Towards A Smart Community Evaluation and Implementation Toolkit - Low-Cost Mini-District Predictive Controls with Flexible Tariffs

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Abstract

The drive to decarbonise the grid through intermittent generation requires an increase in system flexibility. To achieve this all energy assets, regardless of size and location, need to be incentivised to contribute. For smaller and remote assets and microgrids, the ability to participate in the current third-party flexibility markets remains limited. A toolkit has therefore been developed to allow assessment for smaller systems to use standard flexible energy tariffs, orchestrated by a simple, independent locally-situated controller, to achieve financial benefits and assist grid balancing. The toolkit has demonstrated that significant savings are achievable for a small mini-district scheme. The integrated Python-based optimisation engine can be used on low-cost platforms, such as the Raspberry Pi, which indicates that the developed algorithms has the potential to orchestrate microgrids as part of an integrated control system.

Introduction

Decarbonising the UK energy system and allowing greater penetration of low carbon sources, particularly for electricity, is driving major changes to the mechanisms by which energy assets interact with the grid and market. At the larger scale (>100kW), changes to the UK balancing markets and aggregation of assets is allowing market access for smaller assets via third party providers. There, however, remains smaller assets and sites for whom participation at this level is impractical.

The developing mechanisms required to cost-effectively decarbonisation the UK grid are also providing both opportunities and challenges for these smaller community-scale energy assets and systems. Challenges include the uncertainty over future grid export income, but which provides an opportunity for localised storage and smart controls to maximise self-consumption. The availability and increasing penetration of time-of-use energy tariffs and grid balancing services similarly incentivises building flexibility and system visibility within a system to allow for demand shifting to avoid peak charges.

Small, Smart, Independent Systems

The prevalence of smaller energy systems that, for a number of reasons (e.g. size, location, prosumer interest, limited scope for local aggregation), will not participate in the third-party grid flexibility market, at least in the short term, provides an opportunity for independent control systems that provide equivalent benefits.

Cost reductions for PV and battery storage, the availability of flexible energy tariffs and low-cost smart control devices, provide a means for small, independent systems to participate. There is therefore potential for locally implemented, cost-effective smart solutions. It is therefore important to understand if this type of installation can be sufficiently reliable and also achieve gains at least in proportion to the lower installed cost basis.

This paper outlines the initial phase of a toolkit development project that allows the smart potential of a representative 8-dwelling mini-district to be determined, and how the algorithms developed for the toolkit have the potential to be applied for realtime analysis and decision-making in an active installed system.

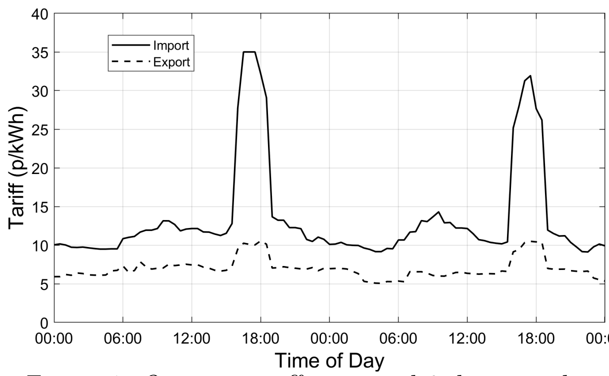

Figure 1: Octopus tariffs - typical 2-day period

Current Technology

There is a developing market for smart, integrated energy systems. The market is currently dominated by managed commercial schemes for large (100kW+) generation and demand assets acting as 'Virtual

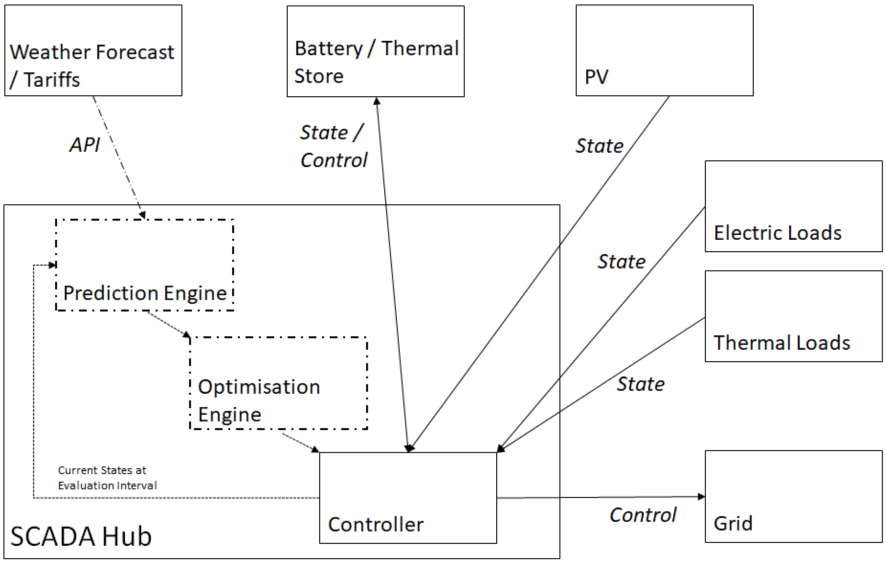

Figure 2: Proposed control system structure

Power Plants'. Examples include EDF's Powershift.

Another developing area is the aggregation of domestic assets to provide a single, flexible resource via automation. Examples of current technology in this sector include Moixa's Gridshare platform. These services, however, require significant number of assets and provide limited control for the asset owner.

There is an existing open-source protocol, OpenADR, that is used by a number of organisations, including the Carbon Coop in the UK, via the OpenDSR platform (BEIS, 2019), for orchestration of larger community scale systems. This is still in the early phases of development and it will be interesting to see how solutions develop.

As an alternative to the third-party 'black-box' approach, and for solutions applicable to single, small microgrids, there are a number of technology alternatives that could be considered as part of a simpler, open-source approach. Raspberry PI and Arduino systems, and platforms that use them as a basis (e.g. Open Energy Monitor Emonpi's), provide a low cost means for orchestrating local energy systems. These allow the integration of algorithms, APIs for sourcing weather forecasts, and communication to external devices using available orchestration tools, such as Node-Red and OpenHAB, and communication protocols, such as MQTT and Zigbee.

Current research in this area include Vargas-Salgado et al. (2019). This work highlights the low cost potential and benefits of this approach for both academic and practical applications.

As part of this research activity, an Emonpi has been installed at Findhorn in an existing 6-flat development to successfully gather required input data and test communication reliability as a first step.

Flexible Tariffs

An important driver for the switch to smarter energy systems will be the increasing prevalence of time-of-use tariffs. These are necessary both to force demand away from periods of greatest supply and demand imbalance and to incentivise storage and demand response technologies that allow effective use of low cost periods. They are also useful in that they allow for low-carbon system optimisation via a standard supply contract, without the need to involve a third-party optimisation provider.

For the initial analysis described below, the Octopus Agile (import) and Export tariffs from 2018 have been used. This is a commercially available tariff, with the import tariff set at 4pm on the prior day. This has the benefit of providing an incentive to shift demand and integrate storage but with the certainty of a tariff fixed far enough in advance for planning purposes. The Agile import tariff broadly tracks the UK Wholesale Electricity market, with a consistently high tariff period between 4pm and 7pm, and low overnight tariffs. The export tariff is directly linked to the Wholesale market basis on a pass-through basis and is not known in advance. An example of a typical 2-day period is shown in Figure 1.

Predictive Controls and Optimisation

To utilise the benefits of flexible tariffs with localised generation and storage requires either a fixed set of control actions, typically involving opportunistic charging of storage during periods of excess generation or low grid import costs, or a more complex set of algorithms that seek to predict future system states over a set timeframe ('horizon') and optimise control actions to provide the maximum benefit (commonly known as Model Predictive Control with Moving Horizon Optimisation). In general terms, this is a commonly used application (e.g. Johansen (2011)) and has found more recent use for microgrid orchestration (e.g. Parisio et al. (2014)).

SCADA System Structure

The proposed structure for the low-cost smart system implementation is shown in Figure 2. A web-connected standalone SCADA (Supervisory Control and Data Collection) Hub is located local to the energy system. The Hub includes sufficient computational capacity to: (1) run Python scripts for future prediction and optimisation; (2) to automatically update weather and tariff information via APIs; (3) to monitor the current state of each element of the energy system; and (4) to communicate control actions based on the output from the most recent optimisation evaluation.

Aim

The overall aim of the toolkit development was to build a flexible tool with sufficient intelligence to allow the potential benefit of simplified flexible tariff optimisation to be gauged and then be relatively straightforward to implement with either simulated or realtime data. Beyond the initial toolkit development phase, the overall aim being a platform that can be used first with synthetic data to test viability but be easily converted to an operating system with equivalent realtime inputs for actual system evaluation and orchestration.

Methodology

At this stage of development, the primary output has been a Python-based toolkit that combines a number of existing and newly developed modules. Python was selected as the platform due to the ease with which it can be integrated with existing low-cost systems (e.g. Raspberry PI and Arduino based systems) and within orchestration platforms (e.g. Node-Red). As outlined, the focus has been on using synthetic and external data that could be easily replicated in a real-time orchestration system with a low-cost control platform.

Predictive Optimisation Toolkit Overview

The overall toolkit combines a number of individual modules. These are as follows:

- Stochastic Appliance and DHW Demand
- Space Heating
- Renewable Generation
- Thermal Storage
- Future Prediction
- Optimisation w/Predictive Outputs

Stochastic Appliance and DHW Demand Modelling

Energy demands for individual households are highly stochastic with considerable behaviour variation between households and day-to-day inconsistency within households. For larger systems (>50-100 households) mean behaviours can be reliably used (Flett, 2017) but for smaller systems, including these behaviour variations is important for modelling accuracy.

Stochastic modelling of occupancy and the appliance and hot water demand for each property is derived from Flett (2017). The aim of this work was to model this stochastic variation to allow it to be integrated within wider modelling activities. For the toolkit development it is used to simulate smart meter data inputs from real households.

Space Heating

A single-zone space heating model has been incorporated within the model to allow the space heating demand to be updated every timestep based on stochastic heating patterns, with heating periods linked to the stochastic occupancy model (see above) and setpoint variation based on analysis of Energy Follow Up Survey 2011 data (DECC/BRE, 2016). The single-zone model is based on the work of Murphy (2012).

Renewable Generation

The generation focus for this work is solar PV integrated behind-the-meter within the mini-district. (The overall toolkit also incorporates wind output prediction which is not reviewed here.) Readily available weather forecast data includes cloud cover, ozone and humidity which can be incorporated with standard solar models to determine the global horizontal radiation. A standard Python solar module ('pvlib') is used to convert incident radiation to PV output. (The same method is also used to estimate solar gains for the space heating model.)

Predicting output from renewable generation from weather forecasts is challenging. Forecasts tend to be instantaneous values 'on-the-hour' and therefore only provide an indication of likely output over the timestep. For the current work, which is focused on solar output, the 'on-the-hour' weather is assumed to be a reliable indicator of output. This is therefore likely to overestimate performance slightly. Further work to incorporate solar output uncertainty and 5-minute forecast data will be included in future versions.

Thermal Storage

A multi-node stratified thermal storage model, based on the work of Duffie et al. (2020), is included. This remains a significant source of uncertainty, with energy added and removed from the store not having a directly proportional impact on useful stored energy

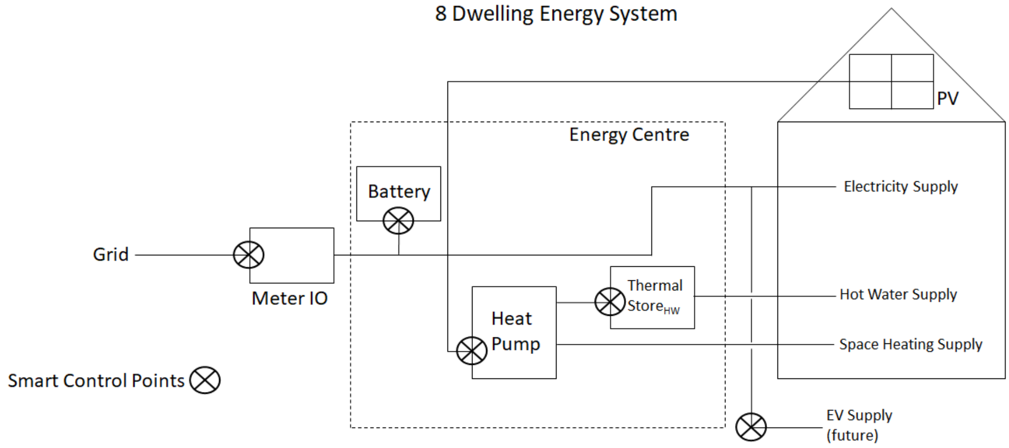

Figure 3: Case Study System Schematic

due to variable node temperatures. The optimisation model cannot currently be configured to recalculate node temperatures at each horizon timestep, therefore future prediction of useful capacity is prone to significant errors. Further work is required to develop a suitable correlation that can be incorporated with linear programming. Heat losses are incorporated in the model giving an incentive to use stored energy sooner.

Future Prediction

The optimisation model (described below) requires a number of inputs that are predicted over the optimisation horizon.

A number of inputs are influenced by the weather, in particular space heating and renewables generation (see above). For the development of the toolkit, hourly weather forecasts for the next 48 hours have been recorded from the Dark Sky website for over 12 months to allow for testing of the method for annual duration models. Equivalent data from this or other websites can be used in realtime for an active installation. This data is readily available using APIs for direct integration within a Python model.

Demand prediction is simulated within the toolkit by using average demand for equivalent days over the preceding month. This assumes that smart metered systems have the capability to provide sufficiently detailed demand profiles (i.e. hourly or better) to allow this information to be available to an implemented systems. Within the toolkit this allows the performance of predictive control to be assessed by comparing stochastic demand patterns against average behaviour values. Future work on the toolkit will seek to increase the sophistication of demand prediction from historical smart meter data for which there is significant existing literature.

Optimisation Model

The Python GEKKO optimisation module has been used to determine the most beneficial operating strategy using Mixed Integer Linear Programming (MINLP) with Moving Horizon Optimisation (MHO). MHO is a commonly used method for energy system optimisation (e.g. Silvente et al. (2015)).

A cost minimisation equation is the primary function of the optimisation, with 14 different potential energy exchanges involving the grid, PV, battery, thermal store and heat pump evaluated and the requirement of no demand shortfall. Equation 1 shows a simplified version of the optimisation basis.

$$Cost = \sum_{h=1}^{Hor} IC \times GI(h) - EC \times PE(h) \qquad (1)$$

where, Hor = Optimisation Horizon, GI = Grid Import (kWh), PE = PV Exported (kWh), IC = Grid Import Cost (p/kWh), EC = Grid Export Cost (p/kWh)

Case Study

Housing Development

A new 8-house development is under development at the Findhorn Ecovillage. This development has been used as an initial case study to test the toolkit, with the potential for the integration of a practical test system. Four two-storey 75m^2 terraced houses and a two-storey block comprising four 37m^2 flats will be built. A central heat source for the development is proposed with each dwelling fed by a mini-district pipe network. This is assumed to be a shallow groundwater-based heat pump. As per other similar systems at Findhorn, the addition of battery storage, thermal storage for hot water, and PV on the available roof space is under consideration. Figure 3 shows the proposed system schematic.

Table 2: Analysis model basis.

Model	Controls	Demand	Generation	Import Tariff
B(aseline)	Opportunistic*	Actual	Actual	Octopus Agile
1	Predictive - 24hrs	Predicted	Predicted	Octopus Agile - 4pm confirmation, previous day for horizon > 8hrs
2	'Predictive'** - 24hrs	Actual	Actual	Octopus Agile - 4pm confirmation, previous day for horizon > 8hrs
3	Predictive - 24hrs	Predicted	Predicted	Octopus Agile - predicted based on timestep average for previous 7 days

** Battery (if in scope) charged if import price is below 7p/kWh and thermal store is charged if RES excess.*
*** 'Predictive' model function but based on actual data (i.e. an ideal, perfect future knowledge baseline case.)*

Table 1: Stochastic Populations

Pop.	Electrical kWh/yr.	Hot Water kWh/yr.	Space Heat kWh/yr.
1	18444	7549	7242
2	14052	8377	9061
3	18648	8177	8153
4	21376	7306	7234
5	16250	9280	5959
6	17329	10514	7141
Avg.	17683	8534	7465

Findhorn has its own microgrid with on-site wind and PV generation. For simplicity the presented analysis does not consider the microgrid commercial arrangements but assumes the new development has a more typical direct connection to the National Grid. The toolkit, however, has the flexibility to prioritise between multiple energy sources, as required.

Analysis as part of the wider project has indicated that 16kW of PV capacity, an 800-litre thermal store for DHW and a 10kWh battery store in conjunction with the PV is broadly optimal in terms of cost effective benefits. This is therefore used as the baseline solution for this analysis.

Stochastic Populations

Six 8-household 'populations' were generated using the modules as defined above. The SAP calculations for the buildings indicated an annual heat demand of 7,200 kWh. This was used as an average target for the generated populations with an allowance for some typical variation. Electrical and hot water demand for the chosen populations was allowed to vary randomly based on the expected variability for these housing types. The annual demands for the six test 'populations' are as shown in Table 1.

Analysis

As shown in Table 2, several versions of the predictive elements for the model have been compared. Model '1' represents the target predictive model basis and 'B' is the baseline model for simple, non-predictive controls. Using the different model parameters as required, the presented analysis considers the following impacts on the viability of localised smart control systems:

- Impact of flexible tariffs
- Impact of simplified predictive control mechanisms
- Impact of optimisation horizon
- Impact of behaviour variation on optimisation benefits
- Impact on grid decarbonisation

Impact of Flexible Tariffs

As expected, a flexible tariff with significant price variation is required for the optimisation approach to be beneficial, with very limited benefits from a more typical dual-tariff arrangement or for a fixed multi-period approach (such as the Green Energy TIDE tariff).

Impact of Simplified Predictive Control Mechanisms

As shown in Table 3, simple predictive controls with a 24-hour horizon and hourly timesteps (Model B vs 1), gives a potential reduction in grid import costs of 15% against a baseline model of simple controls with opportunistic charging and 19% against a system with no battery storage.

The 50% additional improvement between the 4pm fixed flexible tariff basis and an average tariff basis (Model 1 vs 3) indicates the strength of using fixed-in-advance flexible tariffs rather than short-term tariffs, such as the Wholesale market. This provides smaller, simpler installations to take advantage of the reliable market basis for planning, with the wider balancing risk taken by the provider.

Comparing models 1 and 2, there was a limited improvement in performance between demand and generation predicted against average behaviour and actual behaviour. This indicates that simple prediction of demand for larger household groupings is reliable enough at this level of detail. As discussed above, further work is required on the predictive PV model to confirm a realistic assessment of uncertainty is incorporated.

Table 3: Analysis Results - all Population 1

Model	PV kW	ES kWh	GI	GB	GTS	PG	PE	PB	OC £/yr.	AVI £/kWh	CO kg/yr.
			All kWh/yr.								
B	0	0	21,022	0	4,159	0	0	0	3,363	14.88	5,745
B	16	0	15,766	0	1,798	7,544	1,278	0	2,266	14.36	3,750
B	16	10	14,867	201	1,798	7,544	534	0	2,160	14.72	3,817
1	16	10	16,423	4,836	3,081	7,544	1,105	1,295	1,840	11.71	3,737
2	16	10	16,371	4,814	2,944	7,544	1,261	1,313	1,831	11.72	3,694
3	16	10	16,254	4,758	2,982	7,544	1,140	1,098	1,936	12.61	3,689
1	0	10	23,341	6,738	3,547	0	0	0	2,779	11.91	5,675
1	16	10	16,423	4,836	3,081	7,544	1,105	1,295	1,840	11.71	3,737
1	32	10	13,229	3,698	2,290	15,087	2,029	6,206	1,163	11.60	2,712
B	16	0	15,766	0	1,798	7,544	1,278	0	2,266	14.36	3,750
1	16	10	16,423	4,836	3,081	7,544	1,105	1,295	1,840	11.71	3,737
1	16	20	17,203	8,784	3,049	7,544	1,065	1,696	1,758	10.90	3,828

ES = battery, OC = operating cost, GI = grid import, GB = grid=>battery, GTS = grid=>thermal store, PG = PV generation, PE = PV=>export, PB = PV=>battery, AVI = avg. import tariff, CO = grid CO_2

The predictive model does increase the local generation that is exported to the grid. This is a result of PV output being coincident with higher tariff periods allowing for exporting being intermittently more cost effective than local storage. Assuming this exporting is timed to assist grid renewable capacity at peak times, this increase is acceptable.

Impact of Optimisation Horizon

Initial assessments were run with a 24-hour horizon on the assumption that the optimisation model required full visibility of the typical daily demand, generation and tariff cycles for optimal performance. However, weather forecast data is more accurate over shorter horizons and more fine-grained forecasts are becoming available out to 6 hours. Computationally, shorter horizons are also significant less intensive, putting lower stress on the simpler computational devices envisaged.

As shown in Table 4, a reduction in the horizon from 24 to 12 hours does not have a significant impact on performance with the benefit against an opportunistic charging approach reducing by only 0.8%. However, reducing the horizon below 12 hours results in a significant drop in optimisation performance.

This result would appear to be driven by the fixed timing of PV output and the dual peak profile seen in the Octopus tariff (see Figure 1). Optimisation requiring visibility to at least the next peak, if not the overall 24-hr peak. This can be seen in Figure 4 which shows the battery response over 48 hours with optimised charging prior to both peak tariff periods, despite the am tariff peak being significantly lower than the pm peak.

A 12-hour horizon has a considerable benefit over a 24-hour basis, reducing computation time by >60% or allowing a reduction in optimisation timestep, and it would also be expected to improve weather forecast accuracy. This will be considered as the basis for the next phase of work.

Impact of Behaviour Variation on Optimisation Performance

Accurate assessment of optimisation model performance with synthetic data requires data that mimics the stochastic variations seen in actual data. The stochastic nature of the modules used (see above) allows for this but requires multiple runs with different stochastic 'populations' to ensure the mean performance and potential deviations are better understood.

Results shown in Table 5 indicate that the optimisation performance of the baseline 'Population 1' is at the high end of expectations in terms of potential cost savings. The average benefit was c.1% lower than for this population. The results also highlight a significant potential variation in absolute savings for populations of this size (8 dwellings), which is important for cases where potential savings are used to justify investment in storage and RES capacity.

Impact on grid decarbonisation

Table 3 shows that the optimisation models using predictive controls with storage leads to an increase in grid importing and overall energy input due to efficiency losses and additional PV generation exporting during high tariff periods. The cost reduction achieved by the optimisation model is therefore not replicated for CO_2, with only a small reduction of c.1-2%.

The downside of the fixed-in-advance flexible tariff is that is does not necessarily align with optimum grid carbon periods and the grid carbon intensity variation is relatively lower than for the Octopus tariff. Therefore, the frequently cycling of the battery based on the consistent 24-hr tariff variation reduces cost but

Table 4: Analysis Results - Optimisation Horizon - all Population 1 / Model 1

Horizon	**GI**	**GB**	**GTS**	**PE**	**PB**	**OC**	**AVI**	**CO**
hrs	All kWh/yr.					£/yr.	£/kWh	kg/yr.
24	16,423	4,836	3,081	1,105	1,295	1,840	11.71	3,737
12	16,026	4,628	2,887	1,405	941	1,859	11.98	3,613
9	16,025	4,870	2,710	1,336	955	1,903	12.26	3,671
6	15,839	4,755	2,239	1,007	812	2,076	13.41	3,806

OC = operating cost, GI = grid import, GB = grid=>battery, GTS = grid=>thermal store, PE = PV=>export, PB = PV=>battery, AVI = avg. import tariff, CO = grid CO_2

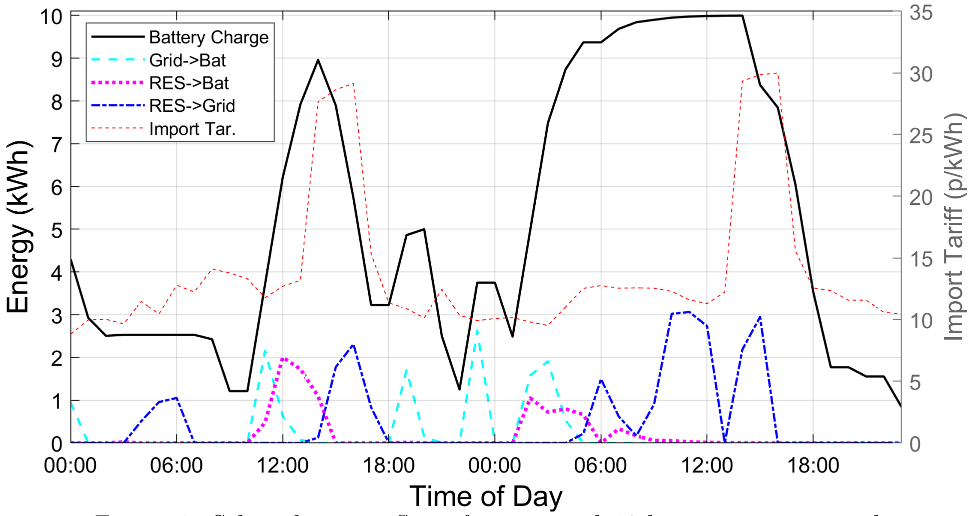

Figure 4: Selected energy flows for a typical 48-hour summer period

Table 5: Analysis Results - Stochastic Populations

Pop	**Model**	**GI**	**GB**	**GTS**	**PE**	**PB**	**OC**	**AVI**	**CO**	**Saving**
		All kWh/yr.					£/yr.	£/kWh	kg/yr.	£/yr.(%)
1	B	14,867	201	1,798	534	0	2,160	14.72	3,817	
1	1	16,422	4,836	3,081	1,105	1,295	1,840	11.71	3,736	320(14.8)
2	B	11,443	208	1,566	0	1,220	1,560	14.22	2,907	
2	1	13,377	4,507	3,259	1,310	2,196	1,349	11.14	2,882	211(13.6)
3	B	15,309	203	1,978	0	462	2,201	14.55	3,919	
3	1	17,046	4,948	3,227	1,114	1,283	1,899	11.64	3,781	302(13.7)
4	B	17,480	201	1,969	0	293	2,585	14.88	4,484	
4	1	19,101	5,049	3,010	1,001	992	2,238	12.05	4,435	347(13.4)
5	B	13,095	200	1,719	0	814	1,853	14.49	3,352	
5	1	14,892	4,448	3,213	1,215	1,779	1,603	11.54	3,314	250(13.5)
6	B	14,524	200	2,294	0	610	2,148	15.01	3,727	
6	1	16,269	4,567	3,775	1,131	1,497	1,846	11.94	3,727	302(14.1)
Avg.										289(13.8)

Pop = Population No., OC = operating cost, GI = grid import, GB = grid=>battery, GTS = grid=>thermal store, PE = PV=>export, PB = PV=>battery, AVI = avg. import tariff, CO = grid CO_2

the impact of battery efficiency results in any reduction from shifted importing being counterbalanced. For some installations, where carbon reduction is as or more important the cost, a different optimisation algorithm will be required with an associated 'carbon-cost' function.

Discussion / Future Work

The toolkit has been successfully implemented at the 1-hour timestep level. At this resolution the optimisation model based on a representation of typical predictive model uncertainties (with a noted caveat re. PV prediction) achieves a meaningful cost saving where a currently available flexible tariff (Octopus Agile) is employed.

Converting the optimisation model output based on fixed time intervals to instantaneous actions within an energy system also needs to be assessed. In an implemented system it is envisaged that the optimisation model would set the broad strategy within the window with an additional layer of controls to react to instantaneous situations. This will also require some inbuilt flexibility within the system, such as a proportion of the storage to be allocated to allow short-term supply and demand imbalances to be handled. Further work is required to determine the appropriate interval between strategy reassessment, given the expected update frequency and granularity of the required input data, and computational demands.

One of the key next steps is to reduce the timestep of the model from 1-hour to allow for more fine grained decision making. Finding a balance between computational speed, optimisation stability (finding optimal minimum cost solutions becomes more challenging with more timesteps) and the ability to make optimal decisions will be required.

Weather forecasting is a key challenge for prediction accuracy and optimisation at smaller timesteps. The currently-used Dark Sky source provides hourly forecasting. Each forecast represents the 'on-the-hour' value. Comparison between actual and predicted wind turbine output based on this snapshot value shows a relationship exists but with significant potential uncertainty. More recently developed weather sources have improved short-term (up to 6 hours) forecasts with 5-minutely data, which will be incorporated as the availability of historical data increases. Further work is required to determine the potential improvements with shorter timestep forecasting and also to consider the impact on PV output prediction accuracy which remains work-in-progress.

The implementation elements of the toolkit (i.e. the prediction and optimisation modules) have been successfully run on a standard Raspberry Pi2 with APIs used for weather forecast downloading. Each analysis timestep takes c. 1 minute. This would be acceptable for typical strategy re-evaluation timesteps (e.g. every 5 minutes based on updated weather forecasts) and should be significantly faster on Pi3 and Pi4 multi-core platforms with increased RAM capacities. This indicates that this type of model can be successfully incorporated in a low-cost control module. Further work with an Pi3-based Emonpi running Node-Red is proposed to generate control signals with the MQTT protocol.

Conclusion

As the first phase of an ongoing activity, the presented work has demonstrated that significant cost savings are achievable with predictive controls in comparison with a simpler control scheme that reacts instantaneous to fixed parameters and charges storage opportunistically. The use of real weather forecast data and stochastic demand inputs has allowed a realistic assessment of the uncertainties of a real system, although further work is required on PV output modelling. As a minimum, therefore, the toolkit has shown relevance for the evaluation of small, micro-grids and mini-districts.

Further work is now required to further assess the viability of the toolkit modules to orchestrate a real system. There is a requirement to reduce the analysis timestep to a degree where the output is suitable for setting system actions. The indication that the optimisation horizon can be reduced from 24 hours will assist the computational viability of running more fine-grained analysis on simple systems, such as the Raspberry Pi, which has shown to be viable on the 24-hour horizon / 1-hour timestep basis used for the initial work. Further work is also required to assess the communication requirements for control signals to the individual energy assets within the overall goal of a system where the cost of installation is consistent with the achievable savings.

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