery was chosen as the optimal battery size as part of the analysis of the CEDISON project. Table 3 summarises the results of this scenario.

Table 3: Impact of battery storage in passive control on community grid imports and exports

Scenario	Imports	Exports	Imports	Exports
	MWh	*MWh*	*% Saved*	*% Saved*
Base	135.2	289	0%	0%
Passive Battery	47.77	205.17	65%	29%

The results of the model indicated a reduction in grid imports of 65%, and exports of 29%, after demand response scenarios were applied.

Active Battery Storage During Peak Hours (combined with active Demand Response strategies)

The addition of a 2MWh passive battery can reduce grid imports and exports by 65% and 29%, respectively. With the exception of 64 days of the year, the community is self-sufficient and does not rely on grid imports to meet the islands demand (Figure 7).

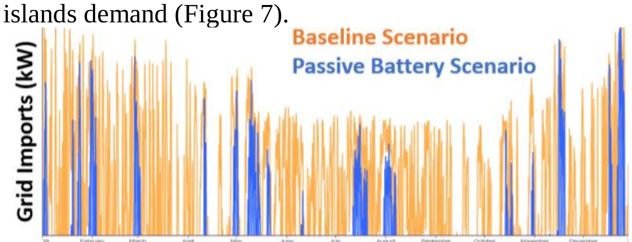

Figure 7: Annual grid imports for baseline vs. passive battery.

The days requiring grid imported energy are as a result of drops in wind levels and insufficient storage available. Without active control, these days have a highly variable load profile (Figure 8). This is problematic for the wider electricity network, particularly during peak hours.

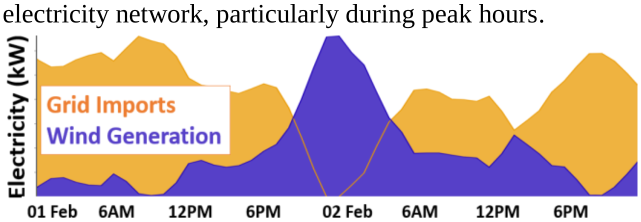

Figure 8: Grid imports vs wind generated electricity

To alleviate this issue, digital twin prediction may be used to apply active battery control for days of low wind availability and insufficient storage to meet demand.

Using historical data and weather data, the ICC can be used to determine the optimum control strategy to minimise peak demand. If the model predicts there is a requirement for grid imports during peak hours (4pm-7pm), it will apply active control. If no demand during peak hours is detected, it will apply passive control. To avoid over-charging the battery or importing more energy than required, digital twin model prediction is used to forecast the energy required during peak hours for the day-ahead, and charge the battery to match this forecasted demand (Figure 9).

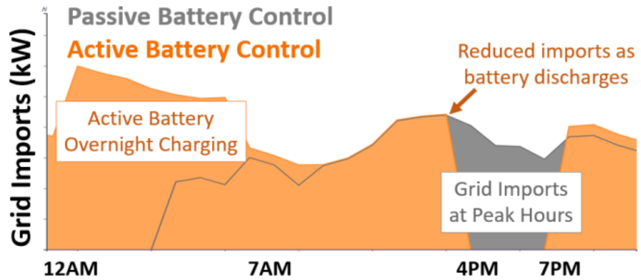

Figure 9: Active control vs. Passive control during peak hours

When active control is applied during peak hours, grid imports during peak hours are eliminated (Table 4).

Table 4: Comparison of Passive vs. Active (Peak) control

Scenario	Grid Imports	Peak Load	Energy Costs
	MWh	*MWh*	*£*
Passive Control	47.77	2.36	6685.50
Active Control (Peak)	47.77	0	6258.04
Savings	0%	100%	6.4%

Table 4 indicates that applying active battery control can be used to minimise grid imports during peak hours, without changing the overall energy consumption of the community. Not only does this relieve the congestion on the electricity network, but energy costs also reduce by a further 6.4% by shifting peak demand to overnight hours.

Active Battery Storage Throughout Day (combined with active Demand Response strategies)

Although successful in minimising peak grid imports, applying active battery control only to times of high congestion does not resolve concerns around grid stability. As shown in Figure 9, implementing such a strategy results in a sudden drop and sudden peak before and after the peak period. To ensure a more robust electricity system these fluctuations should be equalised.

Further active battery control was applied to the integrated digital twin model, to create a constant, balanced load profile. As energy prices were the driver of the control strategies, demand forecasting was used to inform the battery charging strategy by charging overnight and discharging during the day. As indicated in Figure 10, if there is an overnight demand (due to insufficient wind availability), the battery charging profile will adjust accordingly to ensure the overall grid imports overnight remain balanced. This energy then discharges accordingly to meet daytime demand.

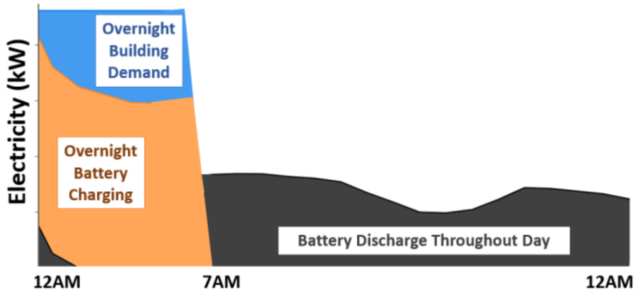

Figure 10: Active Battery overnight charging strategy.

Through using digital twin model prediction, active battery control may be used to produce a constant load profile during off-peak hours, minimising the sudden peaks and drops typically associated with high RES penetration.

Table 5: Comparison of Passive vs. Active (Day) control

Scenario	Grid Imports	Peak Load	Energy Costs
	MWh	*MWh*	*£*
Passive Control	47.77	2.36	6685.50
Active Battery (Day)	47.77	0	4929.97
Saving	0%	100%	26%

Without the addition of further installations, active battery management with digital twin prediction can reduce energy costs by up to 26% in comparison to passive strategies.

The savings for each scenario are summarised in Table 6.

Table 6: Summary of Optimisation Strategies

Scenario	Grid Imports	Peak Load	Energy Costs
	% Saved	*% Saved*	*% Saved*
Baseline	-	-	-
Demand Response	4%	33%	9%
Passive Battery	66%	90%	67%
Active Battery (Peak)	66%	100%	69%
Active Battery (Day)	66%	100%	76%

Although all scenarios involving batteries imported equal quantities of grid electricity, active battery management has the potential to eliminate imports during peak hours of higher grid congestion, and reduce energy costs for the community by up to 76% relative to the baseline model.

Discussion

Digital twin prediction indicated that using heat pumps and flexible plug loads as a DR strategy with ToU tariffs can reduce peak load by up to 33%, reducing overall energy costs by 9% while importantly maintaining the defined indoor conditions and preventing heating energy spikes during the peak period. Due to the variable nature of weather driven RES, peak load DR alone is not sufficient to ensure a balanced energy system. Digital twin models enable prediction of community demand through dynamic energy models for each individual connected building. This could be used for more effective control of community energy storage systems, where precise forecasting of building demand is essential to ensure grid balancing at minimal costs for the local community.

Although passive battery control was successful in increasing self-consumption, it is not a viable solution for long-term grid management. This is due to the unpredictable load profiles for days of insufficient local generation and storage. Digital twin model prediction aids as a decision support mechanism for active battery management from the bottom-up; forecasting the demand of the connected buildings and wind generation, and charging the battery accordingly. For this study, the balancing was driven by the ToU tariffs, charging the battery overnight to meet daytime demand. To ensure a balanced load profile throughout the charging period, the battery's charging profile must adjust to changes in overnight demand. Active battery management was found to reduce energy costs by an additional 26% when compared to passive strategies.

A limitation of this study is that the building energy models were validated at monthly and annual level only. For increased accuracy, measured timeseries data should be used to create a data driven calibrated model at sub-hourly level to ensure sufficient accuracy for informing network control strategies.

The weather driven physics models of the wind turbines in the model also did not account for turbine downtime, leading to an over-estimation of the available wind generation on the island. To eliminate this error, measured data should be used for future analysis.

The integrated network model created was based on the DC Power flow modelling method, which approximates the AC network. To improve the accuracy at network level and to account for network losses, the network model should be upgraded to AC power flow analysis. This AC network should then be validated against network data.

Once the limitations of the model are addressed, future work will involve using the digital twin model for real-time prediction at both building and network level. The addition of real-time tariffs to drive the control strategies in addition to model predictive control for continuous heating (and cooling) optimisation would further the benefit of using the ICC as decision support for advanced network control. This would create a more dynamic community model that reacts to changes in grid energy prices to recommend optimum strategies at each time-stamp for continuous load balancing at community level, without compromising the comfort of the occupants.

Conclusion

This paper investigates digital twin model prediction for intelligent community control through virtual optimisation of the community of Eday, Scotland. The ICC uses a bottom-up approach, balancing the islands load profile to improve grid stability while simultaneously minimising energy costs for the end-user. This was achieved through active DR activities within the constraints of occupant comfort, followed by active battery management to balance the remaining demand and generation.

The digital twin building and integrated network model may be used as a decision support tool to forecast supply and demand and recommend control strategies for local load balancing. Digital twin prediction may be used for more effective demand response management at domestic level through using thermal analysis to identify available load flexibilities and changes in indoor conditions in response to different levels of demand side management. Digital twin models also enable forecasting of building energy demand, which may be used to better facilitate active management of community energy storage systems to balance local supply with local demand in response to changes in available generation and grid imported tariffs.

This approach has the potential to resolve some of the common challenges that traditional methods face in areas with a high penetration of DER, and further work to expand the ICC concept to enable real-time optimisation with digital twins could yield an effective decision support mechanism for grid balancing and reducing local energy costs.

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