Abstract—For the sake of accurate energy resource allocation in smart buildings with hybrid solar energy and main electrical grid, an uncertainty-aware minority-game based energy management system (UAMG-EMS) is introduced in this paper. New uncertainties are considered by agents such as (i) stochastic noise from energy meters/sensors; and (ii) uncertain working behaviors from load side. Firstly, agents can perform Kalman Filter based error-correction algorithm to reduce the stochastic noise coming from energy meters/sensors. Moreover, agents can have supervised learning to predict uncertain energy profiles. Afterwards, agents can play a modified minority game based energy management to allocate the limited solar energy resource. To extend the scalability of agents for the entire building, K-means based classifier is applied to characterize the types of agents and hence can reduce the number of agents for large-scale buildings. Compared with the conventional minority-game based energy management system (MG-EMS) without considering uncertainty, our UAMG-EMS shows about 37% reduction of imbalance in fair solar energy allocation, and also about 23% reduction of noise influence merely based on inaccurate energy meters/sensors.

Index Terms—Multi-agent, Uncertainty aware, Minority game, Energy management system

I. INTRODUCTION

According to [1], there are more than 79 million residential buildings and 5 million commercial buildings in the US together consuming 70% of electricity in the country. As a result, an increasing demand is observed to design energy management system (EMS) for buildings. Smart buildings are expected to be equipped with automatic controller with computer-aided-design (CAD) for EMS. Although have been extensively studied, the traditional EMS [2][3] has the limitations to address the following features: (i) decentralized real-time control; (ii) management of renewable energy resources; and (iii) modeling of stochastic and competitive natures for both energy generation and consumption. Among them, uncertainty in EMS can significantly affect the prediction and decision-making process, which possibly leads to a failure of energy allocation. For example, due to the intermittent nature of renewable energy resources generation [4], it is difficult to predict the energy consumption such that it may degrade the EMS if new energy consumption patterns appear. In addition, measurement error from energy meter [5] also introduces unavoidable uncertainty.

To achieve a better energy allocation and high utilization rate of hybrid energy sources, real-time and decentralized-fashioned EMS is discussed recently. The multi-agent-based EMS (MA-EMS) [6][7][8] is proposed to construct a distributed energy control system, which solves the inherent limitations of centralized systems. The work in [9][10] further considers the competitive nature during energy allocation by minority-game algorithm and hence reduces unfairness to different users. However, without the consideration of the uncertainty such as stochastic noise on energy meters/sensors and stochastic energy supply/consumer behaviors, previous works may severely relies on high-precision energy meters under ideal energy profiles. This may cause an unacceptable expense since quite a few high-accuracy energy meters/sensors are required in the entire building. More importantly, previous works usually need to perform resource allocation based on the fixed energy profiles. As such, fairness on cheap-renewable-energy usage cannot be guaranteed because of the existence of unpredicted consumer behaviors.

In this paper, we propose an uncertainty-aware minority-game based energy management system (UAMG-EMS), which is applied in smart buildings supplied with hybrid solar energy and main electrical grid energy. Given limited amount of cheap solar energy, the UAMG-EMS is deployed by multiple agents to achieve fair solar energy allocation among rooms with time-varying energy demands. Meanwhile, stochastic noise introduced by energy meter/sensor is considered by agents so that the management can rely on valid data. Our contributions can be summarized as: (i) uncertainties in user demand are handled by supervised-learning based energy prediction developed for each agent; (ii) noise of energy meter/sensor is reduced by Kalman-filter for each agent; and (iii) K-means clustering based classifier is applied to characterize and identify the typical agent. After intelligent agents deal with uncertainties, they further play the minority game for reliable and scalable energy resource allocation of smart buildings.

The rest of the paper is structured as follows. In section II, we briefly review the previous work on minority game based EMS (MG-EMS). Section III is the overview of our proposed system. In section IV, our UAMG-EMS algorithm is demonstrated. We separately demonstrate the clustering, supervised learning, and error correcting techniques. In section V, the experiment results are compared with previous works. Finally Section VI concludes this paper.

II. RELATED WORKS

The minority game-based EMS (MG-EMS) for smart building is modeled as a multi-agent system, in which multiple agents get allocated with solar energy resources through specially designed minority game playing strategies [9][10]. This is mainly based on the observation that: 1) the renewable energy resource is relatively cheaper but with limited amount; and 2) individual tenants in either residential or commercial buildings tend to compete for the limited renewable energy resources. As such, one needs to deploy the non-cooperative policy during the energy management.

In minority game, game players (or agents) make their decisions independently based on both historical knowledge and their own preferences. After all players make decisions, the minority side, which contains the least number of players making the same decision, is declared as the winner of the game and will get corresponding benefits. Recently the minority game has gained increased interests for solving various resource allocation problems [11][12][13]. In previous work [9][10], MG-EMS is applied to energy management for smart building and houses. The results show an optimistic result of 51x/147x solar energy utilization rate improvement regarding the fair allocation; and 30.6% reduction of peak hour energy demand for main power-grid electricity.

However, previous works are limited by ignoring the uncertainties in the energy system of buildings. Specifically, energy-profile data collected from energy meters/sensors tends to deviate from real values due to stochastic measurement errors [5][14]. Note that energy meters/sensors can be influenced by various factors such as temperature and humidity. Moreover, another critical concern is the unpredictable behavior of energy consumer. Generally speaking, the energy consumption profile of end users can change with time even for the same customer. Thus, the agent needs to adapt dynamically to the energy consumption behavior of the corresponding consumer,
such that agents can make better decisions to fulfill customer demands. Furthermore, the number of tenants or rooms in modern buildings is so large that it will impose non-negligible computation overhead for the EMS. As such, one needs to find efficient ways to prune the number of agents participating in the MG-EMS and to be scalable for large-scale systems.

III. SYSTEM OVERVIEW

A. Overview

Fig. 1 illustrates the overall system architecture and working flow of our proposed uncertainty-aware minority-game based energy management system (UAMG-EMS). Basically, the smart building is consisted of a large number of rooms with different types, such as commercial and residential rooms. In addition, the building is supplied with hybrid energy resources: renewable solar energy from photovoltaic (PV) arrays on top of the building, and the main electrical grid which compensates the energy gap between the energy demand of the entire building and the solar energy generated. Since the solar energy is much cheaper than the energy from main grid, the UAMG-EMS is utilized to fairly allocate the limited amount of solar energy among rooms such that each room could benefit similarly from the renewable energy.

In our system the minority game players are represented by intelligent agents, which can be implemented with smart controllers. Basically, the UAMG-EMS is carried out at specific time point (e.g., each hour) to decide the solar energy allocation scheme for the next period of time. At each control point, the classification engine is executed first to group rooms into different clusters based on the similarity of energy utilization profile in the past. As such, the complexity of control could be greatly reduced by cluster-level game playing. Then, the supervised-learning based prediction engine is implemented to predict the energy demand of each cluster based on historical data, which resolves the load behavior uncertainty to certain level of confidence. Thirdly, the minority game is played among different clusters to make the solar-energy-allocation decisions. Finally, the Kalman-filter is realized to filter out uncertainties introduced by energy meter/sensor measurement errors. Note that all the learning, game playing and filtering are implemented in the decentralized manner based on multiple agents.

B. Problem Formulation

Formally, we denote the energy demand of room $i$, $1 \leq i \leq N$ and solar energy generated at time $t$ as random variables $D_i(t)$ and $E(t)$, respectively. To make the best utilization of solar energy, we assume the existence of energy storage system (ESS) that could reserve solar energy for its use at peak hours. The outcome of UAMG-EMS is the solar energy allocation decision for each room represented by variable $\sigma_i(t)$

$$\sigma_i(t) = \begin{cases} 0, & \text{if solar energy proportion in total energy use} \\ 1, & \text{if only main electrical grid energy is selected} \end{cases}$$

Furthermore, we design the UAMG-EMS to achieve the following objective: As the solar energy is relatively cheaper compared to the main electrical grid energy, rooms always prefer to use the solar energy. Given the limited amount of solar energy available, the proposed UAMG-EMS is targeted to fairly allocate solar energy among rooms with vastly different energy demands. In other words, one needs to find the set of $\sigma_i(t)$ that minimizes the standard deviation of allocated solar energy to each room after running the system for $T$ times.

$$\arg\min_{\sigma_i(t)} \left( \text{dev}(\int_0^T \sigma_i(t) D_i(t) dt) \right)$$

Note that as one strict constraint, the allocated solar energy must not exceed the available amount at all times

$$\sum_{t=1}^{N} \sigma_i(t) D_i(t) \leq B(t)$$

where $B(t)$ is the amount of solar energy stored in ESS at time $t$.

IV. UNCERTAINTY-AWARE MINORITY-BASED ENERGY MANAGEMENT SYSTEM

In this section, we describe the detailed components and managing procedures of the proposed UAMG-EMS.

A. Room Type Classification and Clustering

As the number of rooms in a modern building often exceeds hundreds, it is beneficial to scale down the number of participants for the energy management to reduce the system complexity for better performance. Intuitively, it is common that several rooms share similar energy usage patterns due to similar life styles, working schedules, etc. As such, we propose to perform smart classifications based on historical data to divide rooms into clusters. After that, only the clusters are used as the representatives to participate in the energy allocation game.

In this paper, the K-means [15][16] clustering technique is utilized for classification. To implement the technique, it is important to translate the energy utilization profile into abstract data point in high dimensional space. In our case, the observation is made that the energy profile demonstrates periodical behaviors. Specifically, the profile repeats in a daily basis. As such, we represent the energy behavior of each room as an 24-dimensional tuple, where each element stands for the average energy demand for the given hour over historical data (i.e., one month):

$$C_{ij} = \frac{\sum_{k=1}^{U} D_{i,k,j}}{U}, \quad U = 30$$

where $C_{ij}$ is the $j$-th element in the tuple of the $i$-th room, and $D_{i,k,j}$ is the energy demand of room $i$ on $k$-th day at hour $j$.

Algorithm. 1 illustrates the pseudo code of the detailed K-means classification engine. Starting with $M$ random centers for each cluster, the Euclidean distance of each room to every center is calculated. Then, each room is decided to be belonged to the center (i.e., cluster) with minimal distance. After that, the position of each center is recalculate as the average of all points within the cluster. The classification is iterated until the position change of all centers is under certain threshold.

According to [17][18], the selection of initial centers will affect the convergence and lead to local minimization. To avoid this case,
we perform the clustering several times with different randomly generated centers to avoid biased cases. In addition, the number of clustering can be changed adaptively based on the error rate of clustering.

B. Supervised-learning based Prediction of Energy Load

Due to different weather conditions, room settings and user behaviors, there exist uncertainties in user energy demands. As the value of energy demand is important for making correct energy scheduling and allocation decisions, one needs to develop an EMS that is able to dynamically capture and react upon these variations at runtime.

Supervised learning [19] is one effective and practical technique for discovering relation, extracting data and self-improving. The goal of the supervised learning is to derive a mapping from \( x \in \mathbb{X} \) to \( y \in \mathbb{Y} \) such that the average mapping error is minimized, given the training sets that consist of input and output pairs. Here, \( \mathbb{X} \) and \( \mathbb{Y} \) denote the input features and measured outputs, respectively. In this work, we propose to adopt the Polynomial regression technique as to predict future energy consumption based on past energy profile data. Specifically, the input feature is time in our approach, while the output is the predicted amount of energy demanded.

Based on clustered result, we can achieve a more scalable prediction work for each cluster instead of for each room. As in any supervised learning engine, the result depends largely on the selection of training set. In our method, we build the training set based on three observations.

Firstly, as the energy profile shows a daily-based periodic behavior, the training is better to be based on a daily basis as well. More specifically, the training set \( T \) contains \( S \) elements, where each element is the energy demand profile of one whole day.

\[
T = \{T_{ij}| 1 \leq i \leq S, 1 \leq j \leq 24\} \quad (5)
\]

Secondly, we observe that later days in the training set shall have larger impact on the prediction result. To introduce such knowledge into the training process, we assign each day with a daily weight \( \sigma_i \), where \( \sigma_1 > \sigma_2 > \ldots > \sigma_{24} \).

Thirdly, we observe that there exist certain days with extreme abnormal behaviors. To avoid such undesired cases, we propose to filter out the abnormal data. Specifically, we compute the average energy utilization \( Q \) over the entire training set:

\[
Q = \frac{\sum_{i=1}^{S} T_{ij}}{S} \quad (6)
\]

Then, we define the upper bound as \( \frac{3}{2}Q \) and lower bound as \( \frac{1}{2}Q \) to recognize the abnormal situation. If the data of any training element exceeds these bounds, a special weakened factor \( \rho \) will be applied to reduce its weight in the training set.

Based on above mentioned training set pruning techniques, we formalize the prediction process as a polynomial fitting problem:

\[
y = a_0 + a_1x^1 + a_2x^2 + \ldots = \sum_{i=0}^{N} a_i x^i \quad (7)
\]

where \( a_i \) are the coefficients to be trained.

The minimization of prediction errors equals to

\[
\arg \min \sum_{i=1}^{S} \sum_{j=1}^{U} \sum_{n=0}^{N} a_n x_n^i - T_{ij}^2 W_i, \quad S = 7, \ U = 24 \quad (8)
\]

where \( W_i = \sigma_i \rho_i \), and in our approach, \( x_j = j \in [1, U] \). By taking first order partial differentiation on \( a_k \) for the above function and let it equal to zero, we get:

\[
\sum_{i=1}^{S} W_i \sum_{j=1}^{U} x_j^k + \sum_{n=0}^{N} a_n = \sum_{i=1}^{S} W_i \sum_{j=1}^{U} T_{ij} x_j^k \quad (9)
\]

where \( k \) is from 1 to \( N \). Rewrite the problem into matrix representation:

\[
Fv = b \quad (10)
\]

where \( F \) is a \( N \times N \) matrix while \( a \) and \( b \) are \( N \times 1 \) vectors. By introducing LU factorization with pivoting technique to solve the equation, the coefficients \( a \) of the polynomial are obtained and thus we can utilize the fitting curve to predict the energy consumption behavior of next day. Note that the training set \( T \) moves along the time axis so that after one prediction, the data of the latest day will be shifted in and the data of the earliest day will be shifted out from \( T \). Using this training window, the prediction engine adapts to more recent changes since latest knowledge is dynamically included with higher weight.

C. Modified Minority Game Playing

To realize decentralized control, the minority-game-playing based method is utilized to make solar energy allocation decisions [10][9]. Since the game rules consider not only real-time demand for energy usage but also the historical resource allocation results, selfish customers cannot monopolize limited solar resources in the building. To formally illustrate the modified minority game, two factors are introduced.

The preference factor decides the tendency for each player to choose the solar energy as supply for the next period of time.

\[ \mathbf{P}_t(t) = \frac{\mathbf{E}_t(t)}{\sum_{t=1}^{U} \mathbf{E}_t(t)}, \quad U = 24 \]  

where \( \mathbf{P}_t(t) \) denotes the preferences at hour \( t \) for cluster \( k \), \( \mathbf{E}_t(t) \) is the predicted energy demand at time \( t \). When a cluster is about to experience a high energy demand period, it will have high willingness for solar energy to reduce the cost of using power-grid energy.

The history factor is used to balance the energy allocation.

\[ \mathbf{H}_t(t) = 1 - \frac{\mathbf{S}_t}{\sum_{k=1}^{N} \mathbf{S}_k} \]  

where \( \mathbf{S}_k \) represents the cost-saving for cluster \( k \) in the past, and \( N \) is the total number of clusters. The cost-saving function \( \mathbf{S}_k \) is defined as

\[ \mathbf{S}_k = \sum_{\tau=0}^{\hat{\tau}} \Delta \text{price}(\tau) \times \mathbf{E}^\text{solar}_t(\tau) \]  

where \( \Delta \text{price}(\tau) \) is the electricity price difference between main power grid and solar energy at time \( \tau \), and \( \mathbf{E}^\text{solar}_t(\tau) \) is the total amount of solar energy allocated for cluster \( k \) at time \( \tau \). Intuitively, the more solar energy one cluster has been allocated before, the less chance for it to receive solar energy in the future.

The minority game is played as follows. At each round, each cluster computes its attractiveness based on preference and history factors using:

\[ \text{Attr}_t(k) = \alpha_k \times \mathbf{H}_t(t) + (1 - \alpha_k) \times \mathbf{P}_t(t) \]  

where \( \alpha_k \) is used to adjust the weight of different factors for cluster \( k \). Then, the cluster with highest attractiveness will be allocated with solar energy. After that, all historical data is updated by actual energy usage, and the game moves to the next control step.

D. Error Correction and Data Update

Due to various factors like noises, there exist measurement errors in smart meters/sensors. As such, it is important to handle the uncertainties for better energy management. Kalman Filter, a widely applied technique in the data fusion domain, is utilized in our proposed UAMG-EMS with the prediction data as priori knowledge and the data collected from meter/sensor as observation correction.

Specifically, the energy consumption profile data is a discrete sequence that can be described as:

\[ \mathbf{x}(k) = \mathbf{A} \mathbf{x}(k-1) + \mathbf{B} \mathbf{u}(k-1) + \mathbf{L}(k) \]  

where \( \mathbf{x}(k) \) is the hourly energy consumption vector of \( k \)-th day, \( \mathbf{A} \) is the transformation matrix and \( \mathbf{L}(k) \) is the process error which is the error introduced by the priori knowledge of prediction. Note that in our approach, we don’t have any input and thus \( \mathbf{u} = \mathbf{0} \). In our approach, the transformation matrix could be further simplified to ratio transformation:

\[ \mathbf{A}_i = \frac{\hat{x}_i(k)}{\hat{x}_i(k-1)}, \quad i \in [1, U], \quad U = 24 \]  

where \( \hat{x}_i(k) \) denotes the predicted value for the \( k \)-th day at the \( i \)-th hour, and \( \hat{x}_i(k-1) \) denotes the \((k-1)\)-th day’s data at \( i \)-th hour provided after last filtering iteration. The energy meter/sensor is modeled as:

\[ \mathbf{z}(k) = \mathbf{H} \mathbf{x}(k) + \mathbf{V}(k) \]  

where \( \mathbf{z}(k) \) is the energy consumption vector provided by meter/sensor, \( \mathbf{H} \) is the observation system parameter matrix which is actually \( \mathbf{1} \) because the meter/sensor is read out directly. In addition, \( \mathbf{V}(k) \) here denotes the error brought by the meter/sensor, which is usually known as observation noise. As a reasonable simplification, we assume that both the process error and the meter/sensor noise meet normal probability distributions, such that the means are zero and covariances are \( \mathbf{Q} \) and \( \mathbf{R} \) respectively. We further assume that \( \mathbf{Q} \) and \( \mathbf{R} \) do not change along with time step \( k \). Without losing generality, other kinds of noise with known covariance can also be handled by Kalman Filter.

Note for the kalman Filter to handle vector data in our case, the corresponding scalar calculation is operated element-wisely. Given an initial estimate error covariance \( \mathbf{P}_t(k-1) \) generated randomly, the Kalman Filter theory [20] applies:

\[ \mathbf{P}_t(k) = \mathbf{A} \mathbf{P}_t(k-1) + \mathbf{Q} \]  

where \( i \) denotes the \( i \)-th hour’s case. Next step is to calculate Kalman Gain \( \mathbf{K} \):

\[ \mathbf{K}_t(k) = \frac{\mathbf{P}_t(k)}{\mathbf{P}_t(k) + \mathbf{R}} \]  

After Obtaining Kalman Gain \( \mathbf{K}_t(k) \), the optimized result \( \hat{x}_i(k) \) is calculated by:

\[ \hat{x}_i(k) = \hat{x}_i(k) + \mathbf{K}_t(k) (\mathbf{z}_i(k) - \hat{x}_i(k)) \]  

Finally, we update the value of \( \mathbf{P}_t(k-1) \) with \( \mathbf{P}_t(k) \), which finishes one filter iteration.

For clarification, the entire flow of the proposed UAMG-EMS is presented in Algorithm 2.

**Algorithm 2 UAMG-EMS Entire Process**

1: BEGIN
2: Perform clustering for \( N \) rooms into \( M \) clusters
3: \textbf{while} \( day \leq 30 \) \textbf{do}
4: \textbf{end while}
5: \textbf{for} Each cluster \textbf{do}
6: \textbf{end for}
7: \textbf{for} Each cluster \textbf{do}
8: \textbf{end for}
9: \textbf{for} Each hour \( t \) in \( \text{day do} \)
10: \textbf{end for}
11: \textbf{for} Each cluster \textbf{do}
12: \textbf{end for}
13: \textbf{for} Each cluster \textbf{do}
14: \textbf{end for}
15: \textbf{for} Each cluster \textbf{do}
16: \textbf{end for}
17: Reading (\( day \)-1)-th data \( \mathbf{z} \) from meter/sensor
18: \textbf{end for}
19: \textbf{for} Each hour \( t \) in \( \text{day do} \)
20: \textbf{end for}
21: \textbf{for} Each cluster \textbf{do}
22: \textbf{end for}
23: \textbf{end for}
24: \textbf{end while}
25: \textbf{end for}
26: END

V. EXPERIMENT RESULTS

To verify our proposed energy management system, we perform simulations based on the data collected from real world testbed from [4][21]. Specifically, we consider the smart building consisted of 24 residential and commercial rooms, and each room is associated with energy load profile recorded per hour for one month (i.e., 30 days). Rooms of different types have different characteristics in load behavior, which could be observed from Fig. 2. Basically, we find that residential rooms reach their peak hour workloads in the evening while commercial rooms tend to consume more energy during daytime. The proposed UAMG-EMS is implemented by C++ and Matlab, and all presented results are computed on an Intel Core i5 with 2.6GHz clock frequency and 4GB of RAM.
TABLE I: UAMG-EMS Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression polynomial order</td>
<td>15</td>
</tr>
<tr>
<td>Gaussian noise scale</td>
<td>3%</td>
</tr>
<tr>
<td>Number of rooms</td>
<td>24</td>
</tr>
<tr>
<td>Number of clusters</td>
<td>2</td>
</tr>
<tr>
<td>Size of training set</td>
<td>7</td>
</tr>
</tbody>
</table>

TABLE II: Center Movement in K-means Clustering

<table>
<thead>
<tr>
<th>TimeStep</th>
<th>Center 1</th>
<th>Center 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>8.2858</td>
<td>9.3377</td>
</tr>
<tr>
<td></td>
<td>4.7144</td>
<td>10.363</td>
</tr>
<tr>
<td></td>
<td>3.8471</td>
<td>9.8615</td>
</tr>
<tr>
<td></td>
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</tbody>
</table>

Fig. 2: Supervised-learning by polynomial regression for prediction of energy load profile

Fig. 3: Workload profiles with measurement error filtered for residential and commercial rooms, respectively

Fig. 4: Workload profiles with accumulated one-month error filtered for residential and commercial rooms, respectively

Fig. 5: Comparisons of solar energy allocation with error filtered and without error filtered, respectively

To account for measurement errors on smart meters/sensors, we add a Gaussian white noise with 3% magnitude on the load profile from [21]. This is reasonable because usually the energy meter/sensor is influenced by various factors like weather, and usually the noise behaves like a normal distribution of $N(0, \sigma^2)$. In addition, we fixed the order of polynomial used in supervised learning as 15, which is obtained through trial and error for the prediction error to be within certain user-specified bounds. Table I summarizes all the parameter settings used in our experiments.

A. Clustering and Prediction Results

The proposed UAMG-EMS starts with room clustering using the K-means technique as mentioned in section IV-A. Table II shows the clustering results for each iteration, in which the number represents the abstract locations of each cluster center (2-norm of center vector). Obviously, the center of each cluster converges quickly after only 3 K-means iterations, which means the clustering process is completed and all rooms are split into 2 main types. Note the number of centers can be decided at run time based on user specified error bounds as well.

1Since each location vector contains 24 dimensions, here we only show the 2-norm of the vector to represent the abstract locations of rooms and centers.

B. Error Correction Results

To account for measurement errors in smart meters/sensors, we need to update the data for latest day by performing a Kalman filtering process such that the accurate data could be recovered. Fig. 3 compares the prediction curve, the observation curve, the Kalman filtered curve and the curve for true values. Meanwhile, prediction error, noise and Kalman filtered data error are also demonstrated in Fig. 4. Clearly, after the Kalman filtering process, an average of 23% total noise perturbation can be reduced. As a result, it can significantly improve the EMS for more accurate energy resource allocation.

C. UAMG-EMS Result

As the baseline system with no consideration for energy profile uncertainties, we also implemented the work MG-EMS in [10] for comparison. Fig. 5 compares the unfairness of solar energy allocation for each cluster using these two EMSs. The unfairness is quantitatively defined as the total amount of unbalanced solar energy allocated to different clusters. In the figure, red curves and blue dotted curves represent solar energy allocated to residential rooms and commercial rooms, respectively. The smaller the mismatch of these two curves, the better the fair energy allocation is achieved. Compared to non-stochastic MG-EMS, a 37% reduction of unbalance in fair solar energy allocation is observed, which verifies the effectiveness of the proposed UAMG-EMS for handling energy profile uncertainties.
VI. CONCLUSION

In this paper, we have developed the uncertainty-aware minority-game based energy management system (UAMG-EMS) for smart buildings. Specifically, the renewable energy allocation is handled by multiple agents represented for rooms or typical rooms. The agents can consider two types of uncertainties from energy load profiles. The user-behavior introduced energy load uncertainties are handled by supervised-learning based prediction. The energy meter/sensor measurement introduced errors are resolved through Kalman filtering. In addition, we have also developed the classification technique to cluster rooms (or agents) with similar behaviors into typical rooms (or agents) such that the scale of the energy management system can be extended to deal with large-scale smart buildings. Compared to conventional non-uncertainty MG-EMS, our UAMG-EMS shows about 23% reduction of noise influence merely based on online utilized data, and 37% reduction of unbalance in fair energy allocation.

REFERENCES


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