Distributed Demand Side Management Among Foresighted Decision Makers in Power Networks

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***Abstract*—We consider a power network with an independent system operator (ISO), and geographically distributed aggregators who have energy storage and purchase energy from the ISO to serve its customers. All the entities in the system are *foresighted*: each aggregator minimizes its own *long-term* payments for energy purchase and operational costs of energy storage by deciding how much energy to buy from the ISO, and the ISO minimizes the *long-term* total cost of the network (i.e. energy generation costs and aggregators' costs) by dispatching energy generation among the generators. The decision making of the foresighted entities is complicated because 1) the information required to make optimal decisions is decentralized among the entities, and 2) the coupling (through the prices) among the aggregators is complicated. We propose a design framework in which the ISO provides each aggregator with a conjectured future price, and each aggregator distributively minimizes its own long-term cost based on its conjectured price as well as its local information. The proposed framework can achieve the social optimum despite the decentralized information and complex coupling among the entities. Simulation results demonstrate significant reduction in the total cost by the proposed foresighted demand side management (DSM), compared to the optimal myopic DSM (up to 60% reduction), and the foresighted DSM based on the Lyapunov optimization framework (up to 30% reduction).**

I. Introduction

The adoption of renewable energy in the power networks introduces high fluctuation and uncertainty in energy generation. To cope with this uncertainty, the demand side of the network is deploying various solutions, one of which is the use of energy storage [6]. In this paper, we study the optimal demand side management (DSM) strategy in the presence of energy storage, and the corresponding optimal economic dispatch strategy.

Specifically, we consider a power network consisting of energy generators, an independent system operator (ISO) that operates the system, and multiple aggregators serving their customers. The ISO receives energy purchase requests from the aggregators as well as reports of (parameterized) energy generation cost functions from the generators, and based on these, dispatches the energy generators and determines the unit energy prices. The aggregators are located in different geographical areas and provide energy for its customers (e.g. households) in the neighborhood. In the literature, the term "DSM" has been broadly used for different decision problems on the demand side. For example, some papers (see [1]–[3] for representative papers) focus on the interaction between one aggregator and its customers, and refer to DSM as determining the power consumption schedules of the users. Some papers [4]–[12] focus on how multiple aggregators [4]–[8] or a single aggregator [9]–[12] purchases energy from the ISO based on the energy consumption requests from their customers. Our paper pertains to the second category of research works.

The key feature that sets apart our paper from most works [4]–[8] is that in our work, all the decision makers in the system are *foresighted*. Each aggregator seeks to minimize its *long-term* cost, consisting of its operational cost of energy storage and its payment for energy purchase. In contrast, in most existing works [4]–[8], the aggregators are *myopic* and seek to minimizing their *short-term* (e.g. one-day or even hourly) cost. In the presence of energy storage, foresighted DSM strategies can achieve much lower costs than myopic DSM strategies. For example, an aggregator can purchase more energy from the ISO than that requested from its customers, and store the unused energy in the energy storage for future use, if it anticipates that the future energy price will be high. Since the aggregators deploy foresighted DSM strategies, it is also optimal for the ISO to make foresighted economic dispatch, in order to minimize the *long-term* total cost of the system, consisting of the long-term cost of energy generation and the aggregators' long-term operational cost. Note that although some works [9]–[12] assume that the aggregator is foresighted, they study the decision problem of a *single* aggregator and do not consider the economic dispatch problem of the ISO. When there are multiple aggregators in the system (which is the case in practice), this approach neglects the impact of aggregators' decisions on each other, which leads to suboptimal solutions in terms of minimizing the total cost of the system.

When the ISO and *multiple* aggregators make *foresighted* decisions, it is difficult to obtain the optimal foresighted strategies for two reasons. First, the information is decentralized. The total cost depends on the generation cost functions (e.g. the speed of wind for wind energy generation, the amount of sunshine for solar energy generation), the status of the transmission lines (e.g. the flow capacity of the transmission lines), the amount of electricity in the energy storage, and the demand from the customers, all of which may change due to supply and demand uncertainty. However, none of the entities knows all the above information: the ISO knows only the generation cost functions and the status of the transmission lines, and each aggregator knows only the status of its own energy storage and the demand from its own customers. Hence, the DSM strategy needs to be decentralized, such that each entity can make decisions solely based on its locally-available information. Second, the aggregators are coupled in a complicated way that is unknown to them. Specifically, each aggregator's purchase affects the prices, and thus the payments of the other aggregators. However, the price is determined by the ISO based on the generation cost functions and the status of the transmission lines, neither of which is known to any aggregator. Hence, each aggregator does not know how its purchase will influence the price, which makes it difficult for the aggregator to make the optimal decision.

To overcome the difficulty resulting from information de-

TABLE I. COMPARISONS WITH RELATED WORKS ON DEMAND-SIDE MANAGEMENT.

	Interaction	Energy storage	Time horizon	Foresighted	Aggregators	Supply uncertainty	Demand Uncertainty
[1][2]	Aggregator-Customer	No	1 day	No	Single	No	No
[3]	Aggregator-Customer	No	1 day	No	Single	No	Yes
[4]	ISO-Aggregator	No	1 day	No	Multiple	No	No
[5]	ISO-Aggregator	No	1 day	No	Multiple	Yes	No
[6]	ISO-Aggregator	Yes	1 day	No	Multiple	No	No
[7][8]	ISO-Aggregator	Yes	1 day	No	Multiple	Yes	Yes
[9][10]	ISO-Aggregator	Yes	Infinite	Yes	Single	No	Yes
[11][12]	ISO-Aggregator	Yes	Infinite	Yes	Single	Yes	Yes
Proposed	ISO-Aggregator	Yes	Infinite	Yes	Multiple	Yes	Yes

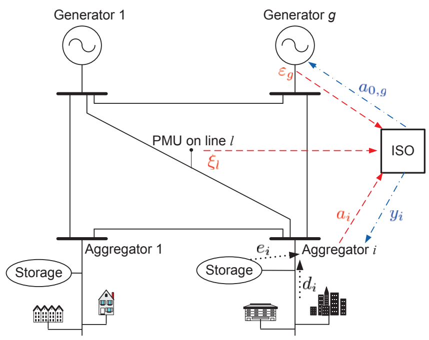

Fig. 1. The system model of the smart grid. The information flow to the ISO is denoted by red dashed lines, the information flow to the aggregators is denoted by black dotted lines, and the information flow sent from the ISO is denoted by blue dash-dot lines.

centralization and complicated coupling, we propose a decentralized DSM strategy based on conjectured prices. Specifically, each aggregator makes decisions based on its conjectured price, and its local information on the status of its energy storage and the demand from its customers. Since the price is determined based on the generation cost functions and the status of the transmission lines, which is only known to the ISO, the aggregators' conjectured prices are determined by the ISO. We propose a simple online algorithm for the ISO to update the conjectured prices based on its local information, and prove that by using the algorithm, the ISO obtains the optimal conjectured prices under which the aggregators' (foresighted) best responses minimize the total cost of the system.

In Table I, we summarize the above discussions on the related work by comparing with them in various aspects.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

We consider a power network with one ISO indexed by 0, G generators indexed by $g = 1, 2, \ldots, G$, I aggregators indexed by $i = 1, 2, \ldots, I$, and L transmission lines (see Fig. 1 for an illustration). In the following, we may refer to the ISO or an aggregator generally as entity $i \in \{0, 1, \ldots, I\}$, with entity 0 being the ISO and entity $i \in \{1, \ldots, I\}$ being aggregator i. The power network can be modeled as a stochastic dynamic system described as follows.

States: The ISO's state is defined as $s_0 = (\boldsymbol{\varepsilon}, \boldsymbol{\xi}) \in S_0$, where $\boldsymbol{\varepsilon} = (\varepsilon_1, \ldots, \varepsilon_G)$ are the parameters of the energy generation cost functions reported by the generators, and $\boldsymbol{\xi} = (\xi_1, \ldots, \xi_L)$ are the status of the transmission lines such as the phases measured by the phasor measurement units (PMUs). Each aggregator i's state is defined as $s_i = (d_i, e_i) \in S_i$, where d_i is the aggregate demand from aggregator i's customers and e_i is the amount of energy left in aggregator i's storage. Each entity's state is known to itself only.

Actions: The ISO's action is how much energy each generator should produce, denoted by $a_0 \in A_0 \subset \mathbb{R}_+^G$. Each aggregator i's action is how much energy to purchase from the ISO, denoted by $a_i \in A_i \subset \mathbb{R}_+$.

Instantaneous Costs: Each entity's instantaneous total cost consists of two parts: the operational cost and the payment. Each entity i's operational cost $c_i : S_i \times A_i \to \mathbb{R}$ is a convex function of its action a_i. An example operational cost function of an aggregator can be

$$c_i(s_i, a_i) = p \cdot \max\{d_i - (e_i + a_i), 0\} + m_i(e_i),$$

where $p > 0$ is the penalty of failing to fulfill the demand (i.e. when $e_i + a_i < d_i$), and $m_i(e_i)$ is the maintenance cost of the energy storage that is convex [6].

The ISO's operational cost $c_0(s_0, a_0) = \sum_{g=1}^G c_g(\varepsilon_g, a_{0,g})$, where $c_g(\varepsilon_g, a_{0,g})$ is the convex increasing energy generation cost of generator g. An example cost function can be

$$c_g(\varepsilon_g, a_{0,g}) = (q_{0,g} + q_{1,g} \cdot a_{0,g} + q_{2,g} \cdot a_{0,g}^2) + q_{r,g} \cdot (a_{0,g} - a_{0,g}^-)^2,$$

where $a_{0,g}^-$ is the production level in the previous time slot. In the cost function, $q_{0,g} + q_{1,g} \cdot a_{0,g} + q_{2,g} \cdot a_{0,g}^2$ is the quadratic cost of producing a_0 amount of energy [1][2], and $q_{r,g} \cdot (a_{0,g} - s_{0,g})^2$ is the ramping cost of changing the energy production level.

Each aggregator i's payment to the ISO is $y_i(s_0, a_i, \boldsymbol{a}_{-i}) \cdot a_i$, where $y_i(s_0, a_i, \boldsymbol{a}_{-i})$ is the unit energy price that depends on the ISO's state s_0, its own purchase a_i, and the other aggregators' purchases $\boldsymbol{a}_{-i}$. Similarly, the ISO's payment to the generators is $\boldsymbol{y}_0^T \cdot a_0$, where $\boldsymbol{y}_0$ is the vector of unit prices for each generator.

Each entity i's total cost $\bar{c}_i$ is the sum of its operational cost and its payment.

State Transitions: We assume that each entity's state transition is Markovian, namely its current state depends only on its previous state and its previous action [5][7][8][11][12]. Under the Markovian assumption, we denote the transition probability of entity i's state s_i by $\rho_i(s_i' | s_i, a_i)$. We also assume that conditioned on the ISO's action a_0 and the aggregators' action profile $\boldsymbol{a}$, each entity's state transition is independent of each other.

We divide time into periods (e.g. hours) $t = 0, 1, 2, \ldots$. In each period t, the entities act according to the time line shown in Fig. 2. Each entity i's *strategy* is a mapping from its set

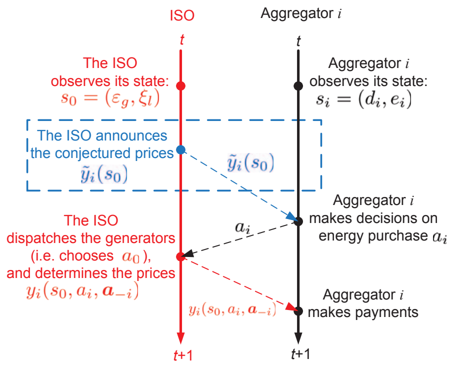

Fig. 2. Illustration of the entities' decision making and information exchange. The action and the message exchange in the dashed box are related to the conjectured prices proposed in the design framework in Sec. III.

of states to its set of actions, denoted by $\pi_i : S_i \to A_i$. Each entity chooses its action based on its strategy in each period.

The joint strategy profile $\boldsymbol{\pi} = (\pi_0, \ldots, \pi_I)$ and the initial state $(s_0^0, s_1^0, \ldots, s_I^0)$ induce a probability distribution over the sequences of states and prices, and hence a probability distribution over the sequences of total costs $\bar{c}_i^0, \bar{c}_i^1, \ldots$. Taking expectation with respect to the sequences of stage-game payoffs, we have entity i's expected long-term total cost given the initial state as

$$\bar{C}_i(\boldsymbol{\pi}|(s_0^0, s_1^0, \ldots, s_I^0)) = \mathbb{E}\left\{(1-\delta)\sum_{t=0}^{\infty}\left(\delta^t \cdot \bar{c}_i^t\right)\right\}, \quad (1)$$

where $\delta \in [0, 1)$ is the discount factor. We define each entity i's expected long-term (operational) cost $C_i(\boldsymbol{\pi}|(s_0^0, s_1^0, \ldots, s_I^0))$ given the initial state in a similar way.

B. Problem Formulation

The ISO aims to minimize the long-term total cost in the network. In addition, we need to satisfy the constraints due to the capacity of the transmission lines, the supply-demand requirements, and so on. We denote the constraints by $\boldsymbol{f}(s_0, a_0, \boldsymbol{a}) \leq \boldsymbol{0}$, where $\boldsymbol{f}(s_0, a_0, \boldsymbol{a}) \in \mathbb{R}^N$ with N being the number of constraints. We assume that the electricity flow can be approximated by the direct current (DC) flow model, in which case the constraints $\boldsymbol{f}(s_0, a_0, \boldsymbol{a}) \leq \boldsymbol{0}$ are linear in each a_i. Hence, the design problem can be formulated as

$$\begin{aligned} \min\nolimits_{\boldsymbol{\pi}} \quad & \sum_{s_0^0, s_1^0, \ldots, s_I^0} \sum_{i=0}^{I} C_i(\boldsymbol{\pi}|(s_0^0, s_1^0, \ldots, s_I^0)) \quad (2) \\ s.t. \quad & \boldsymbol{f}(s_0, \pi_0(s_0), \ldots, \pi_I(s_I)) \leq \boldsymbol{0}, \ \forall (s_0, \ldots, s_N). \end{aligned}$$

Note that in the above optimization problem, we use entity i's operational cost C_i instead of its total cost $\bar{C}_i$, because all the payments are transferred with in the network and are thus canceled in the total network cost. Note also that we sum up the cost under all the initial states. This can be considered as the expected network cost when the initial state is uniformly distributed. The optimal stationary strategy profile that maximizes this expected network cost will also maximize the network cost given any initial state. We write the solution to the design problem as $\boldsymbol{\pi}^\star$ and the optimal value of the design problem as $C^\star$.

III. Optimal Foresighted DSM

A. The aggregator's Decision Problem and Conjectured Price

Contrary to the ISO, each aggregator aims to minimize its own long-term cost $\bar{C}_i(\boldsymbol{\pi}|(s_0^0, s_1^0, \ldots, s_I^0))$. In other words, each aggregator i solves the following problem:

$$\pi_i = \arg\min_{\pi_i'} \bar{C}_i(\pi_i', \boldsymbol{\pi}_{-i}|(s_0^0, s_1^0, \ldots, s_I^0)).$$

Assuming that the aggregator knows all the information, the optimal solution to the above problem should satisfy the following:

$$V_i(s_0, s_i, \boldsymbol{s}_{-i}) = \min\nolimits_{a_i \in A_i} \Big\{ (1-\delta)\bar{c}_i(s_0, s_i, a_i, \boldsymbol{a}_{-i}) + \\ \delta \cdot \sum\nolimits_{s_0', s_i', \boldsymbol{s}_{-i}'} \Big[\rho_0(s_0'|s_0) \prod\nolimits_{j=1}^{I} \rho_j(s_j'|s_j, a_j) V_i(s_0', s_i', \boldsymbol{s}_{-i}') \Big] \Big\}.$$

However, the information (such as the other aggregators' strategies $\boldsymbol{\pi}_{-i}$ and states $\boldsymbol{s}_{-i}$, and the ISO's state s_0) necessary to solve the above problem is never available to aggregator i.

One way to decouple the interaction among the aggregators is to endow each aggregator with a conjectured price. Denote the conjectured price as $\tilde{y}_i$, we can rewrite aggregator i's decision problem as

$$\tilde{V}_i^{\tilde{y}_i}(s_i) = \min\nolimits_{a_i \in A_i} \Big\{ (1-\delta) \left[c_i(s_i, a_i) + \tilde{y}_i \cdot a_i \right] + \\ \delta \cdot \sum\nolimits_{s_i'} \Big[\rho_i(s_i'|s_i, a_i) \tilde{V}_i^{\tilde{y}_i}(s_i') \Big] \Big\}.$$

Clearly, we can see from the above equations that given the conjectured price $\tilde{y}_i$, each aggregator can make decisions based only on its local information.

In Fig. 2, we illustrate the entities' decision making and information exchange in the design framework based on conjectured prices. We can see that in the proposed design framework, the ISO sends the conjectured prices to the aggregators before the aggregators make decisions. This additional procedure of exchanging conjectured prices allows the ISO to lead the aggregators to the optimal DSM strategies. The remaining question is how to determine the optimal conjectured prices, such that when each aggregator reacts based on its conjectured price, the resulting strategy profile miminizes the network cost.

B. The Optimal Decentralized DSM Strategy

We propose a distributed algorithm used by the ISO to iteratively update the conjectured prices and by the aggregators to update their optimal strategies. The algorithm will converge to the optimal conjectured prices and the optimal strategy profile that achieves the minimum total system cost $C^\star$.

At period 5, given the conjectured price $\tilde{y}_i^5$, each aggregator i solves

$$\tilde{V}_i^{\tilde{y}_i^t}(s_i) = \min\nolimits_{a_i \in A_i} \Big\{ (1-\delta) \left[c_i(s_i, a_i) + \tilde{y}_i^t \cdot a_i \right] + \\ \delta \cdot \sum\nolimits_{s_i'} \Big[\rho_i(s_i'|s_i, a_i) \tilde{V}_i^{\tilde{y}_i^t}(s_i') \Big] \Big\}, \quad (3)$$

and obtains the optimal value function $\tilde{V}_i^{\tilde{y}_i^t}$ as well as the corresponding optimal strategy $\pi_i^{\tilde{y}_i^t}$ under the current conjectured price $\tilde{y}_i^t$.

TABLE II. DISTRIBUTED ALGORITHM TO COMPUTE THE OPTIMAL DECENTRALIZED DSM STRATEGY.

Input: Each entity's performance loss tolerance ϵ_i
Initialization: Set $t = 0$, $\bar{a}_i^0 = 0, \forall i \in \mathcal{I}$, $\tilde{y}_i^0 = 0, \forall i = 0, 1, \ldots, I$.
repeat
Each aggregator i solves its decision problem (3)
The ISO solves its decision problem (4)
Each aggregator i reports its purchase request $\pi_i^{\tilde{y}_i^t}(s_i)$
The ISO updates $\bar{a}_i^{t+1} = \bar{a}_i^t + \pi_i^{\tilde{y}_i^t}(s_i)$ for all $i \in \mathcal{I}$
The ISO updates the conjectured prices:
$\tilde{y}_i^{t+1}(s_0) = \left[(\boldsymbol{\lambda}^{t+1})^T \cdot \frac{\partial f(s_0, \boldsymbol{a})}{\partial a_i}\right]^T$, where
$\boldsymbol{\lambda}^{t+1} = \left\{\boldsymbol{\lambda}^t + \frac{1}{t+1} \cdot \boldsymbol{f}\left(s_0, \pi_0^{\tilde{\boldsymbol{y}}_0^t}(s_0), \frac{\bar{a}_1^{t+1}}{t+1}, \ldots, \frac{\bar{a}_I^{t+1}}{t+1}\right)\right\}^+$
until $\lVert \tilde{V}_i^{\tilde{y}_i^{(t+1)}} - \tilde{V}_i^{\tilde{y}_i^t} \rVert \leq \epsilon_i$

Similarly, given the conjectured prices $\tilde{\boldsymbol{y}}_0^t \in \mathbb{R}^G$, the ISO solves

$$\tilde{V}_0^{\tilde{\boldsymbol{y}}_0^t}(s_0) = \min_{a_i \in A_i} \left\{(1-\delta)\left[\sum_g c_g(s_0, a_0) + (\tilde{\boldsymbol{y}}_0^t)^T \cdot a_0\right] + \delta \cdot \sum_{s_0'} \left[\rho_0(s_0'|s_0, a_0)\tilde{V}_0^{\tilde{\boldsymbol{y}}_0^t}(s_0')\right]\right\}, \quad (4)$$

and obtains the optimal value function $\tilde{V}_0^{\tilde{\boldsymbol{y}}_0^t}$ as well as the corresponding optimal strategy $\pi_0^{\tilde{\boldsymbol{y}}_0^t}$ under the current conjectured price $\tilde{\boldsymbol{y}}_0^t$.

Then the ISO updates the conjectured prices using a stochastic subgradient method. The detail of this update, along with the complete description of the algorithm, is given in Table II.

Theorem 1: The algorithm in Table II converges to the optimal strategy profile, namely

$$\lim_{t \to \infty} \left| \sum_{s_0, s_1, \ldots, s_I} \left[\sum_{i=0}^{I} C_i(\boldsymbol{\pi}^{\tilde{y}^t}|(s_0, s_1, \ldots, s_I))\right] - C^\star \right| = 0.$$

Proof: See the appendix in [15]. ■

From Fig. 2, we can see that the amount of information exchange at each period is small ($O(I)$), compared to the amount of information unavailable to each entity ($\prod_{j \neq i} |S_i|$ states plus the strategies $\boldsymbol{\pi}_{-i}$). In other words, the algorithm enables the entities to exchange a small amount ($O(I)$) of information and reach the optimal DSM strategy that achieves the same performance as when each entity knows the complete information about the system.

IV. SIMULATION RESULTS

In this section, we validate our theoretical results and compare against existing DSM strategies through extensive simulations. We use the widely-used IEEE test power systems [13]. We describe the other system parameters as follows:

- One period is one hour. The discount factor $\delta = 0.99$.
- The demand of aggregator i at period t is uniformly distributed among the interval $[d_i(t \mod 24) - \Delta d_i(t \mod 24), d_i(t \mod 24) + \Delta d_i(t \mod 24)]$. We let the peak hours for all the aggregators to be from 17:00 to 22:00. The mean value of aggregator i's demand $d_i(t \mod 24) = 50 + (i-1) \cdot 0.5$ MW in peak hours and $d_i(t \mod 24) = 25 + (i-1) \cdot 0.5$ MW in off-peak hours. The range $\Delta d_i(t \mod 24) = 5$ MW in peak hours and $\Delta d_i(t \mod 24) = 2$ MW in off-peak hours. These values are adapted from [14].
- All the aggregators have the same linear energy storage cost function [6]: $c_i(s_i, a_i) = 2 \cdot (a_i - d_i)^+$.
- All the renewable energy generators have linear energy generation cost functions [14]: $c_g(a_{0,g}) = g \cdot a_{0,g}$, where the unit energy generation cost has the same value as the index of the generator (these values are adapted from [14], which cited that the unit energy generation cost ranges from \$0.19/MWh to \$10/MWh). Although the energy generation cost function is deterministic, the maximum amount of energy production is stochastic (due to wind speed, the amount of sunshine, and so on). The maximum amounts of energy production of all the renewable energy generators follow the same uniform distribution in the range of $[90, 110]$ MW.
- The conventional energy generators have the same energy generation cost function [6]:
$$c_g(a_{0,g}) = \underbrace{0.5 \cdot (a_{0,g})^2}_{\text{generation cost}} + \underbrace{0.1 \cdot (a_{0,g} - a_{0,g}^-)^2}_{\text{ramping cost}}.$$

We compare the proposed DSM strategies with the following schemes.

- Centralized optimal strategies ("Centralized"): We assume that there is a central controller who knows everything about the system and solves the long-term cost minimization problem as a single-user MDP. This scheme serves as the benchmark optimum.
- Myopic strategies ("Myopic") [4]–[8]: In each period t, the aggregators myopically minimizes their current costs, and based on their actions, the ISO minimizes the current total generation cost.
- Single-user Lyapunov optimization ("Lyapunov") [9]–[12]: We let each aggregator adopt the stochastic optimization technique proposed in [9]–[12]. Based on the aggregators' purchases, the ISO minimizes the current total generation cost.

1) Impact of the energy storage: First, we study the impact of the energy storage on the performance of different schemes. We assume that all the generators are conventional energy generators using fossil fuel, in order to rule out the impact of the uncertainty in renewable energy generation (which will be examined next). The performance criterion is the total cost per hour normalized by the number of buses in the system. We compare the normalized total cost achieved by different schemes when the capacity of the energy storage increases from 5 MW to 45 MW.

Fig. 3 shows the normalized total cost achieved by different schemes under IEEE 14-bus system. We can see that the proposed DSM strategy achieves almost the same performance as the centralized optimal strategy. The slight optimality gap comes from the performance loss experienced during the convergence process of the conjectured prices. Compared to

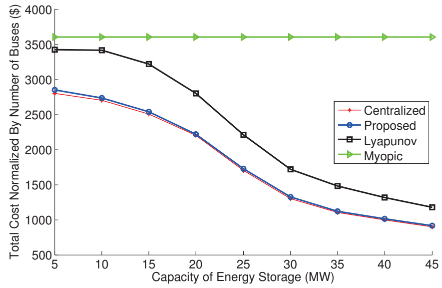

Fig. 3. The normalized hourly total cost versus the capacity of the energy storage.

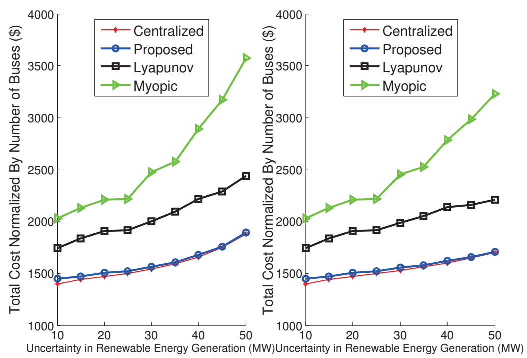

Fig. 4. The normalized hourly total cost versus the uncertainty in renewable energy generation. The aggregators have energy storage of capacity 25 MW and 50 MW in the left and right plots, respectively.

the DSM strategy based on single-user Lyapunov optimization, our proposed strategy can reduce the total cost by around 30% in most cases. Compared to the myopic DSM strategy, our reduction in the total cost is even larger and increases with the capacity of the energy storage (up to 60%).

2) Impact of the uncertainty in renewable energy generation: Now we examine the impact of the uncertainty in renewable energy generation. We let half of the generators to be renewable energy generators. Recall that the maximum amounts of energy production of the renewable energy generators are stochastic and follow the same uniform distribution. We keep the mean value of the maximum amount of energy production to be 100 MW, and vary the range of the uniform distribution. A wider range indicates a higher uncertainty in renewable energy production. Hence, we define the uncertainty in renewable energy generation as the maximum deviation from the mean value in the uniform distribution.

Fig. 4 shows the normalized total cost with different degrees of uncertainty in renewable energy generation, when the aggregators have 25MV and 50MV energy storage. Again, the proposed strategy achieves the performance of the centralized optimal strategy, and has lower total cost compared to the other schemes. We can also see that when the aggregators have larger capacity to store energy, the increase of the total cost with the uncertainty is smaller. This is because the energy storage can smooth the demand, in order to mitigate the impact of uncertainty in the renewable energy generation. This shows the value of energy storage to reduce the cost.

V. Conclusion

In this paper, we proposed a methodology to perform optimal foresighted DSM strategies that minimize the long-term total cost of the power system. We overcame the hurdles of information decentralization and complicated coupling in the system, by decoupling the entities' decision problems using conjectured prices. We proposed an online algorithm for the ISO to update the conjectured prices, such that the conjectured prices can converge to the optimal ones, based on which the entities make optimal decisions that minimize the long-term total cost. We prove that the proposed method can achieve the social optimum, and demonstrate through simulations that the proposed foresighted DSM significantly reduces the total cost compared to the optimal myopic DSM (up to 60% reduction), and the foresighted DSM based on the Lyapunov optimization framework (up to 30% reduction).

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