Distributed Cooperative Energy Management in Smart Microgrids with Solar Energy Prediction

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***Abstract*—Smart Microgrid (SMG), integrated with renewable energy, energy storage system and advanced bidirectional communication network, has been envisioned to improve efficiency and reliability of power delivery. However, the stochastic nature of renewable energy and privacy concerns due to intensive bidirectional data exchange make the traditional energy management system (EMS) perform poorly. In order to improve operational efficiency and customers' satisfaction, we propose a distributed cooperative energy management system (DCEMS). We adopt recurrent neural network with long short-term memory to predict the solar energy generation with high accuracy. We then solve the underlying economic dispatch problem with distributed scalable Alternating Direction Method of Multipliers (ADMM) algorithm to avoid single point of failure problem and preserve customers' privacy. In the first stage, each SMG optimizes its operation decision vector in a centralized manner based on one-day ahead solar energy generation prediction. In the second stage, all SMGs share their energy exchange information with directly connected neighboring SMGs to cooperatively optimize the global operation cost. The proposed DCEMS is deployed in our distributed SMGs emulation platform and its performance is compared with other approaches. The results show that the proposed DCEMS outperforms heuristic rule-based EMS by more than 30%. It can also protect customers' privacy and avoid single point of failure without degrading performance too much compared to centralized EMS.**

***Index Terms*—Demand-side management, Energy management system, Microgrid emulation platform, Information prediction, Distributed algorithms**

I. Introduction

Smart Microgrid (SMG) has been evolved during the past decade and become a sophisticated cyber-physical system characterized by the bidirectional communications, large-scale penetrations of renewable energy, and the complex interactions among distribution networks, electricity markets, and dynamic energy demand. The widely adopted hierarchical SMG control model has three levels. From the bottom to the top are layered as primary control level, secondary control level and tertiary control level [1]. On the tertiary control level, the primary goal of an energy management system (EMS) in energy network is to balance the supply and demand given its scheduling horizon. To make it cost efficient, there is a need to consider not only the stochastic nature of renewable energy, but also the dynamic changes of electricity price. This is also known as the economic dispatch problem (EDP) [2]. Recently, neural network has drawn a lot of attention in the community of renewable energy. Comparing to traditional prediction method like Angstrom model, conventional linear, nonlinear and fuzzy logic models, the neural network approach has shown to give a superior performance [3].

In recent years, privacy and security issues of SMG arose due to the vulnerable nature of cyber-physical systems. The high frequency energy consumption information transmitted by the smart meters can reveal sensitive personal information about the activities inside a house [4]. Privacy concern is one of the reasons hindering general deployment of the SMGs in many countries.

Centralized approaches have been widely used to solve the EDP in the past. Mixed integer programming [5], sequential quadratic programming [6] and look-ahead multi-steps optimization [7] are proposed for energy management. These centralized approaches have the single point of failure risk. In addition, customers may reject the requests of sharing their explicit energy usage information with other entities due to privacy concern [8]. This will cause the proposed centralized algorithms become infeasible in real life.

Distributed approaches for SMG EMS have also been examined in the past. Shi et al. [9] proposed a distributed EMS where the SMG central controller and the local controllers jointly compute an optimal solution. Dong et al. [10] presented a fully distributed Demand and Response algorithm for SMG with the objective of optimizing social-welfare. Chaouachi et al. [11] presented a generalized formulation for the EMS of an SMG considering the stochastic nature of the renewable energy and used a fuzzy logic expert system to solve the problem.

The above studies only considered single SMG. Large-scale distribution networks often consist of multiple SMGs. Both SMG owners and customers can benefit from a more reliable, lower operation cost and economical energy supply [12]. In [13], the authors considered the operation of multiple SMGs, and proposed a two-layer optimization algorithm for both distribution network and SMGs. However, similar to [9] and [11], their proposed distributed algorithm still requires a central data fusing point which will suffer from the single point of failure risk.

The main contribution of this paper is in developing a distributed cooperative EMS (DCEMS) considering solar energy, energy storage system (ESS) and dynamic electricity price. We predict solar energy generation using recurrent neural network (RNN). The DCEMS offers privacy protection to each SMG by exchanging aggregated energy usage information. The

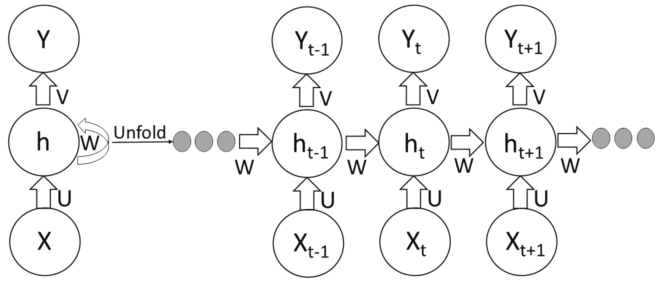

Fig. 1. A typical RNN and the unfolding in time of the computation.

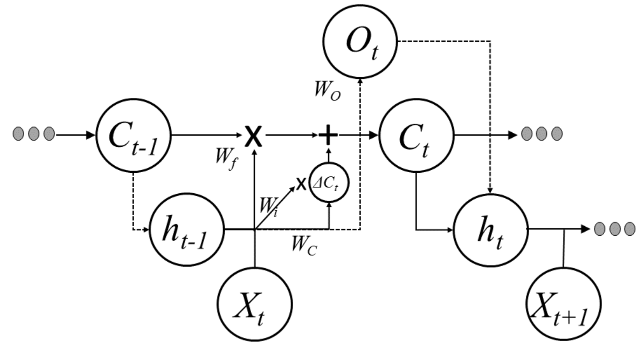

Fig. 2. The LSTM unit we used for the solar energy prediction model.

DCEMS also grants autonomy to each SMG to optimize SMG-specific objective subject to SMG-specific constraints. At the beginning of each optimization horizon, the EMS initializes its own decision vector randomly. In the first step of optimization, each SMG solves its own optimization problem in a centralized way using local information and solar energy prediction from RNN. In the next step, each SMG in the network shares its own aggregated energy exchange information with directly connected neighboring SMGs to cooperatively optimize the global operation cost. This process is repeated until all SMGs reach convergence.

The rest of this paper is organized as follows. We introduce the RNN and long-short term memory (LSTM) in Section II. We then present the system model in section III. We then formulate the economic dispatch problem (EDP) and give a distributed solution to the proposed DCEMS in section IV. In section V, we show the simulation results obtained from our simulating platform followed by the concluding remarks given in section VI.

II. Solar Energy Prediction with LSTM

Unlike "normal" feed-forward neural network, by feeding a large amount of sequential training data into recurrent neural network (RNN), the RNN can capture the dynamic temporal behavior within the input data [14]. An RNN realizes this ability by recurrent connections between the neurons as shown in Figure 1.

In order to have sufficient training data for the neural network, for SMG i, we assume its administrator has access to a large volume of historic data of the solar panels (SP). For each time instant t in the past, we are given the SP status vector $\mathbf{X}_t$= $\{x_{t,i,w},\ x_{t,i,s}\}$, where $x_{t,i,w}$ denotes a collection of weather measurements received from the sensor network, such as temperature, humidity, sky condition, etc., and $x_{t,i,s}$ denotes the total energy generated at time t by SP.

The LSTM is based on RNN. An LSTM has a special neuron structure called memory cell. These memory cells have the ability to carry information over an arbitrary time. The input, output and forget gate together control the information flow into and out of the neurons memory cell [15]. The LSTM structure is shown in Figure 2. The variables $\mathbf{X}_{t-T}...\mathbf{X}_t$ are the input SP status vector with time steps T. Also, $h_{t-T}...h_t$ and $C_{t-T}...C_t$ are the hidden vector and memory cells, respectively. The output of the LSTM, denoted by O_t, will be the predicted solar energy generation in the next time step. That means that, by training the LSTM, we can use T historic SP status vector from $t-T$ to t to predict the solar energy at time instant $t+1$.

The first step in LSTM is to decide which part of information will be thrown away from the previous cell state C_{t-1}. This decision is made by a sigmoid layer, also known as forget gate, which takes h_{t-1} and $\mathbf{X}_t$ as input, and outputs a number between 0 and 1, where 0 means to completely forget this part, and 1 means to completely remember this part. The second step decides which part of the new information will be stored in the next cell state C_t. An input gate and a $\tanh$ layer work together to update the state. The above two steps can be written as:

$$f_t = \sigma(W_f[h_{t-1}, \mathbf{X}_t]), \tag{1}$$

$$i_t = \sigma(W_i[h_{t-1}, \mathbf{X}_t]), \tag{2}$$

$$\Delta C_t = \tanh(W_C[h_{t-1}, \mathbf{X}_t]). \tag{3}$$

We then update the old cell state C_{t-1} to the next cell state C_t as:

$$C_t = f_t * C_{t-1} + i_t * \Delta C_t. \tag{4}$$

The LSTM is composed of four groups of neurons with different weights W_f, W_i, W_C, W_O. To predict the solar energy O_t, we need both the input vector $\mathbf{X}_t$ and the hidden vector h_{t-1}. Therefore, we also need to keep track of the newest hidden vector h_t. This can be expressed as:

$$O_t = f_O(W_O[h_{t-1}, \mathbf{X}_t]), \tag{5}$$

$$h_t = O_t * f_h(C_t), \tag{6}$$

where f_h and f_O are the hidden layer activation function and the output layer activation function, respectively. They are smooth, bounded functions such as a logistic sigmoid function or a hyperbolic tangent function. At the beginning, all the weights are initialized randomly. With historic input data $\mathbf{X}_t$ (for $t = 0, 1, ..., T$), O_t is calculated based on the weights. By doing back-propagation using stochastic gradient descent (SGD) with respect to all weights, $\theta = \{W_f, W_i, W_C, W_O\}$

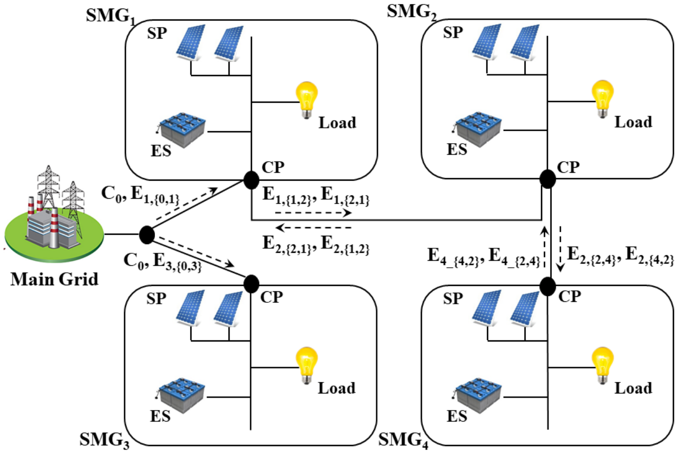

Fig. 3. Illustration of the SMGs network structure and data sharing between four SMGs and main grid.

is obtained to minimize the regression loss defined in the following mean-square-error (MSE) form:

$$\min_{\theta} L(\theta) = \sum_{t=0}^{T} ||O_t - x_{t+1,i,s}||_2^2. \tag{7}$$

By solving the above problem, we obtain the SP prediction model $O_t = f_{LSTM}(\mathbf{X}_{t-T}, ..., \mathbf{X}_t)$. In other word, f_{LSTM} maps the input vector $\mathbf{X}_t$, which consists of weather measurements and solar energy data, to future solar energy generation as closely as possible.

III. System Model

A. Microgrids Model

Consider a network of SMGs as an interconnection of K SMGs as shown in Figure 3. For the low-voltage SMG i, its distribution network typically has a radial structure [16]. The hub of the SMG is the connection point (CP) to main grid and other SMGs. The connections to SP, ESS and loads will be branches. For convenience and simplicity, we consider that each SMG only connects with one SP, ESS and aggregated load. All the CPs, SPs, ESSs and loads in the SMGs are attached with agents that are able to: (1) read real-time data from the corresponding power unit, and control the corresponding power unit, and (2) communicate with other agents via a two-way communication infrastructure. The set of SMG i's neighbors is denoted by N_i. Some SMGs $i \in [1, K]$ in the network not only connect to their neighboring SMGs $j \in N_i$, but also have a connection to the main grid (indexed with 0). All the SMGs can exchange energy and communicate with their neighboring SMGs. We use matrix $\mathbf{L}$ to quantify the energy loss on the distribution lines, where $\mathbf{L}_{i,j}$ denotes the energy loss coefficient from SMG i to SMG j. Matrix $\mathbf{L}$ is hence symmetric with all diagonal elements equal to 0.

As illustrated in Figure 3, the information of energy flow on distribution lines is denoted by $E_{i,\{i,j\}}$, also known as energy exchange information. In $E_{i,\{i,j\}}$, the first i indicates the source of this information, and $\{i, j\}$ indicates the energy exchange from SMG i to SMG j. Let us denote the maximum allowed energy flow on distribution line by $E_{\{i,j\},max}$. The energy flow constraint can be written as:

$$-E_{\{i,j\},max} \leq E_{i,\{i,j\}} - E_{i,\{j,i\}} \leq E_{\{i,j\},max}. \tag{8}$$

Parameter C_0 in Figure 3 is the real-time electricity price received from the main grid. In this paper, we use a discrete-time model with a finite horizon for optimization. We consider a time period (a scheduling horizon) denoted by H, which is divided into T equal intervals.

B. Load Model

We consider that all loads in the SMGs are controllable and deferrable. A controllable and deferrable load can be shifted in time as long as it consumes the required amount of energy before the deadline. For the SMG i, we denote the energy consumption of its load at time t by l_i^t. It is bounded by

$$0 \leq l_i^t \leq l_{i,max}, \tag{9}$$

where $l_{i,max}$ is the possible maximum active energy consumption of load l_i. We also denote its required energy consumption before deadline by $l_{i,req}$. This can be written as:

$$\sum_{t=0}^{t=T-1} l_i^t = l_{i,req}. \tag{10}$$

C. Energy Storage Model

Although there are many ways to store electric energy directly, or transfer that to other energy forms that are easier to store, here we only consider batteries as the ESS units in the SMGs. For the SMG i, we denote its ESS energy output at time t by b_i^t, which is positive when battery is charging and negative when battery is discharging. An ESS in SMG i can be modeled by the following constraints:

$$-b_{i,max} \leq b_i^t \leq b_{i,max}, \tag{11}$$

$$0 \leq s_{i,0} + \sum_{t=0}^{t=T-1} b_i^t \leq s_{i,max}, \tag{12}$$

where $b_{i,max}$ is the maximum charging rate, $-b_{i,max}$ is the maximum discharging rate, and $s_{i,max}$ is the maximum allowed energy stored in the battery. Furthermore, $s_{i,0}$ is the energy initially stored in the battery at the beginning of the scheduling horizon.

IV. Economic Dispatch Problem

A. Problem Formulation

The goal of our proposed SMGs EMS is to solve the Economic Dispatch Problem (EDP) in a distributed manner without the need for a central data point. The objective of the EDP is to minimize the global monetary energy purchasing cost of the SMGs, while delivering reliable, high-quality and continuous energy to the loads.

For simplicity, we make certain assumptions to ensure that the system is economically reasonable and as close as possible to the real-life situation. The first assumption is that the utility is not willing to buy back the power from the users due to the unstable power quality and government regulation. Another assumption is that we know electricity price one-day ahead. Due to the uncertainty of electricity market, such assumption is necessary.

Let us denote the decision vector as $\mathbf{D}_i = [\mathbf{b}_i, \mathbf{l}_i, \mathbf{E}_{0,i}, \mathbf{E}_{i,\{i,j\}}]$ with $j \in N_i$. Parameter $\mathbf{E}_{0,i}$ is the energy exchange between the main grid and the SMG i. Each entry of $\mathbf{D}_i$ is a vector of the respective variable in different time slots, e.g., $\mathbf{b}_i = [b_i^0, ..., b_i^{T-1}]$. The total monetary energy purchasing cost is the summation of all SMGs' purchasing cost. The cost function for SMG i can be written as:

$$P_i(\mathbf{D}_i) = \sum_{t=0}^{T-1} C_0^t |E_{0,i}^t|. \tag{13}$$

Furthermore, the local energy supply-demand balance constraint at time instant t for SMG i can be written as:

$$b_i^t + O_i^t + \mathbf{L}_{0,i} E_{0,i} + \sum_{j \in N_i} \mathbf{L}_{i,j}(E_{i,j}^t - E_{j,i}^t) = l_i^t, \tag{14}$$

where O_i^t is obtained from the solar energy prediction model based on LSTM. SMG i can communicate with the neighboring SMGs to retrieve $E_{j,i}^t$. Hence, all SMGs can locally optimize the loads, ESS and other decision variables within the scheduling horizon. Let us extend the decision vector to include information retrieved from neighboring SMGs as $\tilde{\mathbf{D}}_i = [\mathbf{D}_i, \mathbf{E}_{i,\{j,i\}}]$. The $\mathbf{E}_{i,\{j,i\}}$ is a copy of $\mathbf{E}_{j,\{j,i\}}$ of SMG j stored in SMG i. The global objective function of EDP can be written as:

$$\min_{\mathbf{D}} \sum_{i=1}^{N} P_i(\tilde{\mathbf{D}}_i), \tag{15}$$

subject to:

$$(8) - (12), (14)$$

$$\mathbf{E}_{i,\{i,j\}} = \mathbf{E}_{j,\{i,j\}}, \forall i \in [1, K],\ \forall j \in N_i$$

B. Distributed ADMM-based Solution

The optimization problem in the form of (15) only involves local and neighboring SMGs' information. For SMG i, it only needs to share its $\mathbf{E}_{i,\{i,j\}}$ with neighboring SMGs. Therefore, the EDP can be solved by the scalable Alternating Direction Method of Multipliers (ADMM) presented in [17]. The SMG i can update its $\tilde{\mathbf{D}}_i$ as:

$$\tilde{\mathbf{D}}_i(n+1) = \arg\min_{\tilde{\mathbf{D}}_i} P_i(\tilde{\mathbf{D}}_i) + \mathbf{M}_{i,j}(n) + \mathbf{M}_{j,i}(n). \tag{16}$$

Here, We define the adjacent weight matrix $\mathbf{A}$ as:

$$\mathbf{A}_{i,j} = \begin{cases} \tau \geq 0 & j \in N_i \\ 0 & \text{otherwise,} \end{cases} \tag{17}$$

where τ is a user defined positive number. Using r to denote both i, j and j, i, $\mathbf{M}_r$ can be written as:

$$\mathbf{M}_r(n) = \sum_{j \in N_i} \mathbf{A}_{ij} (\mathbf{E}_{i,\{r\}}(n) - \mathbf{B}_{i,\{r\}}(n))^2. \tag{18}$$

This nonlinear constraint can be relaxed to

$$\mathbf{M}_r(n) = \sum_{j \in N_i} \mathbf{A}_{ij} |\mathbf{E}_{i,\{r\}}(n) - \mathbf{B}_{i,\{r\}}(n)|, \tag{19}$$

where

$$\mathbf{B}_{i,\{r\}}(n) = \mathbf{E}_{i,\{r\}}(n) + \mathbf{u}_{i,\{r\}}(n) + \mathbf{\Lambda}_{i,\{r\}}(n), \tag{20}$$

$$\mathbf{u}_{i,\{r\}}(n) = \mathbf{A}_{i,j}(\mathbf{E}_{j,\{r\}}(n) - \mathbf{E}_{i,\{r\}}(n)), \tag{21}$$

$$\mathbf{\Lambda}_{i,\{r\}}(n) = \begin{cases} 0 & n = 0 \\ \mathbf{\Lambda}_{i,\{r\}}(n-1) + \mathbf{u}_{i,\{r\}}(n) & n \geq 0. \end{cases} \tag{22}$$

Algorithm 1

```
procedure INITIALIZATION
    for i ∈ [1, K] do
        n = 0
        Receive C_0 from main grid
        D̃_i(0) ← random values
        ε_p(n), ε_d(n) ← +∞
    end for
end procedure
while ε_p(n) + ε_d(n) ≥ ε_s(n) do
    for i ∈ [1, K] do
        Send out E_{i,{i,j}}(n), E_{i,{j,i}}(n)
        Receive E_{j,{i,j}}(n), E_{j,{j,i}}(n), j ∈ N_i
        Calculate u_{i,{r}}(n), Λ_{i,{r}}(n)
        n = n + 1
        if n ≥ 1 then
            Calculate B_{i,{r}}(n − 1), D̃_i(n)
        end if
    end for
    Calculate ε_p(n), ε_d(n)
end while
```

All SMGs will execute the above algorithm simultaneously until convergence. The convergence of the ADMM-based algorithm can be decided by its primal residue $\epsilon_p(n)$ and dual residue $\epsilon_d(n)$ defined by [18]:

$$\epsilon_p(n) = \sum_{i=1}^{K} \sum_{j \in N_i} ||\mathbf{E}_{i,\{i,j\}}(n) - \mathbf{E}_{j,\{i,j\}}(n)||_2^2, \tag{23}$$

$$\begin{aligned} \epsilon_d(n) = \sum_{i=1}^{K} \sum_{j \in N_i} ||&\mathbf{E}_{i,\{i,j\}}(n) - \mathbf{E}_{i,\{i,j\}}(n-1) + \\ &\mathbf{E}_{j,\{i,j\}}(n) - \mathbf{E}_{j,\{i,j\}}(n-1)||_2^2. \end{aligned} \tag{24}$$

We define the final stopping criterion as $\epsilon_s(n)$. When $\epsilon_p(n) + \epsilon_d(n) \leq \epsilon_s(n)$, it means the system has reached convergence. Algorithm 1 shows the detailed procedure of the proposed distributed algorithm.

V. Simulation Results and Discussions

A. Simulation Platform

We designed and implemented an innovative distributed SMGs simulation platform, as shown in Figure 4, based on Common Open Research Emulator (CORE) and GridLAB-D power simulator. The CORE is a tool for simulating networks on one or more machines. We can also connect these simulated networks to real networks [19]. GridLAB-D is an evolving energy system simulation and analysis tool that provides valuable information to users who design and operate distribution systems. It incorporates the most advanced modeling techniques, with high-performance algorithms to deliver the best in end-use modeling [20].

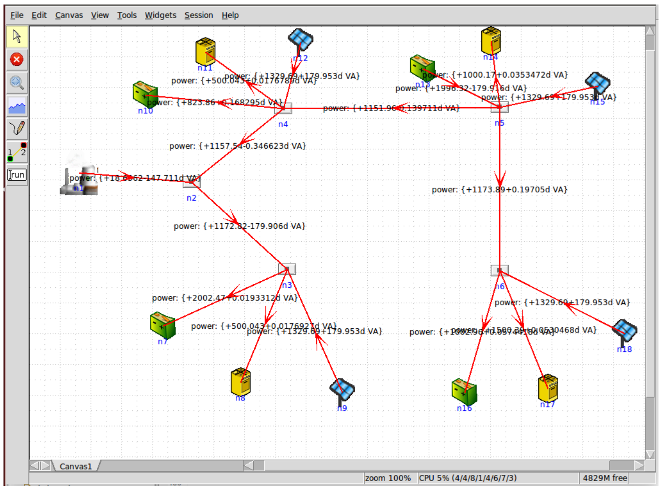

Fig. 4. Distributed SMGs simulation platform

Our simulation platform is able to display real-time energy flow on the distribution network. It records voltage, current, frequency and other essential data with high frequency. Furthermore, it provides full customization so that different power units such as loads, batteries, solar panels, regulators, etc, can be implemented in the simulation platform. Figure 4 demonstrates our implementation of the proposed SMGs network of Figure 3 in our platform.

B. Case Study

We implement the LSTM for solar energy prediction in Tensorflow. The key parameters of the training and mean squared error (MSE) are listed in Table I. We choose the best parameter set and feed the LSTM with three years (1991-1993) of historic hourly solar energy data from National Renewable Energy Laboratory. The prediction result is illustrated in Figure 5.

TABLE I
SOLAR ENERGY PREDICTION

LSTM Training Parameters and Results			
Time Steps	***Years of Data***	***Batch Size***	***MSE/Hour***
5	3	100	1.14
5	3	10	1.82
10	3	100	1.01
10	1	100	4.47
5	1	100	3.17

Centralized EMS, rule-based heuristic EMS and DCEMS are all implemented in the simulation platform as well. For the test case, the scheduling horizon is chosen as entire day (24 hr) with $T = 24$. Furthermore, τ is set to 0.1, and ϵ_s is set

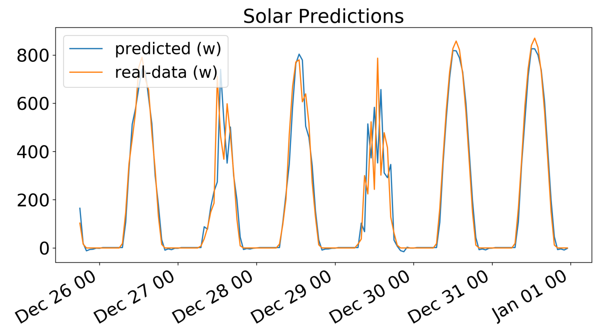

Fig. 5. Solar energy generation prediction result with LSTM

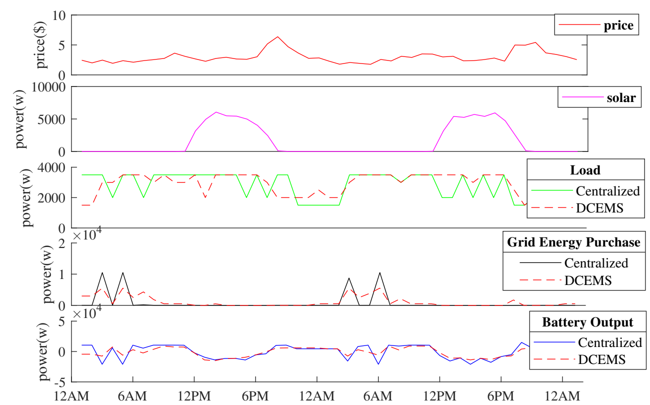

Fig. 6. DCEMS operation profile compared with centralized EMS

to 0.01. Normally, the algorithm reaches convergence around 100 iterations. Figure 6 shows detailed operation profile of the DCEMS compared to centralized EMS. We can see that the SMGs purchase large amount of energy from the main grid when the electricity price is low during 12am to 6am. The battery is in charging mode when the solar energy reaches the maximum value. Part of the loads has been shifted from the

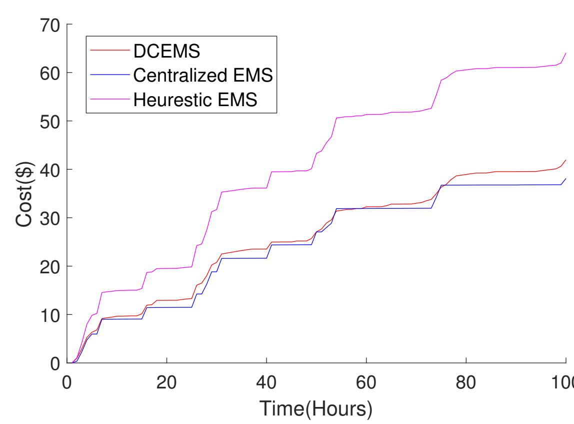

Fig. 7. Cumulative monetary cost comparison using different approaches

busy hours (8pm to 11pm) to other time window.

For the 4 SMGs case, compared to the rule-based heuristic algorithm, the centralized EMS and DCEMS can reduce operation cost by more than 30% as shown in Figure 7. Moreover, the figure clearly shows that the performance of DCEMS is very close to that of the centralized approach. By considering the advantage of avoiding single point of failure while preserving customers' privacy, the negligible amount of performance degradation is totally acceptable.

VI. CONCLUSION

In this paper, we propose a DCEMS to minimize the energy purchasing cost of SMGs. An LSTM-based solar prediction model is also presented to capture the uncertainty of solar energy. Using the real data, we demonstrate the high accuracy of our prediction model. We also compare the performance of DCEMS with heuristic and centralized EMS methods. The proposed DCEMS outperforms the heuristic rule-based EMS and has a very close performance to the centralized approach. However, the DCEMS makes the entire grid more robust against extreme weather or faults. Furthermore, it can protect customers privacy by only sharing the cumulative information of entire SMG with outside. No personal data and usage history can easily be inferred from the cumulative data.

Future research includes improving the solar energy prediction accuracy with advanced deep learning techniques; online learning RNN also suits this problem very well.

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