A Storage Pricing Mechanism for Learning Agents in Masdar City Smart Grid

Fatimah Ishowo-Oloko[1], Perukrishnen Vytelingum [2], Nick Jennings[2], Iyad Rahwan[1,3]
[1]Masdar Institute of Science & Technology, UAE
[1]University of Southampton, UK
[3]Massachusetts Institute of Technology, USA

ABSTRACT

Masdar City in the United Arab Emirates is designed to be the first modern city powered solely by renewable energy. However, the stochastic nature of renewable energy generators has remained a major challenge in their sole and large-scale deployment. Traditional approaches couple large-scale storage systems to renewable generators to mitigate the intermittency in their supply pattern. More recent approaches also study how emerging technologies such as electric vehicles and micro-batteries can be used as consumer-side storage. Future smart grids are however likely to contain both large and micro batteries and it is unclear how both technologies will work together. Hence in this paper, we present a novel model of joint-storage management that allows both renewable energy suppliers and consumers to coordinate in a decentralized manner by gradually adopting storage abilities. For this model, we present a dynamic storage-pricing mechanism that makes use of the storage information from the renewable supplier to generate daily, real-time electricity prices which are communicated to the consumers. We empirically evaluate the system and show that, when all homes are equipped with storage devices, the supplier can significantly improve the efficiency of the system by up to 23%, while the consumer reduces its costs by up to 35%.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent systems*

General Terms

Economics,Experimentation

Keywords

Energy and emissions, Simulation

1. INTRODUCTION

The growing threat of climate change and the depletion of non-renewable energy sources have led to the growth of sustainable development. In particular, sustainable urban development has been advocated as one of the factors in changing the way we use and produce energy. For example, urban planning in the future would not only involve designing buildings that minimize in-house energy use, it would also have to consider the effects of distributed energy resources like wind turbines and solar panels on land-use patterns. Furthermore, these technologies will have to be economically feasible, for them to be adopted on a wide scale and non-intrusive, in order not to detract from the living experience. Thus, future cities would have to be designed in ways that are sustainable, attractive and commercially viable. Masdar City[1] is built to be a pioneer model for such future cities.

Masdar city is currently fully powered by onsite renewable energy. This includes a 1MW roof-top, solar photovoltaic plant and a 10MW photovoltaic farm covering 22 hectares of land. However, as the city grows, its energy demands will increase beyond what can be provided on-site. As such, the remaining demand will need to be sourced from outside the city. Likely off-site sources include the 100MW Concentrated Solar Power (CSP) plant and the 10MW wind farm to be built in the western region and the island respectively.

Given the above features of the Masdar city grid and inherent intermittency of renewable energy generators, there arises the challenge of balancing supply and demand on a constant basis. Previously, conventional energy suppliers ensured the matching of supply and demand by maintaining a generation capacity that was always much higher than demand. As such, this resulted in excess generation capacity during off-peak hours. With renewable generation, maintaining excess capacity does not solve the problem as excess capacity is still subject to intermittency and cannot be dispatched at will. Therefore, it becomes crucial for renewable energy suppliers to avail themselves of emerging technologies to encourage their consumers' demand to respond to their particular generation pattern.

Demand response have typically involved the use of direct load control strategies by the consumer or the utility [8, 13]. While these strategies have been effective in influencing demand, they are highly dependent on the active participation or information revelation of the consumers. However, active participation of the consumer is not guaranteed just as consumers might also be reluctant in revealing their true preferences to the utility to avoid exploitation. Renewable energy generators thus require a dynamic control signal that is linked to the variability in their generation patterns and an enabling technology to dampen (supply power during deficits and store power during excesses) its volatility.

To address these challenges, electricity storage devices in the form of large utility-scale batteries and small domestic (household) batteries have been proposed for use with renewable energy generators. These storage devices could act as "shock-absorbers" to the system by providing energy when needed and thereby increasing the reliability and ef-

[1]www.masdarcity.ae

ficiency of energy supply. Moreover, they reduce the need to over-build capacity and thus ensuring a higher return on investment in renewable generation technologies.

In this paper, we propose the use of both utility-scale and domestic batteries to form a decentralized energy storage-solution that can be coupled with sole, large-scale renewable generators in sustainable cities. Given the decentralized nature of the domestic storage and the different consumption patterns of houses, each storage unit is best represented as an autonomous agent that aims to maximize its own preferences. In particular, with the advent of smart meters, it is possible to envisage that software agents could be installed on meters to optimize the energy consumption of houses. Now, this storage-solution could also be widely applied for other smart grids as it makes a case for decentralizing storage. Clusters of houses with similar consumption patterns could be grouped together and provided with medium scale storage devices.

On the policy side, amongst the key goals of the Abu Dhabi Economic Vision 2030 are sustainable development and economic diversification by the year 2030. Thus, the government is committed to increasing the penetration of renewable energy as well as providing a conducive regulatory environment. For this, we provide a novel mechanism by which renewable generators can determine the best price signal to send to their consumers giving their particular seasonal and daily patterns. This dynamic pricing mechanism improves the system efficiency and consumer savings by up to 23% and 35% respectively. Thus, it outperforms the existing fixed price mechanism and further promotes the integration of renewable energy generators into the wider Electricity Grid.

This is the first paper that addresses the novel challenge of joint-storage management with the use of a multiagent system framework. We thus demonstrate that multiagent system paradigm can provide fully sustainable cities (and others) with solutions that help with the sole and/or large-scale deployment of renewable energy generators. It is important to note that while this research has been carried using simulations, it is close to actual deployment as Masdar City is currently testing a fleet of Mitsubishu i-MiEVs[2] electric vehicles for use in the city.

Thus, this paper contributes to the state of art in the following ways:

1. We present the first smart grid framework which combines both centralized utility-side storage and distributed consumer-side storage.

2. We develop novel algorithms and a pricing mechanism to enable both the renewable energy supplier and the consumers to optimize generation and storage decisions taking into account the intermittency of renewable energy.

3. We empirically evaluate our approach and show that our mechanism (compared to the existing pricing mechanism of Masdar City) results in up to 23% improvement in efficiency for the supplier and up to 35% savings for the consumer agents.

2. MODEL DESCRIPTION

In this section, we present the models of the energy requirements of Masdar City. The city is designed to be powered solely by renewable energy with a residential population of about 40,000. Thus, the grid consists of renewable generators and batteries (at the supply end) and homes with electrical appliances and micro-batteries or electric vehicles (at the consumer end). In the following sections, we detail each element of our system by providing specific models of Masdar energy supplier (wind and solar power generation using real data) and homes (each represented by its agent) which may possess electricity storage capacity (either batteries or electric vehicles). In our models, we consider fixed time intervals consisting of single days, each divided into a set of half-hourly intervals I = 1, 2, ..., 48 such that each participant needs to decide its behavior (typically a day ahead) for each interval.

2.1 The Renewable Supplier

The wind speed data at an elevation of 10m was obtained from Masdar City Meteorological station for the period of August 2008 to June 2009. As the speed of wind varies with height, the data was projected to the wind turbine[3] hub height (84m). The projection was done using the power law equation [3] shown below:

$$v_h = v_r \times \left(\frac{h}{r}\right)^n \tag{1}$$

where v_h is the wind speed at hub height, v_r is the wind speed at reading height, h is the hub height, r is the reading height which in our case was 10m high and n is the power-law exponent (roughly about 0.1429 for open land [14])

We modeled the stochastic process of the wind speed with the Weibull probability distribution [14] given by equation 2.

$$p\left(v_h\right) = \left(\frac{s}{z}\right)\left(\frac{v_h}{z}\right)^{z-1} \exp\left[\left(\frac{-v_h}{z}\right)^s\right] \tag{2}$$

where v_h is the wind speed at hub height, s is the scale parameter and z is the shape factor. The parameters of the distribution (s, z) were estimated using the Maximum Likelihood (ML) method. The estimated parameters are $[4.88, 2.32]$.The power curve of the wind turbine was approximated by a five-orders polynomial function [14] (as the best fit for the curve was found at that order) given in equation 3. The power outputs of the wind turbine at recorded speeds for each time interval $i \in I = \{1, 2, 3 \ldots 48\}$ were thus obtained.

$$o_i^{wt}\left(v_h\right) = \begin{cases} o_{max}^{wt}, & v_h \geq v_{max}^h \\ (-0.024v_h^5 + 1.88v_h^4 & \\ -53.33v_h^3 + 668.49v_h^2 & \\ -3293.92v_h + 5476.07), & v_{min}^h < v_h < v_{max}^h \\ 0, & v_h \leq v_{min}^h \end{cases} \tag{3}$$

Where $o_i^{wt}\left(v_h\right)$ is the power output of wind turbine for a given mean wind speed v_i^h, o_{max}^{wt} is the rated power output of the wind turbine, v_{min}^h denotes the cut-in wind speed of the wind turbine and v_{max}^h is the cut-off wind speed of the wind turbine.

For the solar generator, the time data series of the power output from a test PV panel located at Masdar City PV contest site was used. The output was recorded every 5

[2]http://www.mitsubishi-motors.com/special/ev/

[3]http://nozebra.ipapercms.dk/Vestas

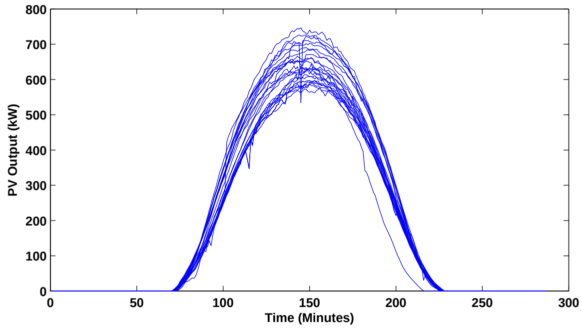

Figure 1: PV panel output for all days in the month

minutes (288 readings per day) for the period of August 2008 to June 2009. Figure 1 shows the PV output for all days in the month of June 2009. The average of the six readings in each half-hour readings was then obtained for each time interval $i \in I$.

The utility-scale storage was modeled based on the Sodium Sulphur (NaS) deep-cycle batteries produced by NGK[4]. Our choice was based on their high power, energy density and capacity which makes them suitable for utility scale storage. They also have a high efficiency and virtually no self discharge.

Each generator and battery model has an associated daily cost c^g for $g \in G = \{b, pv, wt\}$. This includes fixed costs (capital,installation) and annual costs (operations and maintenance (O&M)). We derive the levelized daily costs by summing all incurred costs and dividing by the expected lifetime in days. The approximate values for all costs were obtained from the manufacturers at the World Future Energy Summit 2011 which took place in Abu Dhabi.[5]

2.2 The Capacity Planning Problem

We model our supplier as being required to satisfy all of its consumers' demand, solely from the energy produced from its renewable generators. To do this, the supplier needs to determine the optimal capacity configuration for the generators and batteries to be installed. A number of potential ways of finding the optimal design has been proposed in the literature. This includes analytical approaches as in ([12] and [15]), simulation approaches ([5] and [6]) and optimization ([1], [4] and [7]). A key challenge here is for the renewable supplier to be able to compete favorably in the wider electricity market to promote the adoption of renewable energy. Thus, it needs to ensure that it minimizes the amount of optimal capacity to install in order to provide its consumers with competitive electricity prices. Other options are to design suitable mechanisms that incentivize its customers to respond to its generation patterns. Here, we present a cost optimization model and further options such as the use of a pricing mechanism and learning mechanism are shown in next section.

The optimization model finds the number of wind turbines and PV panels that need to be installed and also specifies the amount of power to either charge into the battery or discharge from it for each time period (i.e. the storage profile of the battery). Now, the possible power output of each wind turbine (Equation 3) during time interval i is constrained by the maximum output power given by:

$$o_i^{wt} \leq o_{max}^{wt} \tag{4}$$

Also, the output of each PV panel during time interval i is constrained by the watt-peak rating of the panel:

$$o_i^{pv} \leq o_{max}^{pv} \tag{5}$$

where o_{max}^{pv} is the rated maximum output (in Watt-peak) of the PV panel.

Each battery has a capacity constraint which limits the amount of power flow into and out of it at each time interval. The power flow of the battery can be calculated as the difference between stored energies of two consecutive intervals. As there are two possible power modes, charging and discharging, we define when the battery is charging i.e. $e_i^b < e_{i+1}^b$

$$p_i^{ch} = \left(e_{i+1}^b - e_i^b\right) / \Delta i \tag{6}$$

And when it is discharging $e_i^b > e_{i+1}^b$:

$$p_i^{dch} = \eta \cdot \left(e_i^b - e_{i+1}^b\right) / \Delta i \tag{7}$$

where p_i^{ch} is the power input to the battery at time i, p_i^{dch} is the power output from the battery at time i, e_i^b is the energy stored in the battery at time i, η is the discharging efficiency of the battery and Δi is the length of a time interval (which is 30 minutes in our model).

The power output of each battery during time interval i is also constrained by the maximum charging and discharging rates:

$$p_i^{ch} < p_{max}^{ch} \tag{8}$$

$$p_i^{dch} < p_{max}^{dch} \tag{9}$$

Lastly, for a sustainable city, total power output from renewable generators and batteries should exactly satisfy the total load demand D_i^A at all time intervals. This supply-demand matching equation for interval i can be expressed as:

$$Q_i + P_i^{dch} = D_i^A + P_i^{ch} \tag{10}$$

Here Q_i represents the total output from both wind turbines and PV panels, P_i^{ch} is the power input to all batteries, P_i^{dch} is the power output from all batteries and D_i^A is the total demand from consumer agents.

Equation 10 is the objective function which completes the capacity determination model for Masdar City Grid.

2.3 The Home Agents

Here we describe our agent model of the consumer, which is built upon the recent model for homes equipped with smart meters by Vytelingum et al [17]. Specifically, we define the set of consumer agents as A and each agent $a \in A$ has a load (consumption) profile C_i^a $\forall i \in I$ defined as the actual amount of electricity used (consumed) by agent a for time interval i during each day. In our model we assume that this load profile is fixed: an agent wants to use certain amounts of electricity at certain times of the day and would rather not change its behavior nor reveal its preferences to its supplier. Thus, we do not attempt to change

[4]http://www.ngk.co.jp/english/products/power/nas/index
[5]http://www.worldfutureenergysummit.com/en/wfes-exhibitors/2011-exhibitor-list.aspx

the consumption profile of agents rather by giving the agent storage ability, the time when electricity is demanded can be decoupled from the time when the electricity is actually consumed. Thus, we define the demand profile $D_i^a\ \forall i \in I$ as the amount of electricity demanded (purchased) by the agent from the energy supplier for time interval i during each day. Furthermore, each agent $a \in A$ may also have some storage available to it, with capacity q^a, daily costs c^a and efficiency η^a.

3. THE STORAGE PRICING MECHANISM

In this section, a storage pricing mechanism (SPM) is proposed to help the renewable energy supplier maximize the efficiency of its system given the intermittency problem of renewable generation. The mechanism uses the availability of real-time storage information (measured in kWh and representing the amount of electric energy stored in the batteries) that is known to the supplier. This information involves no extra communication overhead as the state of its batteries are easily known to the supplier. For every time interval, the supplier (in our case study Masdar City) generates electricity from both its wind turbines and photovoltaic panels. The amount generated is used to satisfy the demand of its consumers. Whatever is in excess of demand is then stored in the batteries. Thus the amount of electric charge in the batteries captures the amount of renewable generation that is available but not being demanded by the consumers.

So this storage information embodies two signals:

1. It informs the supplier of the specific periods when generation exceeds (or lags) demand.

2. It quantifies energy generation i.e. it tells the supplier how much the excess or deficit is.

Using this information, the supplier can then determine when to decrease its electricity price to encourage more demand and also by how much it should decrease the price in order to signal to the consumers by how much they should also increase their consumption and vice versa. Therefore, our mechanism uses the correlation between the amount of charge (or discharge) and the excess (or deficit) generation. As opposed to [16] where the aggregate consumption of the homes is divided into two in terms of the amount satisfied by the supplier and the amount sourced from the grid, the supplier here identifies two different time periods. The first period $i^{bat} \in I$ are times when the aggregate demand of the homes exceeds generation such that $D_i^A > Q_i$ and the second period $i \in I$ when the demand $D_i^A \leq Q_i$.

During period $i^{bat} \in I$, the demand in excess of generation is supplied from the batteries and thus the supplier incurs a storage cost ϵ (/kWh). This storage cost is measured in (\$/kWh) and represents the cost in dollars per kilowatt-hour of energy delivered from the batteries to the homes. More formally, from the optimal configuration derived from the solution to equation 10, we define the ϵ at each interval as

$$\epsilon = \frac{c_b \times n_b}{\sum_{i \in I} P_i^{ch}} \tag{11}$$

where c_b is the levelized daily cost of each battery, n_b is the optimal number of batteries installed and P_i^{dch} is the power output from all batteries at time i.

The intuition behind this is that dividing the cost of the batteries by the amount of useful charge that is obtained from them gives the marginal cost of using batteries. So the supplier offers the consumer the incentive of savings in line with how much it saves when it avoids using storage by reducing the price by ϵ or it charges them the marginal cost it incurs by having to supply their demand from batteries. Thus, we provide retail rates for different periods of time as follows:

1. For the times $i^{bat} \in I$, the electricity is priced based on the retail price of electricity p_i^{retail}.

2. For all other times $i \in I$, i.e., the time periods when the amount demanded can be directly satisfied by the supplier from its generation Q_i at that time, the electricity is priced at ϵ less than the retail price of electricity i.e. p_i^{retail} - ϵ.

By the above, the supplier incentivizes its consumers to use the green energy it produces directly rather than having to store it and later providing it to them from storage. It is important to note that our storage pricing mechanism does not just shift storage from suppliers to the consumers. Rather the pricing mechanism can still be used successfully to incentivize consumers without storage or with other forms of demand management systems (such as load control programs). Also, our pricing mechanism differs from the traditional time-varying mechanisms because we do not aim to smooth out peaks. Rather we encourage peak consumption periods as long as such periods are highly correlated with periods of peak renewable generation.

4. THE AGENTS' ADAPTIVE RESPONSE

Given the above dynamic pricing mechanism, a self-interested agent (with storage ability) that is interested in minimizing its cost responds by adapting its storage profile in line with changes in daily electricity prices. In more detail, our model adopts the day-ahead best-response adaptive strategy for agents by [17]. As opposed to their model however, the agent does not need to predict the next day's price for each time slot as this is given by the supplier on a day-ahead basis. Rather, it calculates the storage profile for day $(t+1)$ based on the published market prices it receives on day (t). As the storage profile depends largely on the storage capacity, the agent also has to decide how much storage capacity it should have. Thus, the agent needs to first learn its optimal storage capacity as a best-response to changing electricity prices and then optimize its storage profile based on the determined storage capacity.

The Widrow Hoff Learning mechanism used by [17] is based on a two-pass approach. In the first pass, the agent computes the optimal storage capacity ξ^a (maximum energy stored daily) required for it to minimize its cost by making capacity q^a, a decision variable in the optimization function (Equation 12). The agent also obtains the storage profile, $b^a = b_i^{ch,a} - b_i^{dch,a}$ for that day[6] by minimizing the same function. Then in the second pass, the agent gradually adapts both its capacity and profile.

$$\arg\min_{b^a} \sum_{i \in I} \left(p_i \left(b_i^{ch,a} - b_i^{dch,a} + C_i^a \right) + c^a b_i^{ch,a} \right) \tag{12}$$

[6] We used IBM ILOG CPLEX 12.2 to implement and solve the optimization problem

Constraint 1: discharge efficiency

$$\sum_{i \in I} b_i^{dch,a} = \eta^a \sum_{i \in I} b_i^{ch,a}$$

Constraint 2: rated maximum charging capacity

$$b_i^{ch,a} \leq b_{max}^{ch,a}, \forall i \in I$$

Constraint 3: rated maximum discharging capacity

$$b_i^{dch,a} \leq b_{max}^{dch,a}, \forall i \in I$$

Constraint 4: energy that can be stored at a time interval

$$b_i^{dch,a} \leq q^a - b_0^{ch,a} + \sum_{j=1}^{i-1} \left(b_j^{dch,a} - b_j^{ch,a} \right), \forall i \in I$$

Constraint 5: energy that can be used at a time interval

$$b_i^{dch,a} \leq \eta^a \left(b_0^{ch,a} + \sum_{j=1}^{i-1} \left(b_j^{dch,a} - b_j^{ch,a} \right) \right), \forall i \in I$$

Constraint 6: no-reselling allowed

$$C_i^a \geq b_i^{dch,a}, \forall i \in I$$

In more detail, constraint 1 expresses the fact that the amount of energy that can be discharged from the battery is limited by the efficiency of the battery. Constraint 2 and 3 ensures that the amount of energy that can be charged or discharged in any time slot is always less than the rated maximum charge and discharge capacity of the battery. Constraint 4 and 5 captures the fact that the state of the battery in any time slot depends on the previous cycles of charge and discharge. Finally, the last constraint implies that the amount discharged should be at most the electricity consumption at that time interval. This means that the agent cannot discharge from its battery for the purpose of selling back to the grid.

Starting from day (t = 0) where the storage capacity $q^a_{(0)} = 0$, the agent gradually adapts its storage capacity towards the optimal capacity ξ^a obtained from solving the cost minimization function using Equation 13

$$q^a_{(t+1)} = q^a_{(t)} + \alpha \left(\xi^a - q^a_{(t)} \right) \tag{13}$$

where α is the learning rate of the storage capacity q^a of agent a.

In the second pass, the agent computes the optimal storage profile required for it to minimize its cost while fixing its capacity at $q^a_{(t+1)}$. The objective function of the optimization problem thus becomes:

$$\arg\min_{b^a} \sum_{i \in I} p_i \left(b_i^{ch,a} - b_i^{dch,a} + C_i^a \right) + c^a q^a_{(t+1)} \tag{14}$$

and a new optimal storage profile ($b^{a,*}$) is obtained.

Next, the agent adapts its daily storage profile towards the optimal profile ($b^{a,*}$ as below:

$$b^a_{(t+1)} = b^a_{(t)} + \beta \left(b^{a,*} - b^a_{(t)} \right) \forall i \in I \tag{15}$$

where $b^{a,*}$ is the optimal storage profile subject to a fixed storage capacity of $q^a\,(t+1)$ and β is the learning rate of the storage profile. In the next section, we evaluate our storage pricing mechanism for different proportions of the population with storage devices and for different learning rates of consumer agents.

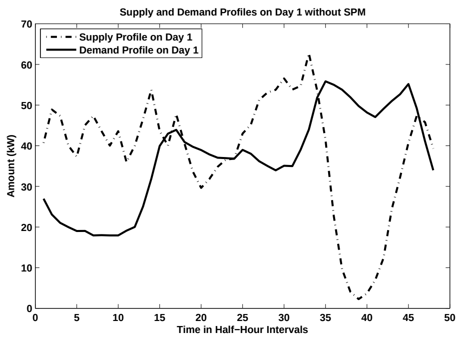

Figure 2: Supply Profile compared with Aggregate Demand Profile on Day 1 without the SPM

5. EMPIRICAL ANALYSIS

This section presents an empirical evaluation of the SPM applied to the Masdar City Model of a renewable energy supplier and a group of consumers. The aim is to show that the proposed mechanism increases the system efficiency and effectively incentivizes consumers to respond to renewable generation patterns. We do this by showing how the demand profile responds to the supply profile thereby resulting in less storage capacity on the part of the supplier. Next, we demonstrate how the consumers benefit as they gradually adopt storage. We evaluate this benefit by varying the proportion of consumers having storage and by varying the learning rate at which they adapt their storage capacities and profiles.

5.1 Experimental Setup

The retail price of electricity was set at 0.04$/kWh which is the current fixed-price of electricity in Abu Dhabi where Masdar City is located. Our SPM then computes the deviation (equation 11) from the retail price based on the state of the utility batteries to generate the real-time prices for the consumers. Each simulation was run for 100 days consisting of 48 half-hourly periods. Running the simulation for a longer number of days did not offer changes to the system as it converges after 100 days. The simulation was run for varying proportions of the population with storage and with varying learning rates. The results were collected and presented in the following sections.

5.2 Effect of SPM on Consumers' Demand

Given that the main aim of the paper was to incentivize consumers to respond to renewable generation patterns, the first result we present is the change in the demand profiles of the consumers with storage ability. We show that in the system with storage pricing mechanism, the consumers' (with storage) demand profiles gradually begin to follow the supply profile until convergence is reached. Figures below show the change in demand patterns for 100% of the population with storage devices and with learning rates (α, β) of 0.05. The optimal storage population and learning rates used here are based on the results of the other experiments presented later in Sections 5.5 and 5.6.

As can be seen from Figure 2, the demand profile (without SPM) on day 1 of the simulation shows large deviations from the supply profile. Specifically, while the demand profile peaks in the evening when the consumers are at home

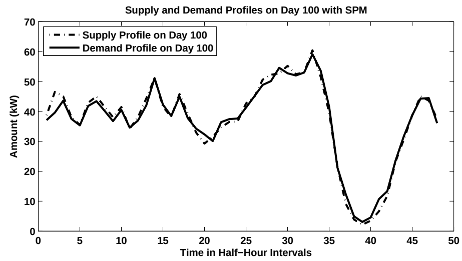

Figure 3: Supply Profile compared with Aggregate Demand Profile after the simulation has been run with SPM for 100days

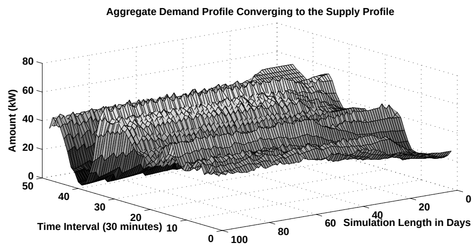

Figure 4: Aggregate Demand Profile of Consumers Changing in response to Renewable Generation Pattern

and using a lot of electricity, the supply profile dips in the evening due to the absence of solar irradiation. When the simulation is run without SPM for 100 days, the demand profile stays the same as there is no incentive for the consumers to change their profiles. However, when the simulation is run with SPM, the demand profile begins to align itself with the supply profile (Figure 4) until there is a near perfect alignment at day 100 as seen in Figure 3. This result shows that the behavior of a self-interested consumer agent with storage capability in the presence of SPM is to optimize its cost by changing its demand profile to align with the supply profile. By so doing, the agent fulfills its electricity demand at minimum cost. This in turn leads to greater system efficiency as the percentage of renewable energy that is used directly by the consumers increase.

5.3 Effect of SPM on System Efficiency

Given that the SPM helps to achieve demand response as shown in the previous experiment, we now analyze quantitatively how the efficiency of the system improves. We measure the efficiency of the system as the ratio of the amount of electricity that is demanded immediately by the consumers and the total amount of electricity supplied. We benchmark the SPM against an optimal system where there is no storage taking place and all the energy produced by the supplier is immediately demanded by the consumers. Such a system will have an efficiency of 100% which is the maximum efficiency attainable. From Figure 5, we see that the system is only 74.4% efficient with the current fixed pricing mechanism. This translates to about a quarter of the energy produced by the supplier is being stored. With the use of our storage-pricing mechanism however, the efficiency of the system gradually increases and approaches the optimal efficiency. The efficiency converges at about 97.4% with the

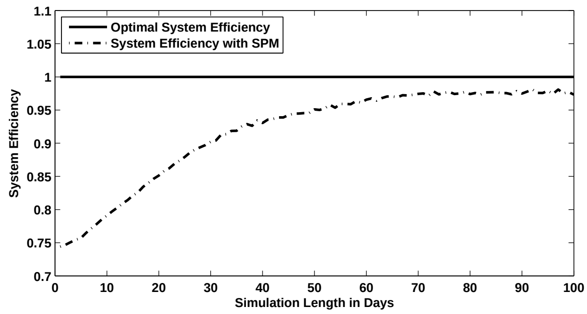

Figure 5: Storage efficiency of the system with SPM. At the start of simulation, the system is only 74.4% efficient

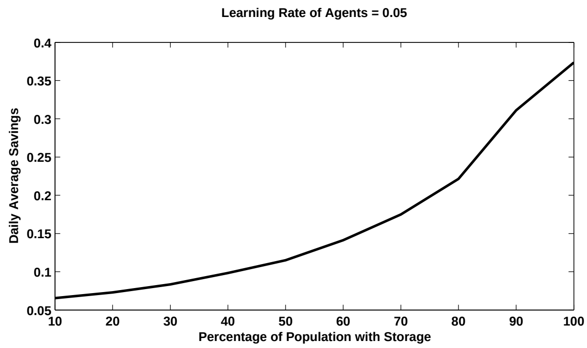

Figure 6: Average savings on electricity cost for consumers with storage and with electricity prices determined by SPM for different proportions of the population with storage.

whole population adopting their micro-storage with a learning rate of 0.05. We show in section 5.5 that the efficiency of the system still increases even with smaller proportions of the population adopting micro-storage.

5.4 Effect of SPM on Consumers' Electricity Cost

In this section, we evaluate the effect on the electricity bill of consumers given a fixed pricing mechanism versus the storage pricing mechanism. Specifically, we consider the cases where the cost of using utility storage is priced via a fixed pricing mechanism versus via our storage pricing mechanism. The question we wish to answer here is: should the supplier adopt utility storage alone and charge the consumers for its use or the should consumers adopt micro-storage (distributed on the grid) and pay the cost of their individual storage. We know that if the utility alone adopts storage, all consumers pay a fixed price of electricity which comprises of the retail cost of producing electricity and the marginal cost of storage. This fixed cost is independent of the consumers' demand profiles and the generator's supply pattern. An individual consumer cannot reduce its costs in any way (given a fixed price of electricity) either through the use of storage or through load control. For the second scenario however, we see in Figure 6 an increase in savings for consumers as an increasing proportion of the population adopt storage. This is because an increase in population of

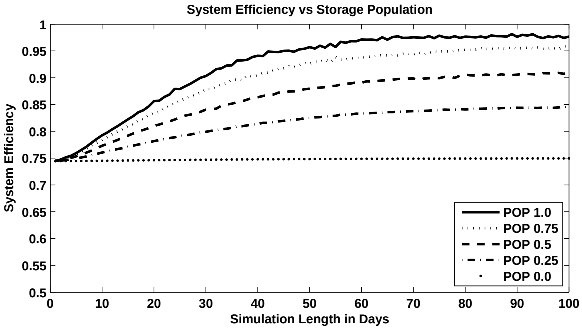

Figure 7: System efficiency for different populations of consumer with storage and with electricity prices

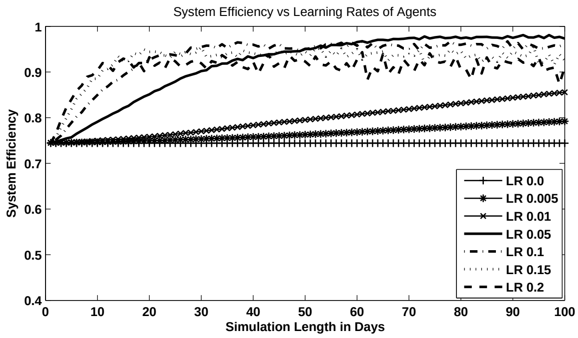

Figure 8: System efficiency for different learning rates of consumer agents and with electricity prices determined by SPM

micro-storage means there is more collective response to the supply patterns.

5.5 Effect of Consumers' Learning Rate and Storage Population on System Efficiency

Here, we analyze the sensitivity of the system efficiency (the ratio of the amount of electricity that is demanded immediately by the consumers and the total amount of electricity supplied) to the storage population and learning rates of the agents. Figure 7 shows that the smaller the storage population, the less efficient the system. This is to be expected as a smaller storage population means that fewer consumer agents are able to respond to the storage pricing mechanism. Thus, the supplier still has to use utility-storage to meet the demands of consumers without storage. In fact, we see that when there is no storage in the system, the system efficiency remains constant at 74.4%. As the storage population begins to increase, the efficiency of the system increases until it converges at 97.4%. Thus, the system is most efficient when all the consumers have storage and are able to optimize their demand profiles in response to the storage pricing mechanism. Next, we show the sensitivity to the learning mechanism. When the consumer agents are learning at higher rates ($\alpha = 0.25$, 0.2 e.t.c.), the system efficiency improves faster initially but then it converges to a lower equilibrium value. As we reduce the learning rate, the convergence is steeper, smoother and results in a higher equilibrium value. From Figure 8, we see that the system achieves the best possible efficiency at a learning rate of 0.05.

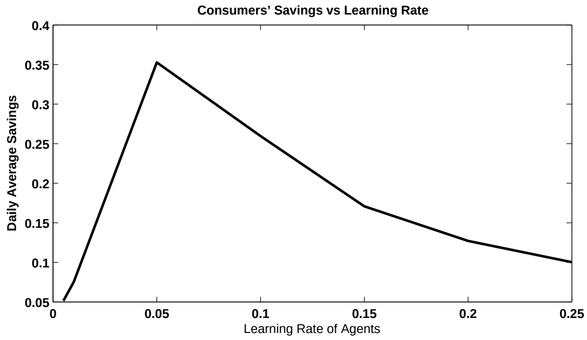

Figure 9: Average savings on electricity cost for consumers with storage and with electricity prices determined by SPM for different learning rates

5.6 Effect of Learning Rate on Consumers' Benefits

Similar to the experiment above, here we analyze the effect of the learning rate on the benefits to consumers. The effect of storage population size on consumer savings has been previously analyzed. We see from Figure 9 that as the learning rate of agents increases, the average savings also increases until it peaks at a learning rate of 0.05. Thereafter, the savings only decrease with increasing learning rate. This result is consistent with the results obtained for the system efficiency with varying learning rate in Section 5.5 above. Thus, the maximum savings to the consumers and also to the supplier is achieved when the consumer agents are learning to adapt their storage at a learning rate of 0.05.

6. RELATED WORK

The use of large-scale storage systems with renewable generators has been extensively studied in the literature. There is however no known published work on the coupling of both utility-scale storage and micro-storage. Similarly, a number of pricing incentives have been proposed in the literature to help achieve demand response and field trials have been carried out to evaluate the effectiveness of these mechanisms. For example, California's utilities [2, 9] conducted the Statewide Pricing Pilot to evaluate the effect of Time-Of-Use mechanism (this mechanism divides the day into slots with fixed prices) and showed an estimated reduction in peak period energy use of 5.9% during the summer months. Furthermore, Xcel Energy [10, 11] also conducted a pilot program that tested the effectiveness of Critical Peak Pricing mechanism (this identifies some exceptional days with very high demand) given an enabling technology with participants achieving reductions of about 44.81%. Yet another pricing mechanism, Peak-Time Rebate (PTR) was evaluated by Wolak [18]. In this, participants received a rebate of 0.35$/kWh for reductions relative to their typical peak period consumption on non-PTR days. Participants however have the potential to game the system (as discovered by [18]) by increasing their electricity use during the period in which baselines are established. While the aforementioned pricing mechanisms have the ability to effect a reduction in peak demand, they usually involve active participation on the part of the consumers. Also, these mechanisms often just shift the peak demand to other times that have been deemed to be off-peak. We believe that given the variability in the renewable energy generation, there is a need to synchronize and influence exactly where the shifted peak goes to in order to ensure system stability. In general, none of these pricing mechanisms deal specifically with the variability of supply when renewable energy generators are involved. In this regard, we note the recent work by Ramchurn et al [16] where they present a carbon pricing mechanism that is designed specifically for a renewable energy supplier that is operating in the electricity market. This paper is inspired by their work, but differs in that we look at the issue of a renewable energy supplier that has storage capability. Also, our work is targeted at the Masdar City model of a totally self-sustained city. This implies that, unlike their work, the supplier does not have the ability to meet the demand that exceeds its supply from the external electricity grid.

7. CONCLUSION

In this paper, we presented a multiagent framework for joint-storage management and a pricing mechanism, SPM, for renewable energy suppliers and consumers with storage devices. We simulated the performance of the mechanism based on the Masdar City model and evaluated it in terms of the system efficiency and consumer benefits. The results showed that unlike the fixed pricing mechanism (currently in use in UAE) which achieves a system efficiency of 74%, the storage pricing mechanism achieved a system efficiency of up to 97.4% with all consumers having storage devices and smart meters installed in their homes. Moreover, the consumers with storage devices were able to make an average savings on their electricity bills of 35% when all the consumers are equipped with storage devices. Due to lack of availability of high-resolution household data in the UAE, we utilized time-shifted UK data. Having said that, our work provided a proof-of-concept for policy recommendation to the UAE government to not only install smart meters in homes, but we also showed that the adoption of a dynamic pricing mechanism for Masdar City Grid will increase the efficiency of the system. Furthermore, the institution of policies (e.g. subsidies) which facilitate the wider adoption of joint-storage solutions will help in the integration of renewable energy generators to the National Grid.

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