Household Level Distributed Energy Management System integrating Renewable Energy Sources and Electric Vehicles

Daniel Gosselin
Graduate Management and Strategy
Transport for London
London, UK
Email: danielgosselin@cwgsy.net

Jing Jiang, Hongjian Sun
School of Engineering and Computing Sciences
Durham University
Durham DH1 3LE, UK
Email: {jing.jiang, hongjian.sun}@durham.ac.uk

***Abstract*—To reduce the burden on data communication in smart girds, household level distributed energy management systems have become increasingly vital due to their capability of distributed intelligence and scheduling devices. This paper studies the optimal management of storage and electric vehicles at a household level when subject to financial constraints. A model using a real-time pricing structure is used to minimise the final consumer cost, whilst responding to power consumption limits set by the supplier. Implementation of the limits and pricing structure allow the supplier to better balance changes and discrepancies in both demand values and generation values. Using real data, models for solar generation, household load demand, and the pricing structure are proposed and integrated into the overall model for the household system. The model for the household system optimises the power taken from the grid and the power stored for the lowest end cost to the user. A series of laboratory evaluations are run to compare the effects of the electric vehicle, solar generation and limits on the household, and considerations are made to the financial and practical implications of these effects. Evaluation results show important benefits from soft limiting household consumption. This allows a more robust and efficient smart grid system that creates better communication between the supplier and the consumer.**

I. Introduction

The smart grid (SG) is an intelligent grid system that uses information and communications technology to monitor and actively control generation and demand for providing a more reliable and cost effective electricity system from generators to homes, business and industry [1]. The huge amount of data (including metering data, renewable energy data, energy storage data, control data, etc.) and the growing needs of highly frequent data exchange have posed a significant challenge on the scalability and reliability of smart grid communication systems. There are two perspectives to address this challenge: One perspective is to implement a scalable distributed communication infrastructure in order to improve the system throughput and communication reliability, so that more data communication demands can be supported, as discussed in [2], [3]. Another way is to use distributed decision-making scheme, i.e., enable distributed intelligence and localized goal setting. This could not only reduce the amount of data to be delivered through SG communication networks, but also facilitate more local SG services and engage more SG stakeholders.

Household level Distributed Energy Management Systems (HDEMSs) allow consumers to participate in the optimal management of energy storage, renewable energy, and electric vehicles (EVs) whilst satisfying the limits or constraints set by the distribution network operators. By scheduling appliances in the home for the most efficient use, HDEMS improves demand side response, and is a key part of the smart grid. This scheduling allows for the movement of the peak consumption times, as well as ensuring that the grid generation is able to balance with demand. Most existing works of HDEMSs focus on the algorithmic approach: Fuzzy learning algorithms are proposed to schedule appliances in [4]; further work on appliance scheduling to meet consumer preferences with aim to minimise user discomfort can be seen in [5] and [6] .

One key aspect in HDEMSs is the integration of storage. Distributed energy storage systems (DESS) and/or EVs can be used to provide energy storage. The integration of DESSs into the smart grid is complex due to the levels of control required at the micro grid level, meaning complex topologies and control systems are required [7]. The integration of EVs into storage systems is another challenging issue. In [5] EVs are modelled as simple consumers, and in [8], a bidirectional model is implemented where the EV is used as a storage device which can also discharge if required by HDEMS.

Different from existing research, this paper investigates the integration of bi-directional charging of EVs and DESSs in the same household. This is to be done with variable demand limits and a real-time pricing (RTP) scheme based on existing data, as well as introducing financial disincentives for large demand levels. This paper creates a model to suitably predict the charge and discharge levels of both storage devices and EVs for home use, to allow for the most efficient use of electricity and to allow for responses to varying grid demand and generation. Additionally, the paper implements a soft limit penalty scheme, and shows the effects and benefits of a scaled penalty factor on power consumption from the grid for both the consumer and the supplier.

The rest of this paper is organized as follows. Section II specifies the system model. The optimal management of storage and EVs in HDEMSs with financial constraints is analyzed in Section III. Simulation results are shown in Section IV, and Section V concludes the paper.

II. System Model

We consider a single household where energy consumption can be monitored and controlled using a HDEMS. The household is modelled with a storage device and an optional EV. Both of these devices can be used to charge or discharge power into the system. Models for cost and time of year are integrated into the system. The data used for the load demand, RES, and cost models is based upon historic data averages for the UK. The intention is that if this was to be implemented in the home the data recorded by the HDEMS could be used to increase model accuracy. This would allow for further savings for the consumer and supplier. The model is split into time periods of length t_p in hours, where P_g^t represents the amount of power taken from the grid at time t.

A. EV and Storage Model

The storage model used is similar for both the EV and the household storage system, with the EV model holding special constraints for plug in and unplug times. The model used for the storage system defines the storage level at time t of the battery in the household storage and EV as P_s^t and P_v^t, respectively, and the per hour charge rate is therefore represented by dP_s^t and dP_v^t, respectively. As a result we can say that for the next time period the stored power in the EV and household storage is represented by:

$$P_s^{t+1} = P_s^t + dP_s^t \cdot t_p \tag{1}$$

$$\alpha_v^t \cdot P_v^{t+1} = \alpha_v^t \cdot P_v^t + \beta_v^t \cdot dP_v^t \cdot t_p \tag{2}$$

where α_v^t and β_v^t are matrices used to represent the time at which the EV is plugged into the system where α_v^t is used for the storage level and β_v^t is used for the charge rate. To allow for user variation the hour of the day at which the EV is plugged in and unplugged is given the factor t_{vi} and t_{vo}, respectively, this is assumed to be constant for each day of the model. Due to the user variation the period of time the EV is at the household can vary, and so if $t_{vi} < t_{vo}$ then the EV is not plugged in at the start of the day and is therefore available for use between t_{vi} and t_{vo}. Therefore we have:

$$\alpha_v^t = \begin{cases} 1 & t_{vi} \leq t \leq t_{vo} \\ 0 & \text{otherwise} \end{cases}, \quad \beta_v^t = \begin{cases} 1 & t_{vi} \leq t \leq t_{vo} - t_p \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

It is seen here that as it is unplugged when $t = t_{vo}$ that it is not possible for the EV to be charged in this time period and therefore the last charge will take place at the previous time period. This equation ensures that $\alpha_v^{t_{vo}} = 1$ and $\beta_v^{t_{vo}} = 0$.

If $t_{vi} > t_{vo}$ then the EV is assumed to be plugged in at the beginning and end of the day, so we have:

$$\alpha_v^t = \begin{cases} 0 & t_{vi} < t < t_{vo} \\ 1 & \text{otherwise} \end{cases}, \quad \beta_v^t = \begin{cases} 0 & t_{vi} < t < t_{vo} - t_p \\ 1 & \text{otherwise} \end{cases} \tag{4}$$

Here we once again see the same principle as in the previous case as the EV cannot be charged in the same time period as the one in which it is unplugged.

Otherwise we have, as if $t_{vi} = t_{vo}$ no charging can occur and therefore for $\forall t$:

$$\alpha_v^t = 0, \ \beta_v^t = 0 \tag{5}$$

It must be noted that to ensure that the charge rate at any given time doesn't cause the battery to over charge, the following conditions must be applied to the system:

$$P_s^{min} - P_s^t \leq dP_s^t \leq P_s^{max} - P_s^t \tag{6}$$

$$P_v^{min} - P_v^t \leq dP_v^t \leq P_v^{max} - P_v^t \tag{7}$$

where P_s^{min}, P_s^{max}, P_v^{min}, and P_v^{max} represent the minimum and maximum storage values for DESS and EV, respectively.

B. Load Demand Model

The load demand data is based on the Household Electricity Survey [9]. This data shows 10 minute breakdowns of households for various months and house types. For the purposes of our model demand the data has been simplified and assumed to be constant over an hour long period. Data is then generated for each time period using a randomly generated value based on the hourly average +/- a single standard deviation, calculated from the data in [9]. The data output can be varied by month and house type (bungalow, detached, end-terrace, flat, mid-terrace, or semi-detached) or an average of all house types and/or months. This model outputs P_L^t, which is the load power required at t, for all values of t in the model range.

C. RES Model

We consider solar contributions for the RES. To model the solar panel, we have used SunPower®E20-327 panels which have a solar efficiency of 0.204 [10]. We have assumed the house to have two of these panels, which are 1.046m by 1.559m each, giving a total area of 3.261 m^2. Using the solar cell efficiency equation in (8):

$$P_r^t = \eta \cdot E^t \cdot A_c \tag{8}$$

where P_r^t is the Power ouput, η is the solar efficiency, A_c is the area the solar panel covers and E^t is the solar irradiance received in the area at time t in W/m^2. The data for E^t was taken from the European solar radiation database, "Photovoltaic Geographical Information System" (PVGIS), created by the European Commission [11]. Data for this was collated at three locations across the UK for each month, the three locations represent northern, central and southern areas of the UK. The panels were set to be at 35° inclination and at 0° azimuth, equivalent to south facing. The location data can be seen in Table I.

Using the calculated P_r^t from the PVGIS data it was possible to gain an average and standard deviation for each half hour period. For this model a value between 0 and the sum of the average value and standard deviation at each time period is randomly generated at each time period. These bounds are

TABLE I
LOCATION OF SOLAR PANELS

Location	**Longitude**	**Latitude**
Northern UK	1°53′22” West	53°42′27” North
Mid UK	1°42′49” West	53°17′1” North
Southern UK	0°43′30” West	51°32′30” North

used to allow for the potential losses due to cloud cover. This model outputs P_r^t, which is the power generated by the RES at t, for all values of t in the model range.

D. Cost Model

The cost model is based on historic data from British Energy Trading and Transmission Agreements, using the previous years buy and sell prices. The data had been calculated from Elexon's Balancing Mechanism Reporting website [12]. Using this data an hourly average and standard deviation is once again calculated, and then a randomised value between its average and a standard deviation on each side is generated for each time period or hour, depending on the user preferences. The user is given the option of a fixed buy/sell price or an hourly or time period based real-time price structure (Hourly RTP or Time-period RTP), as well as selecting which month of the year it is and to represent the unpredictability of solar power. This model outputs C_s^t and C_b^t which is the cost function of for selling power to the grid and buying power from the grid respectively.

E. Cost Penalties Model

The method chosen aims to keep the consumption as close to the limit without forcing a fixed limit which, as shown in paper [13] where the fixed limit can cause new peaks following shifts between low and high limits, restricting limit levels.

In this model we introduce soft limits. Soft limits allow the user to exceed the limits, however they will be financially penalised if they do. Therefore the supplier, who would usually implement fixed household limits which can cause issues for the consumer and generally do not offer suitable trade off between the two, we use soft limits to implement a penalty factor f_p when the limit is exceeded. This penalty factor is applied to the cost of any generation above the defined soft limit. The difference between the soft limit at time t, P_{limit}^t, and P_g^t is represented by P_{excess}^t. In the model we offer two forms of the penalty factor, a fixed percentage value and an increasing convex function seen in (9). Here Q represents a fixed factor, which must be greater than 1, normally a value of 1.4 is used, however this can be varied by the model user.

$$f_p^t = Q^{\left(\frac{P_{excess}^t}{100}\right)} - 1 \tag{9}$$

If soft limits are applied then P_{excess}^t is defined by (10), otherwise $P_{excess}^t = 0, \forall t$.

$$P_{excess}^t = \begin{cases} 0 & P_g^t < P_{limit}^t \\ P_g^t - P_{limit}^t & \text{otherwise} \end{cases} \tag{10}$$

III. PROPOSED HDEMS

A. Optimisation Model

This paper focuses on reducing the end cost to the user by making use of the periods of lower cost or higher RES generation to charge the battery of the storage unit or the EV so that it can be released at the optimal times, and as a result achieves the lowest cost to the user. The aim is to assist balancing out both storage and RES in the home, as well as providing new insight on the impact of the EV.

As aforesaid, the objective function may be defined by (11)

$$\min_{dP_v^t, dP_s^t, P_g^t, P_s^t, P_v^t} = \sum_{t=1}^{T} t_p \cdot \left[C_b^t \left(P_{buy}^t + f_p P_{excess}^t\right) - C_s^t P_{sell}^t\right] \tag{11}$$

subject to (1), (2), (6), (7), (13), (14), (15),(16), and (17). t_p is used to factor the power to kWh for the cost function.

The optimisation uses the variables dP_v^t, dP_s^t, P_g^t, P_s^t, and P_v^t. All other inputs to the optimisation are considered independent of these and are therefore fixed prior to start, this makes use of the RES model, cost model and load demand model as described above. P_{sell}^t and P_{buy}^t are factors of power taken from the grid at time t, P_g^t, and

$$P_{sell}^t = \begin{cases} 0 & P_g^t > 0 \\ -P_g^t & \text{otherwise} \end{cases}, \; P_{buy}^t = \begin{cases} 0 & P_g^t < 0 \\ P_g^t & \text{otherwise} \end{cases} \tag{12}$$

The optimisation is subject to the constraints of the EV and Storage model as seen in (1), (2), (6), and (7). The constraints represent the flow of energy into and out of the batteries and ensure that storage levels do not exceed P_s^{max} or P_v^{max}.

Additionally the EV is subject to:

$$P_v^{t_{vi}} = P_v^{arrive}, \; P_v^{t_{vo}} \geq P_v^{leave} \tag{13}$$

which ensures that at the time the EV is plugged in at t_{vi} the EV is at the expected charge level for when it returns to the household (P_v^{arrive}), and that when it is unplugged at t_{vo} the charge level meets the required charge set by the user for their commute (P_v^{leave}). These levels are then repeated on a daily basis. To ensure that the values of load demand are met, the optimisation is also subject to (14)

$$P_L^t = P_r^t + P_g^t - t_p \cdot \left(dP_s^t + \beta_v^t dP_v^t\right) \tag{14}$$

which uses the RES (P_r^t) and load model (P_L^t) data to ensure that the required load demand for each time period is met.

In addition there are also the following upper and lower bounds applied:

$$-dP_s^{max} \leq dP_s^t \leq dP_s^{max}, -dP_v^{max} \leq dP_v^t \leq dP_v^{max} \tag{15}$$

$$0 \leq P_s^t \leq P_s^{max}, 0 \leq P_v^t \leq P_v^{max} \tag{16}$$

$$P_{gmin}^t \leq P_g^t \leq P_{gmax}^t \tag{17}$$

where (15) is to limit the rate of charge and (16) represents the max storage levels on the DESS and EV. Whilst (17) represents the maximum power available to and from the grid.

B. Solving the Optimisation

The Matlab®function *fmincon* is used to solve this problem, using it's Sequential Quadratic Programming (SQP) function. SQP finds the minimum of the defined objective function for a set of linear and non-linear constraints. To initialise the values of dP_v^t, dP_s^t, P_s^t, and P_v^t the average value of their bounds was chosen, whilst the value for P_g^t was set to P_L^t.

In Matlab®the *fmincon* SQP function closely mimics Newton's method for contained optimisation. At each major iteration the function approximates the Hessian of the Lagrangian function. This can then be used to form a search direction for a line search procedure. This then allows the equation to be solved based on the constraints given.

The SQP solving method was chosen in this case due to it's efficiency at solving the problem as well as it's robustness against infinite or not-a-number outputs that can cause the interior-point method to get stuck in a repeating loop and cause it to be unable to solve the objective function. If the SQP algorithm does return one of these values, it will simple take a smaller step to ensure it can continue with the optimisation.

IV. Simulation Results

A. Simulation Set Up

To allow for consistency all simulations were subject to the conditions seen in Table II. When running groups of simulations the data generated for load, RES and cost are kept consistent, where applicable, to allow for better comparison between factors. All simulations were run for 4 day periods, the data used for analysis was taken from the central 48 hours. This is done to remove errors at the beginning and the end of simulation due to full charge or discharge of the batteries happening, which would lead to unrealistic simulations.

TABLE II
CONDITIONS FOR ALL SIMULATIONS

Variable	Value	*Variable*	Value
House Type	Standardised	***Days***	4
Location	Mid UK	***Month***	January/July
t_{vi}	18:00	***Cost Model***	Hourly RTP
t_{vo}	08:00	P_s^{max}	500
t_p	15 minutes	P_{gmax}^t	$3000\forall t$

B. RES and EV Investigation

For the initial investigations the constraints of $f_p = 40\%$ and $P_{limit}^t = 800\forall t$, unless the constraint in question was varied itself, were used. Simulations were run to compare with and without RES as well as with and without EV.

C. Limit Considerations

To investigate the effect of the soft limit and the penalty factor the limits as seen in Table III were applied, as well as a control with no penalty factors applied. Lower limits were applied in January; this is to represent the lower levels offered by solar generation and increased consumer power usage in this period, which would lead to higher pressure on non-RES power sources.

TABLE III
LIMIT VALUES

Time	Morning Limits (W)	Evening Limits (W)	Both Limits (W)
00:00 - 06:00	800	800	800
06:00 - 10:00	300/200	800	300/200
10:00 - 12:00	500/300	800	500/300
12:00 - 16:00	800	800	800
16:00 - 19:00	800	300/200	300/200
19:00 - 00:00	800	400/300	400/300

D. Effect of RES or EV

The results of the EV investigation are outlined in Table IV. It can be seen for both investigations that the EV leads to both a greater P_{grid} and P_{excess}. This is to be expected as the presence of the EV requires additional power to be put into the system. Based the data from the simulation it can be calculates that the EV adds and extra 11.8 pence per day to the household bill in January and 8 pence per day in July, this means that an average additional yearly expenditure for the EV would be £36.12. This assumes that the car only travels 20 miles each day on it's home charge and does so in a Tesla Motors Model S. It is assumed that further charging is done when it is parked to keep it topped up.

TABLE IV
EV INVESTIGATION RESULTS

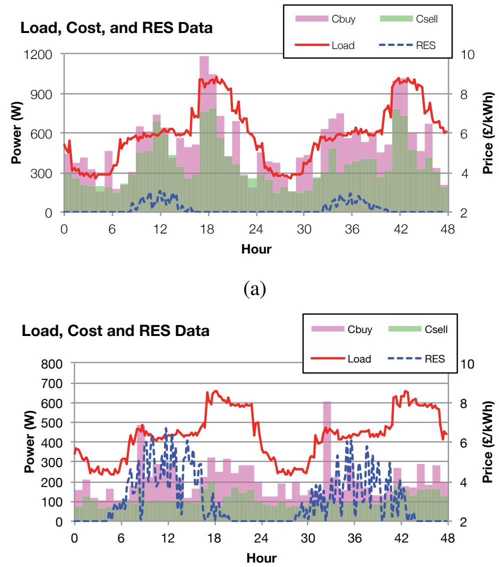
Case	P_g^{total} (Wh)	P_{buy}^{total} (Wh)	P_{excess}^{total} (Wh)	P_{sell}^{total} (Wh)	Cost (Pence)
Jan., EV&RES	30839	30839	3567	0	190
Jan., only RES	27679	27679	1509	0	166
July, EV&RES	18836	18872	872	35	86
July, only RES	15677	15677	0	35	70

This low cost shows it's benefit over the carbon outputs and cost of traditional petrol vehicles. These cost households and average of £15.70 a week (or £816.40 a year). While our estimations may be low and do not account for external charging it shows the vast difference in the cost of the two.

TABLE V
RES INVESTIGATION RESULTS

Case	P_r^{total} (Wh)	P_g^{total} (Wh)	P_{buy}^{total} (Wh)	P_{excess}^{total} (Wh)	Cost (Pence)
Jan., EV&RES	959	30805	30805	3496	185
Jan., only EV	0	31764	31764	3499	191
July, EV&RES	5029	19119	19119	836	87
July, only EV	0	24148	241148	972	109

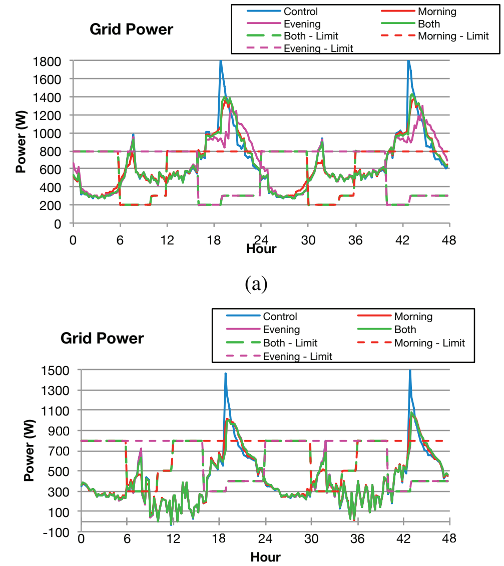
The results of the RES investigation are outlined in Table V, where $P_{sell}^{total} = 0$ for all the cases. It is seen here the clear cost savings of installing solar, where in our simulation up to 11.2 pence per day could be saved on the electricity bill. We also note that 5029W is generated by the RES in July, meaning this amount of electricity is not taken from the grid, meaning less centralised generation needs to be used. Clearly there are issues inherit in Solar Generation in the UK, where



(a)

(b)

Fig. 1. RES, load, and cost model output for (a) January and (b) July.



(a)

(b)

Fig. 2. P_g^t and P_{limit}^t for (a) January and (b) July.

solar radiation is a lot lower than other countries, as well as the initial set up costs involved with the system. This may not make Solar seem viable in isolation, however through use of government grants it is still possible to see tangible benefits for the consumer on top of the environmental benefits.

E. Effects of the Limit on Storage

Fig. 1 shows the outputs of the load, RES and cost model data used for all simulations in each month. Figures 2, 3, and 4 show the results of the factors that have been optimised.

Fig. 2 show the power taken from the grid (P_g^t) over the 48 hour period. The plot contains all the data for the different limit types applied (P_{limit}^t) and representation of these soft limits using dashed lines. It also shows the control value used where no limits were applied. It can be seen that the control evening and morning peaks are much higher than the peaks when limits are applied and the limited data has a smoother overall plot. This is the desired effect of the limiting factors.

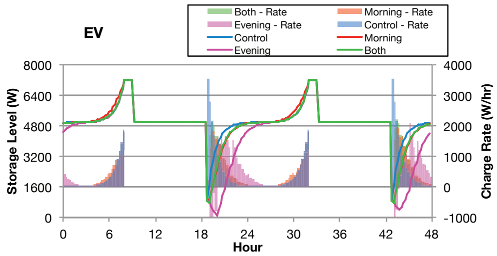
In July there are much larger contributions from the RES and this, paired with the lower demand, means that there is much less power required from the grid. With higher limits applied during this period, we see much lower costs on grid usage, where we only see an 80.2% increase on costs from the control value showing that there is less excess power used. As a result of these factors, it is noted when comparing Fig. 2(a) and Fig. 2(b) that a lower proportion of the graph is above the limits, but also that there is less variation in when different limits are applied in July than January. When considering this and additional investigations into variations in the size of f_p the response of the system can be seen to be heavily dictated by the cost function. The variable factor of f_p acts as the driving factor in keeping the overall system price low, the incentive is to ensure that the consumer uses as little power as possible that is over this limit, and therefore by using these the supplier could increase DR. This can be seen at hour 32 in the July data, where the high value of C_{buy}^t causes the storage system to discharge across all time periods.

An important point worth noting is that the different limits periods do not have show large variations in consumption, and that in times of higher limits they tend to follow different plots. This is felt to mainly be due to the lack of appliance scheduling for appliances other than the EV. The evening limits have a larger effect on the evening peaks, whilst the morning limits tends to have larger effect on the morning peaks. The evening peak is reduced over all limits due to it's size, as it goes over the maximum limit value used.

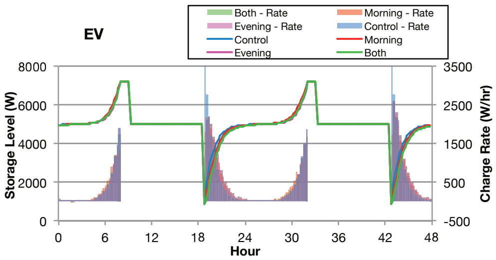
Fig. 3 and 4 show both the storage levels and charge rate of the EV and the household storage. The line represents the amount of power stored (P_v^t and P_s^t respectively) for the different limits as well as a control. The rate (dP_v^t and dP_s^t respectively) is also provided as a bar behind for reference.

In January, where the limits and RES contributions are lower the biggest cost variations are seen, with sharp increases when both morning and evening demand limits are in place, causing a 437% increase in costs from the control value. The effect of these heavy limits is seen in the smoothing of the grid consumption seen in Fig. 2(a), here we see for all limits a reduction in peak electricity draws from the system. The largest peaks are caused by the charging required for the EV, which occur during the evening limits, as a result when these are applied we see the heaviest reduction and delay in these peaks, seeing a reduction of over 600W. This shows that by using this optimisation it is possible to smooth the peaks in electricity usage, which can allow for DR.

Many of these benefits come from the household storage built into the system, we can see in Fig. 4(a) the large variation in the charging patterns between the different limits. This

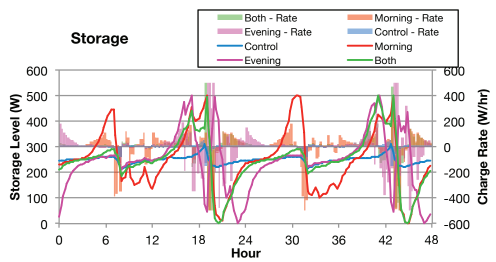


(a)

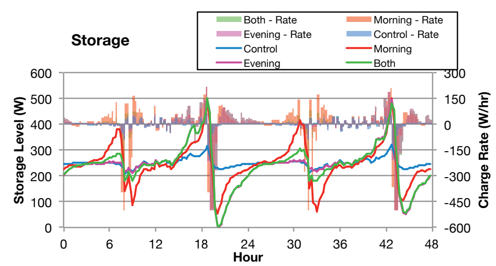


(b)

Fig. 3. P_v^t and dP_v^t for (a) January and (b) July



(a)



(b)

Fig. 4. P_s^t and dP_s^t for (a) January and (b) July

shows the benefits of even small amounts of household storage in assisting the consumer in not only cutting costs but also assisting in allowing a better DR system.

The interactions of the storage unit and the EV in both July and January show the storage unit charging to full over the periods where the EV is not plugged in and costs are lower and then transferring this electricity upon its return to the system. This shows the use of lower limits and prices to allow for the large amount of charging required by the EV to be a cost effective as possible. The data for the EV is incredibly predictable and therefore in system like this the consumer can use storage systems to minimise the costs of charging an EV.

V. Conclusions

In this paper, a method to optimise the cost of the demand of a household is proposed with considerations for household storage and the use of EVs. It uses a time-based cost structure and fixed load and uses the storage of both the EV and the household to find the lowest cost to the user. It uses existing data to predict household energy demand and to schedule changing and discharging. The use of penalty factors is also investigated, where both fixed and function-based penalties are implemented when the consumer exceeds certain limits, through use of this method it is seen that the demand of a household can be adapted to better respond to generation. The results seen in the report show the financial and power-levelling benefits of this method. This allows for a more robust grid system that creates better communication between the supplier and the consumer, allowing for better implementation of large scale RES based generation in the future.

Acknowledgment

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