A Distributed Agent Based Mechanism for Shaping of Aggregate Demand on the Smart Grid

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***Abstract*—For electrical grid systems with significant levels of intermittent renewables it will be essential to shape aggregate demand to match periods of cheap renewable supply. For example, the Irish grid will have approximately 40% of its electricity coming from intermittent wind turbines by 2020. Currently at 18%, the turbines are curtailed when they reach 50% of instantaneous supply for control reasons. This could be avoided if the aggregate demand could be shaped to follow these periods of high renewable supply.**

This paper develops a distributed agent based mechanism for shaping of aggregate demand on the smart grid. Our previous work developed two set point control algorithms that a transformer agent implements to keep the aggregate demand from going above the maximum limit of the transformer. We now extend this to enable the transformer agent to shape the aggregate demand over the 24 hour period. Since the demand is now constrained to a given shape, we must ensure the utility of the devices being charged. We develop an urgency protocol with inherent backoff that each device agent implements to guarantee the utility of its device. Finally, we develop a method for the transformer agent to determine the bounds of shape that the network will tolerate.

***Keywords:* Agent based control, Demand shaping, Set point control, Smart grid.**

I. Introduction

For electrical grid systems with significant levels of intermittent renewables it will be essential to shape aggregate demand to match periods of cheap renewable supply. For example, the Irish grid will have approximately 40% of its electricity coming from intermittent wind turbines by 2020 [1]. Currently at 18%, the turbines are curtailed when they reach 50% of instantaneous supply. This curtailment is enforced to ensure stable operation of the grid system. Ideally, the system operator would like to schedule demand to match these periods of high renewable supply.

Most demand response approaches only have the objective of reducing the peak in the daily demand pattern [2]–[5]. These approaches employ price incentives to shift flexible load from the peak hours to off peak hours. They achieve an overall flattening of the demand but this control is very coarse and does not enable accurate scheduling of demand. There have also been many papers that address the problem of controlled charging of electric vehicles (EVs) on a constrained distribution grid [6]-[13]. These methods enable more tightly controlled charging of the EVs to ensure that the aggregate demand does not exceed the transformer limits.

In our previous work [14] we developed two set point control algorithms that tightly control the EV load to ensure the aggregate demand remains under the transformer limit. These two algorithms form the basis for accurate scheduling/shaping of the aggregate demand for flexible load devices.

Again, we propose that in a future smart grid scenario there will be two types of demand, a load which can be influenced by dynamic pricing (termed base load) and a more tightly controlled flexible load that can be used to shape the overall aggregate demand. Fig. 1 shows an example row of houses being fed by a single transformer. The aggregate demand at this transformer is being controlled to a varying set point level (see Fig. 2).

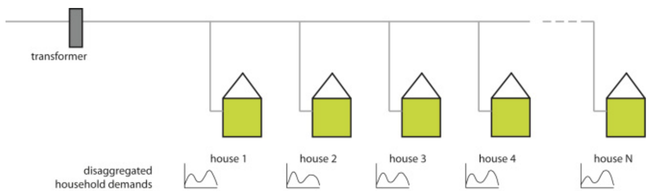

Fig. 1. A row of houses being fed by a transformer.

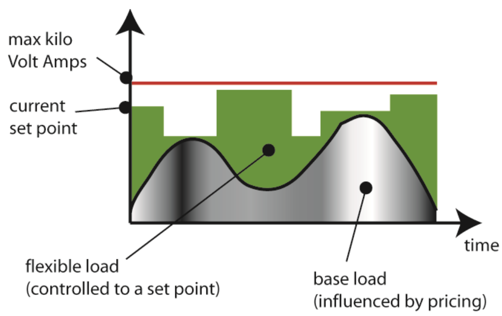

Fig. 2. Aggregate demand controlled to a varying set point.

The aggregate demand is made up from the variable base load and the flexible load being controlled to a set point schedule. Flexible load consists of appliances that have significant energy consumption and have storage so they can accept energy from the grid flexibly and deliver their service to the customer when they require it. Key examples of this flexible load are EVs, electric hot water heating and electric storage heating.

This paper develops a distributed agent based mechanism for shaping of aggregate demand on the smart grid. The transformer agent shapes the aggregate demand over the 24 hour period. Since the demand is now constrained to a given shape, we must ensure the utility of the devices being charged. For example, an EV must be fully charged before its departure time or a water heater must have enough hot water. We develop an urgency protocol with inherent backoff that each device agent implements to guarantee the utility of its device. Finally, we develop a method for the transformer agent to determine the bounds of shape that the network will tolerate.

Section II presents the design of the distributed agent based mechanism, the two set point control algorithms, the urgency protocol with inherent backoff and the method to determine the shape bounds. Section III presents the experimentation and results, and finally Section IV gives conclusions and future work.

II. Algorithm Design

This section presents the design of the distributed agent based architecture and the two algorithms for the transformer agent to implement set point control. Then the urgency protocol with inherent backoff is detailed and finally a method for determining the bounds on the shape of the demand is outlined.

A. Agent Based Architecture

The basic architecture of the algorithms developed consists of a transformer agent that resides at the transformer level and broadcasts a control signal (0-100%) to the set of device agents (see Fig. 3). A set point schedule for the 24 hour period is given to the transformer agent and the agent attempts to shape the overall aggregate demand to this pre-determined set point schedule. The transformer agent uses the set point control algorithms that were developed in [14] to do this. We assume the intermittent supply can be predicted over this 24 hour period so we know how to schedule the demand.

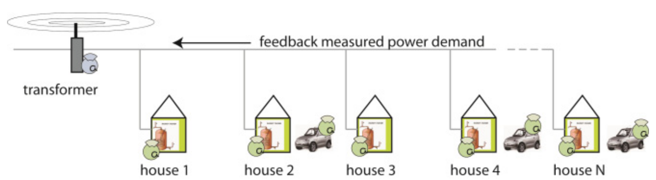

Fig. 3. Distributed agent based architecture.

The device agents are responsible for implementing the urgency protocol to guarantee their device utility. Guaranteeing the utility of the controlled flexible devices is essential if this type of control is to gain user acceptance. The device must be able to deliver its service when the user requests it. For example, enough battery charge to drive to work or enough hot water to have a shower. There is a trade-off between the transformer agent shaping the demand to the devices and the device agents providing their service to the end users. The urgency protocol with inherent backoff guarantees the device utility and provides a feedback signal to the transformer agent when it is over constraining the demand.

Finally, a method is developed which uses this feedback signal to determine the bounds in which the demand can be shaped.

B. Set Point Control Algorithms

Two set point control algorithms were developed in [14]. Here we give a brief explanation of them. The variable charging rate algorithm uses a more sophisticated variable rate EV charger whereas the variable connection rate algorithm uses a much simpler on/off type charger. The advantages of the on/off charger are that it is significantly cheaper to produce and also does not cause noise and harmonics on the electrical network as the variable rate charger does.

The variable rate charging algorithm broadcasts from the transformer agent the charging rate (0-100%) that each of the available device agents should charge at. The feedback is the measured power demand at the transformer. Fig. 4 shows the simple control operation of the charging rate. If the power demand is less than the set point limit, then the charging rate is increased by one and if the demand is greater than the set point limit, then the charging rate is decreased by one.

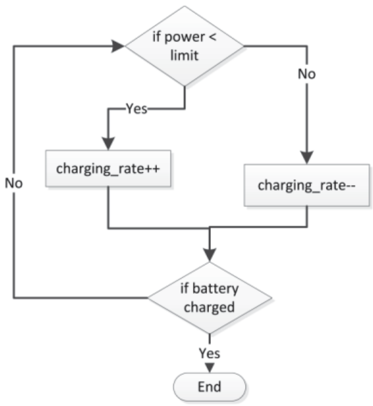

Fig. 4. Variable charging rate algorithm.

The variable connection rate algorithm is similar to the previous algorithm but includes the use of probability to control the connection rate as in Turitsyn et al. [13]. In this algorithm the connection rate (0-100%) is broadcast from the transformer agent at a frequency of once per minute, so each EV charger will attempt to connect once per minute with the given connection rate probability. The feedback of total power demand is measured at the transformer. The control operation is the same as shown in Fig. 4, except we are controlling a connection rate instead of a charging rate.

At the end of each minute interval, the EV chargers will again attempt to connect with the connection rate probability.

The random process for connecting ensures that each of the EVs has a fair access to the available power. In essence, the EVs are multiplexed along the time domain in one minute intervals. Fig. 5 shows an example EV charger connecting (blue bar) with varying connection rate over time.

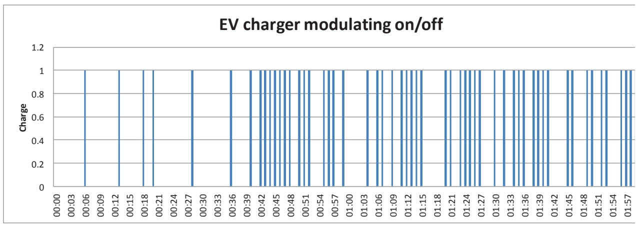

Fig. 5. EV charger modulating on/off.

We have extended the set point control mechanism to enable the set point to vary over time. A set point schedule can be sent to the transformer agent that will shape the aggregate demand for the 24 hour period. Now that the device agents are not charging as quickly as possible, it is important to guarantee their utility.

C. Urgency Protocol with Inherent Backoff

The urgency protocol with inherent backoff provides a mechanism for guaranteeing device utility. Each device agent implements its own urgency protocol in a distributed fashion. The device agent monitors the time it will take to achieve a full charge and the time left to the next utility event. When the time to charge gets close to the time left (< 10 minutes difference), the device agent changes to the urgent state and starts to charge fully at each time step (see Fig. 6). This action ensures that the device will be fully charged by the time of the utility event. We assume the time of utility events is known. This can either be intelligently learned by past usage or preprogrammed by the user.

Since the device agent is charging fully, it increases the demand measured at the transformer agent and therefore the charging/connection rate will inherently backoff to reduce the aggregate demand down to the current set point. So, devices in the urgent state leave the set point control and start to charge fully to ensure their own utility.

The problem now is that if the transformer agent constrains the charging too much, then many of the devices will fall into the urgent state and potentially the set point control will be overridden. The transformer agent needs a mechanism to ensure that the total demand delivered to the devices is sufficient to meet their utility needs over the period.

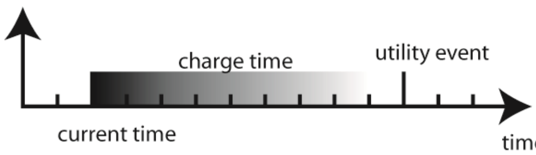

Fig. 6. Current time plus charge time close to utility event.

D. Method to determine the bounds on shape of demand

The transformer agent needs a method to determine what possible shapes of demand can be achieved by the combined base load and flexible loads. At times the set point may not be achievable as there is not enough flexible load to switch on (under charge capacity) and at other times the set point may be exceeded (over charge capacity) as the flexible load has switched to the urgent state and is fully charging.

The method is fully explained in Section III where the experimental results show examples of determining the shape bounds.

III. Experimentation and Results

A power system simulator, GridLab-D [15], was used to experiment with the algorithms and agent based mechanism. A test distribution system with one transformer feeding 90 houses within a neighbourhood was modelled. Each of the houses has one EV and one water heater that take part in the flexible load control. The EV has a routine of going from home to work and back again. Charging of the EVs only happens at home. The water heater has hot water drawn from it at periods during the day.

The base load for each of the houses is derived from measurements taken in Ireland during the Commission for Energy Regulation smart meter trial [16]. There is a separate base load for each of the 90 houses and the measurements are average power in kilo watts (kW) in half hourly intervals.

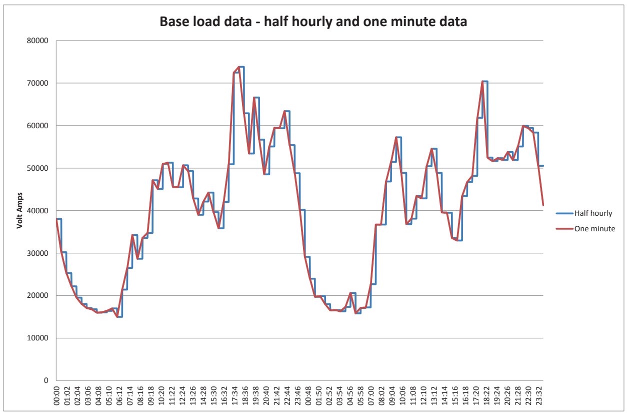

Fig. 7. The interpolated one minute base load data.

We interpolated this data to one minute periods in order to smooth the load profile so there are no sudden jumps in the demand (see Fig. 7). Having finer grained measured data of power demand would be preferable for testing purposes.

The departure and arrival times of the EVs were calculated using SUMO [17], an open source traffic simulator. It is a microscopic traffic simulator that simulates individual vehicles as opposed to just traffic flows. Traffic in Dublin city centre was simulated for the morning period. The 1.5km by 2km map of Dublin was obtained from the OpenStreetMap website [18]. The traffic traces were constructed from vehicle counts available from the Dublin city council website [19].

The trace contained approximately 450 vehicles of which 90 were electric vehicles for the GridLab-D simulation.

Water heater demand was derived from a set of water demands that were already present in GridLab-D. The demands are well spread out with overall peaks in the early morning and late afternoon.

A. Set Point Control Results for EVs

First we test both set point control algorithms with just the EV demand. Fig. 8 shows the variable charging rate algorithm operating over a 48 hour period for just the EVs. Initially the charging rate starts at zero and it must ramp up over a period of time.

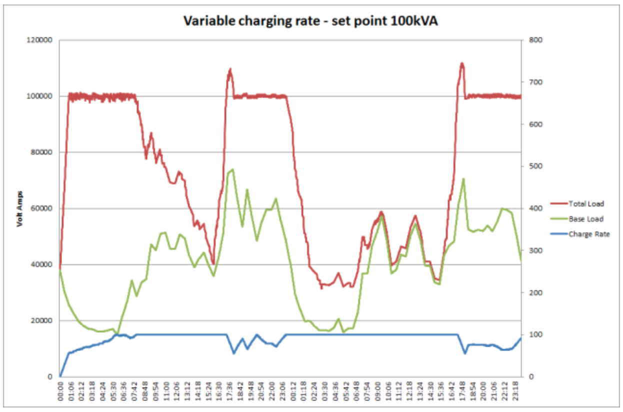

Fig. 8. Variable charging rate at the limit of transformer.

The results show that the algorithm can closely follow a constant set point limit of 100 kilo Volt Amps (kVA). During the periods of tracking the set point, the mean aggregate demand is 99.8 kVA and the standard deviation is 0.73 kVA.

For both of the days there is an overshoot. This occurs as the sharp rise in evening peak demand is coincident with the EVs arriving home from work. The controller is not fast enough to reduce the charging rate of the EVs from its 100% value (reached during off peak demand and few EVs available). Setting the set point below the max limit can address this over shoot in the controller.

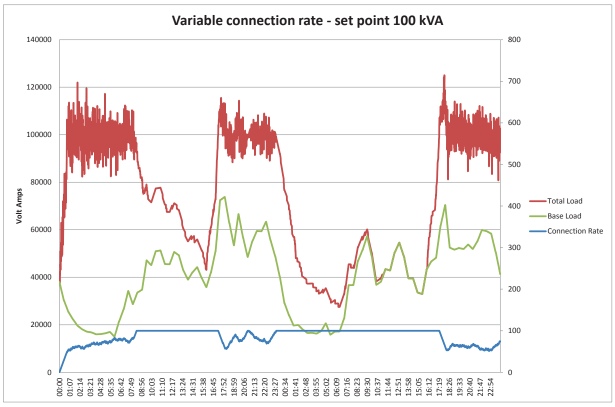

Fig. 9. Variable connection rate at the limit of transformer.

The variable connection rate results are similar to the charging rate results, but more erratic around the set point (see Fig. 9). The controller does not follow the set point limit as closely because of the random process for generating the probability to decide whether to connect or not. For example, the broadcast connection rate may be 75% but not exactly 75% of the EV chargers will connect due to the inherent error in the random probability process.

For these results, during the set point tracking periods, the mean was 99.2 kVA and the standard deviation was 6.52 kVA. The standard deviation is greater than in the variable rate control and the set point would have to be set below the limit by a greater margin.

For both algorithms it has been shown that they fairly divide out the available power to each of the EVs [14].

B. Method to determine the bounds on shape of demand

We now implement the full agent based mechanism. EVs are controlled using the variable charging rate algorithm and the water heaters are controlled using the variable connection rate algorithm. This demonstrates that it is possible to use both variable chargers and on/off chargers in the control mechanism. The EVs use the more expensive variable rate chargers, whereas the water heaters use the cheap on/off chargers (switches). Each of the device agents is implementing the urgency protocol to guarantee its own utility. Fig. 10 shows the aggregate demand being controlled to a constant set point of 100kVA over a period of three days for both EVs and water heaters.

We now develop a method for determining the bounds that the transformer agent can shape the demand to. Initially the transformer agent uses a straight line constant set point for the 24 hour period. It starts with the constant set point at the maximum transformer limit and observes the actual aggregate demand that is delivered to the network (see Fig. 10).

It can be seen that in the afternoon periods the set point is not reached and the charging rate is at 100%. These are periods of under charge capacity where there are not enough available flexible devices to meet the set point. In this case most of the devices are either fully charged or in the case of EVs, away from their home charging points. Therefore, given this under charge capacity, it is possible to reduce the set point to constrain the charging further.

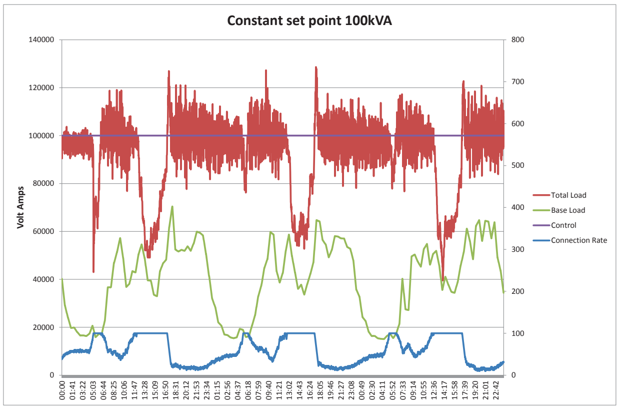

Fig. 10. EV battery charge over time.

Figure 11 shows the aggregate demand constrained to 90kVA. There is now no under charge capacity and the average demand is 90kVA. This is the average power that is needed in order to serve the base load and the charging of the flexible load devices.

Figure 12 shows the aggregate demand reduced to 80kVA. A spike can now be seen at the start of the morning peaks on the second and third day. The set point has been exceeded and the charging rate is at zero. This is due to devices that have been over constrained in their charging and need to charge fully before their utility event. In this case it is mainly EVs that need a full charge before their departure in the morning.

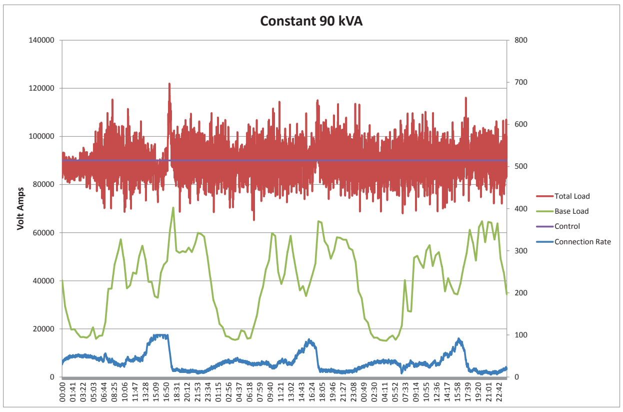

Fig. 11. EV battery charge over time.

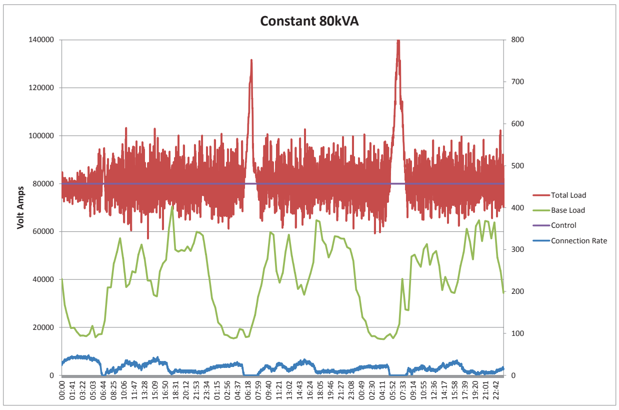

Fig. 12. EV battery charge over time.

This method of gradually reducing the set point to reduce the under charge capacity areas and find the utility spikes shows the average power required by the network to be around 90kVA in this instance.

On average this amount of power must be delivered to ensure servicing of the base load and flexible load without causing utility spikes in the aggregate demand. The same method can now be applied to finding the level of a shaped demand. The shaped demand is initially set at a high level and gradually lowered to reduce under charge capacity areas and until utility spikes begin to occur.

C. Shaped demand for EVs and water heaters

The previous figures have shown the combined control of the EVs and water heaters together for a constant set point control. We now look at varying the set point to give a shaped demand over the 24 hour periods.

Figure 13 shows the aggregate demand being shaped over three 24 hour periods. The levels go from 80kVA to 100kVA to 120kVA. By following the methodology developed in Section B, it can be seen that there are under charge capacity areas in each of the control sections and therefore the demand shape can be further constrained.

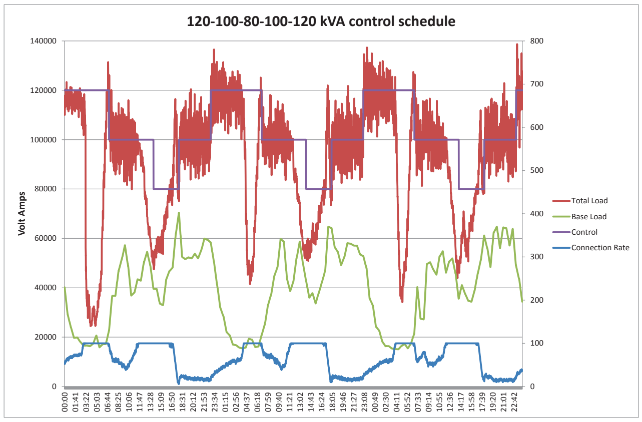

Fig. 13. EV battery charge over time.

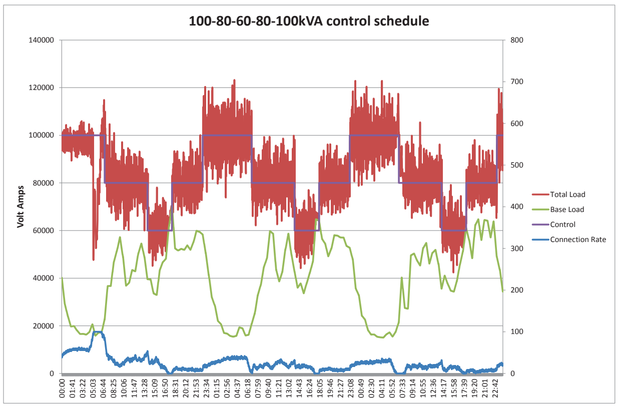

Fig. 14. EV battery charge over time.

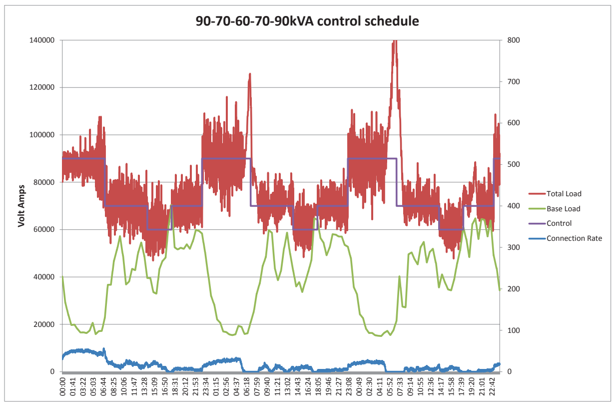

Fig. 15. EV battery charge over time.

Figure 14 shows the demand shaped reduced by 20kVA in each section and the under charge capacity has reduced significantly. The lowest section at 60kVA is now just touching the base load and it cannot be reduced further than this.

We reduce the other sections by 10kVA but see that there are utility spikes in the 90kVA section during the morning peak. The limit for the demand shape is therefore around the 100-80-60-80-100 kVA limit in this instance.

IV. Conclusions and Future Work

Our previous work developed two set point control algorithms for limiting aggregate demand to the maximum limit of the transformer [14]. This paper develops a distributed agent based mechanism for actually shaping the aggregate demand over the 24 hour period. The transformer agent uses the set point control methods to shape the aggregate demand to a given set point schedule. Now that the aggregate demand is being constrained, a mechanism is needed to ensure the utility of the devices. An urgency protocol with inherent backoff is developed to guarantee device utility. This protocol is implemented by the device agents. Finally, a method for determining the bounds on the shape of demand that can be tolerated by the network is developed. The distributed agent based mechanism is composed of these three components.

A distribution network with 90 houses, 90 EVs and 90 water heaters was simulated in detail. Base load was derived from measured real household energy consumption. The simulation results show the agent based shaping mechanism to be able to accurately shape the aggregate demand within the bounds of the network.

Future work will look at addition of electric storage heating into the network to further add to the charging capacity. We would also like to look at control of a number of low voltage distribution networks and how this control aggregates up to the medium voltage transformer that feeds them.

Acknowledgment

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