This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TPWRS.2017.2771279, IEEE Transactions on Power Systems

A Decentralized Electricity Market Scheme Enabling Demand Response Deployment

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***Abstract*—In smart grid, demand response (DR) programs can be deployed to encourage electricity consumers towards scheduling their controllable demands to off-peak periods. Motivating the consumers to participate in a DR program is a challenging task, as they experience a *confidential* discomfort cost by modifying their load demand from the desirable pattern to the scheduled pattern. Meanwhile, to balance the load and generation, the independent system operator (ISO) requires to motivate the suppliers towards modifying their generation profiles to follow the changes in the load demands. Additionally, to protect the entities' privacy, the ISO needs to apply an effective well-designed pricing scheme. In this paper, we focus on proposing a decentralized DR framework considering the operating constraints of the grid. In our proposed framework, each individual entity responds to the control signals called conjectured prices from the ISO to modify its demand or generation profile with the locally-available information. We formulate the centralized problem of the ISO that jointly minimizes the suppliers' generation cost and the consumers' discomfort cost. We also discuss how the ISO determines the conjectured prices to motivate the entities towards an operating point that coincides with the solution to the centralized problem. The performance of the proposed algorithm is evaluated on a modified IEEE 14-bus in reducing the suppliers' and consumers' cost, as well as the transmission lines congestion.**

***Keywords*: demand response, discomfort cost, power flow problem, decentralized algorithm.**

I. INTRODUCTION

One of the fundamental goals of the stable and efficient operation of power networks is to balance the supply and load demand [1]. Conventionally, a major portion of the demand has been supplied by bulk power plants [2]. This task is the responsibility of the independent system operator (ISO) to determine the proper generation levels to maintain the optimal operation of the power networks [3]. Nowadays, with the deployment of intelligent devices and communication infrastructure in smart grid, the demand side is able to play an active role in the energy management task to balance demand and supply [4]–[6]. In particular, a well-designed price-based demand response (DR) program can motivate consumers towards modifying their demand voluntarily in reaction to the electricity price fluctuations in the market [7], [8].

Manuscript was received on May 6, 2017, revised on Sept. 23, 2017, and accepted on Nov. 4, 2017.

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The responses of different consumers in a DR program mainly depend on their load demand flexibility. In particular, each consumer incurs a *discomfort cost* by changing its load demand from the *desired* pattern (without DR) to the *scheduled* pattern (with DR). In this paper, we use a simple but effective model, namely the weighted distance between the scheduled and the desired load profiles to model the consumer's discomfort cost. We take advantage of the weight coefficients for each hour to capture the consumers' discomfort level based on the changes in the load demand in the DR program. Nevertheless, the values of the weight coefficients are *private* information for the consumers. Thus, the ISO is not able to manage the load demand directly in a centralized manner. Instead, the ISO requires to incentivize the consumers toward load shifting using locally available information. It should also encourage suppliers to modify their generation levels to balance the generation and demand.

There have been some efforts in the power system operation literature to tackle the above-mentioned challenges. We divide the related works into two threads. The first thread of the literature is concerned with DR programs and their role in the power system operation analysis. Parvania *et al.* [9] presented a stochastic DR model based on a two-stage stochastic mixed-integer programming in wholesale electricity market. Aghaei *et al.* [10] studied the effect of DR programs on improving the power system's reliability. Parvania *et al.* [11] proposed a hierarchical bidding framework for DR programs considering the customer preferences. Shi *et al.* [12] proposed a DR scheme for residential households considering the AC power flow constraints in distribution networks. Amini *et al.* [13] presented a mixed-integer linear programming to optimize the energy scheduling of home appliances. Li *et al.* [14] formulated the DR problem as an OPF problem, whose objective is to maximize the aggregate consumer payoff and minimize the power line losses. These studies, however, have not considered either the consumers' discomfort from participating in DR program or a decentralized approach to preserve the consumers' privacy.

The second thread of the literature is concerned with modeling the interactions between multi-supplier and multi-consumers in the DR programs. Chai *et al.* [15] studied the DR problem in the system with multiple utility companies

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and multiple residential customers. Deng *et al.* [16] proposed a distributed real-time DR algorithm considering multiple utility companies to determine each consumer's demand and each utility company's supply. To this end, they deployed dual decomposition method to perform the energy allocation. Disfani *et al.* [17] proposed a distributed algorithm to solve DCOPF problem for radial power networks. Mahrjan *et al.* [18] studied the DR program based on a Stackelberg game between utility companies and customers. Haider *et al.* [19] proposed a novel DR scheme based on adaptive consumption level pricing to optimize customers' energy consumption and bill payment. Although the mentioned works focused on modeling the consumers' and suppliers' models, they have neglected the network constraints.

Despite its importance, the possibility of adopting DR programs to achieve an optimal operating point of power network has not been well-investigated. In this paper, we focus on designing a decentralized algorithm to minimize the total cost of the system. The challenges that we address in this paper are protecting the privacy of consumers and suppliers by considering each individual entity's local optimization problem, as well as determining the appropriate control signals for the ISO to motivate the consumers and suppliers toward modifying their demand and generation profiles by taking into account the network's operating constraints. The main contribution of this paper are as follows:

- *Centralized Approach:* We formulate a centralized optimization problem for the ISO to minimize the social cost, i.e., the consumers' discomfort cost and suppliers' generation cost, subject to the power network operating constraints. We show that the solution to the ISO's centralized problem exists and is unique. However, the ISO requires all the private information about the consumers' discomfort cost and the suppliers' generation cost to obtain the solution to the centralized problem.
- *Decentralized Approach:* To maintain the privacy of the consumers and suppliers in the DR program, we propose a decentralized energy trading algorithm. In the proposed algorithm, the ISO provides the entities with control signals. In response, the consumers and suppliers obtain their optimal load and generation levels, respectively. We show that, under some specific control signals from the ISO, the decentralized algorithm will converge to the unique solution of the ISO's centralized problem.
- *Performance Evaluation:* Simulation results on an IEEE 40-bus test system show that the proposed decentralized algorithm can converge to the global optimal solution to the centralized problem of the ISO in about 50 iterations. The proposed algorithm also benefits both the consumers by reducing their cost by 13.5% and the generators by decreasing their cost by 18.8% and reducing the peak-to-average ratio (PAR) by 15.74%. When compared with the centralized approach, our algorithm has a significantly lower computational time. when compared with a centralized method with AC power flow in different test systems, our approach has a lower running time at the cost of 3% to 8% error due to the DC power flow approximation.

The rest of this paper is organized as follows. Section II introduces the system model. Section III presents the formulation for the ISO's centralized and decentralized problems. A distributed algorithm is proposed to solve the decentralized problem. Section IV provides the simulation results to evaluate the performance of the proposed algorithm. Section V concludes the paper.

II. System Model

Consider a transmission network with a set $\mathcal{N}$ of buses and a set $\mathcal{L} \subseteq \mathcal{N} \times \mathcal{N}$ of lines. Each bus $i \in \mathcal{N}$ may have an electricity supplier or load demand. Each bus is equipped with a bus service entity (BSE), which is responsible for providing the electric services to the suppliers and consumers connected to that bus. Each BSE uses the two-way communication infrastructure to exchange information about the amount of electricity that the suppliers and consumers in that bus are willing to either sell to or purchase from the market. The ISO is a neutral entity aiming to provide the BSEs with a proper access to the electricity market, as well as managing the power flows. The planning horizon is denoted by $\mathcal{H} = \{1, \ldots, H\}$, where H is the number of time slots with an equal length.

A. Power Network Model

The ISO considers the DC power flow to study the power flow through the transmission lines and the generation-load balance [20], [21]. Let $\delta_{i,h}$ denote the phase angle of the voltage in bus $i \in \mathcal{N}$ in time slot $h \in \mathcal{H}$. Let vector $\boldsymbol{\delta}_h = (\delta_{i,h},\, i \in \mathcal{N})$ denote the profile of voltage phase angles in all buses in time slot h. Let $P_{i,h}$ denote the injected active power to bus $i \in \mathcal{N}$. Also, let $\mathbf{P}_h = (P_{i,h},,\, i \in \mathcal{N})$ denote the vector of injected active power in all buses in time slot h. The power balance equation in time slot h can be represented as the following matrix equation:

$$\mathbf{P}_h = \mathbf{B}^{\mathrm{T}} \boldsymbol{\delta}_h, \qquad h \in \mathcal{H}, \tag{1}$$

where $\mathbf{B}$ is the network admittance matrix, and $\mathbf{B}^{\mathrm{T}}$ is the transpose of matrix $\mathbf{B}$. The entry $B_{i,j}$ corresponding to row i and column j of matrix $\mathbf{B}$ is

$$B_{i,j} = \begin{cases} \sum\limits_{(i,k)\in\mathcal{L}} b_{i,k}, & \text{if } i = j, \\ -b_{i,j}, & \text{otherwise.} \end{cases} \tag{2}$$

where $b_{i,j}$ represents the susceptance measured in Siemens of transmission line $(i, j) \in \mathcal{L}$. Let $P^G_{i,h}$ denote the output power of the supplier in bus i in time slot h. Let $l_{i,h}$ denote the load demand in bus i in time slot h. From (1) and (2), we have the following power balance equation:

$$P^G_{i,h} - l_{i,h} = \sum_{j:(i,j)\in\mathcal{L}} b_{i,j}(\delta_{i,h} - \delta_{j,h}), \;\; i \in \mathcal{N}. \tag{3}$$

We assume that bus one is the slack bus. Thus, we have

$$\delta_{1,h} = 0, \qquad h \in \mathcal{H} \tag{4}$$

Let $P_{i,j}^{\max}$ denote the maximum line flow limit of line $(i,j) \in \mathcal{L}$. Considering (1) and (2), we can determine the line flow constraint as follows:

$$-P_{i,j}^{max} \leq b_{i,j}(\delta_{i,h} - \delta_{j,h}) \leq P_{i,j}^{max}, \ \ (i,j) \in \mathcal{L}, \, h \in \mathcal{H}, \quad (5)$$

One can also take into account the contingency scenarios for transmission lines outage. It is sufficient to construct the admittance matrix $\mathbf{B}$ corresponding to the possible contingency scenarios and include constraints (3)$-$(5) for the phase angles and power flows in the contingency scenarios.

B. Bus Service Entity (BSE) Model

The BSEs can be classified based on their *types*. We partitioned the set of BSEs in the system to *active flexible* BSEs and *passive non-flexible* BSEs. An active flexible BSE sets the generation profile of the supplier and the demand profile of the consumer connected to the corresponding bus. A passive non-flexible BSE does not have any control on the generation and load levels of its entities since the generator connected to that bus may be non-dispatchable and the consumer may not prefer to modify their demand profiles.

The generation cost function of supplier i in time slot h is denoted by $C_i(P_{i,h}^G)$. It is generally an increasing convex function of the output power $P_{i,h}^G$ [22]. The class of polynomial generation cost functions is well-known since it can be estimated by Taylor polynomials [23]. It can be expressed as:

$$C_i(P_{i,h}^G) = \alpha_m \left(P_{i,h}^G\right)^m + \cdots + \alpha_1 P_{i,h}^G + \alpha_0, \quad (6)$$

where m is the degree of the function, and $\alpha_m, \dots, \alpha_0$ are the coefficients [23]. The active flexible BSE$_i$ can manage the output power the generator in bus i. Therefore, $P_{i,h}^G,\ h \in \mathcal{H}$ is a decision variable for BSE$_i$. Whereas, $P_{i,h}^G,\ h \in \mathcal{H}$ is a priori known for a passive BSE$_i$. The generation cost function in (6) is a *private information* of the BSE$_i$, who wants to actively participate in the energy market. Let $\mathbf{P}_i^G = (P_{i,h}^G,\ h \in \mathcal{H})$ denote the generation profile during the operation horizon $\mathcal{H}$ for the supplier connected to bus i. The total generation cost of the supplier in bus i is obtained as

$$C_i(\mathbf{P}_i^G) = \sum_{h \in \mathcal{H}} C_i(P_{i,h}^G), \quad i \in \mathcal{N}. \quad (7)$$

The generation level of the supplier in bus i is within the minimum and maximum limits $P_i^{G,\min}$ and $P_i^{G,\max}$. We have

$$P_i^{G,\min} \leq P_{i,h}^G \leq P_i^{G,\max}, \qquad \forall\, i \in \mathcal{N},\, \forall\, h \in \mathcal{H}. \quad (8)$$

Similar to [24], [25], one can also consider other operating constraints (e.g., spinning reserve, ramp up/down constraints) for the generators. In addition to controlling the output power of the generator, the active BSE$_i$ may modify the demands of its consumers to benefit from the electricity price fluctuations over the time. The demand $l_{i,h}$ in bus i in time slot h consists of a fixed baseload demand $l_{i,h}^{\mathrm{b}}$, as well as the flexible demand $l_{i,h}^{\mathrm{c}}$ of a set $\mathcal{A}_i$ of controllable loads for the consumers in bus i.

Although BSE$_i$ considers the scheduling horizon $\mathcal{H}_{a,i} \subseteq \mathcal{H}$ to schedule each controllable load $a \in \mathcal{A}_i$, different controllable loads have different characteristics. We divide the set of controllable loads in bus i into set $\mathcal{A}_i^1 \subseteq \mathcal{A}_i$ of controllable loads of type 1, and set $\mathcal{A}_i^2 \subseteq \mathcal{A}_i$ of controllable loads of type 2. A controllable load of type 1 has a hard deadline. That is, it should be operated within the scheduling horizon and turned off in other time slots. Examples include the household's electric vehicle (EV) and production line of an industry. A controllable load of type 2 is more flexible, and can be operated in the time slots out of the scheduling horizon, but at the cost of a relatively high discomfort for the consumer, e.g., the lighting in households, packing process in industries, and air conditioner in commercial buildings.

Considering the demands $x_{a,i,h}$ of controllable loads $a \in \mathcal{A}_i$ in time slots $h \in \mathcal{H}$ as the decision variables for BSE$_i$, we have the following operational constraints:

$$x_{a,i,h} = 0, \qquad a \in \mathcal{A}_i^1,\ h \notin \mathcal{H}_{a,i}, \quad (9a)$$

$$x_{a,i,h} \geq 0, \qquad a \in \mathcal{A}_i^2,\ h \notin \mathcal{H}_{a,i}, \quad (9b)$$

$$x_{a,i,h}^{\min} \leq x_{a,i,h} \leq x_{a,i,h}^{\max}, \qquad a \in \mathcal{A}_i^1 \cup \mathcal{A}_i^2,\ h \in \mathcal{H}_{a,i}, \quad (9c)$$

$$X_{a,i,h}^{\min} \leq \textstyle\sum_{h \in \mathcal{H}} x_{a,i,h} \leq X_{a,i}^{\max}, \quad a \in \mathcal{A}_i^1 \cup \mathcal{A}_i^2. \quad (9d)$$

Constraints (9a) and (9b) are obtained from the flexibility of loads of types 1 and 2, respectively. Constraint (9c) indicates limited demand variation for load a in time slot h. Constrain (9d) indicates limited total energy demand of load a to complete its task.

Scheduling the controllable loads usually results in a discomfort cost for the consumers of the BSE$_i$. The discomfort cost for type 1 loads only depends on the total power consumption deviation from the desirable value (e.g., a consumer cares about the total charging level of its electric vehicle). For the scheduled power consumption profile $\mathbf{x}_{a,i} = (x_{a,i,h},\ h \in \mathcal{H})$ and desirable profile $\mathbf{x}_{a,i}^{\text{des}} = (x_{a,i,h}^{\text{des}},\ h \in \mathcal{H})$, a viable candidate for the discomfort cost of loads of type 1 is

$$\Upsilon_{a,i}(\mathbf{x}_{a,i}) = \omega_{a,i} \sum_{h \in \mathcal{H}_{a,i}} (x_{a,i,h} - x_{a,i,h}^{\text{des}})^2, \quad a \in \mathcal{A}_i^1, \quad (10)$$

where $\omega_{a,i}$ in \$/(kWh)^2 is a nonnegative constant. The discomfort cost for type 2 loads depends on both the amount of power consumption and the time of consuming the power. The following discomfort cost function is a viable candidate:

$$\Upsilon_{a,i}(\mathbf{x}_{a,i}) = \sum_{h \in \mathcal{H}_{a,i}} \omega_{a,i,h}(x_{a,i,h} - x_{a,i,h}^{\text{des}})^2 + \sum_{h \notin \mathcal{H}_{a,i}} \omega'_{a,i,h}\, x_{a,i,h}, \qquad a \in \mathcal{A}_i^2, \quad (11)$$

where $\omega_{a,i,h}$ in \$/(kWh)^2 and $\omega'_{a,i,h} \gg \omega_{a,i,h}$ in \$/kWh are *time dependent* nonnegative coefficients. By defining $\mathbf{x}_i = (\mathbf{x}_{a,i},\ a \in \mathcal{A}_i)$ for bus i, the total discomfort cost is

$$\Upsilon_i(\mathbf{x}_i) = \sum_{a \in \mathcal{A}_i^1 \cup \mathcal{A}_i^2} \Upsilon_{a,i}(\mathbf{x}_{a,i}). \quad (12)$$

III. Problem Formulation

In this section, we first assume that the BSEs reveal all information about the generation cost of the supplier and discomfort cost of the demand in their corresponding bus to the ISO. We propose a centralized approach to determine the optimal operating point of the network in the energy market.

A. Centralized Approach for the ISO

Let vector $\mathbf{x} = (\mathbf{x}_i,\, i \in \mathcal{N})$ denote the vector of load demand profiles of all consumers in the network. Also, let vector $\mathbf{P}^G = (\mathbf{P}_i^G,\, i \in \mathcal{N})$ denote the vector of generation profiles of all suppliers in the network. We define the objective function $f^{\rm ISO}\left(\mathbf{P}^G, \mathbf{x}\right)$ of the ISO as

$$f^{\rm ISO}\left(\mathbf{P}^G, \mathbf{x}\right) = \sum_{i \in \mathcal{N}} \Big(\theta_i \Upsilon_i(\mathbf{x}_i) + (1-\theta_i) C_i(\mathbf{P}_i^G)\Big), \quad (13)$$

where $\theta_i,\, i \in \mathcal{N}$ are the weight coefficients in the interval $[0,\, 1]$. Minimizing $f^{\rm ISO}\left(\mathbf{P}^G, \mathbf{x}\right)$ will enable timely adjustment of the control settings to jointly optimize the consumers' discomfort cost and the suppliers' generation cost. Thus, it can improve the economic efficiency of the system operation. We formulate the ISO's centralized problem as

$$\begin{aligned} &\underset{\mathbf{P}^G,\, \mathbf{x},\, \boldsymbol{\delta}}{\text{minimize}} \ f^{\rm ISO}\left(\mathbf{P}^G, \mathbf{x}\right) \\ &\text{subject to constraints (3)–(5), (8), and (9).} \end{aligned} \quad (14)$$

We characterize the optimal solution to problem (14) in the following proposition.

Proposition 1: The solution to the ISO's centralized problem (14) exists and is unique.

Proof: Our proof involves two steps. We first show that (14) is a convex optimization problem with closed and bounded feasible space. Second, we show that the objective function (13) is lower bounded. Consequently, if problem (14) has a feasible solution, then it will have a unique minimizer.

The objective function (13) is convex with respect to variable vector $\boldsymbol{\psi}^{\rm ISO}$ because the discomfort cost $\Upsilon_i(\mathbf{x}_i)$ is a quadratic function (and thus a convex function) of $\boldsymbol{x}_{a,i}$ and the generation cost function $C_i(\mathbf{P}_i^G)$ is a convex function for (8). The constraints of problem (14) are all linear, and by considering one bus as a slack bus (e.g., bus 1 with $\delta_{1,h} = 0,\, h \in \mathcal{H}$), the feasible space would be closed and bounded. Therefore, problem (14) is a convex optimization problem. In addition, all terms in the objective function (13) are nonnegative, and thus the objective function (13) is lower bounded by zero. The proof is completed. ■

To solve problem (14), the ISO requires complete information about the consumers' discomfort cost and suppliers' generation cost at all buses. However, these information are never available to the ISO in practice. Instead of a centralized approach, we can develop a decentralized algorithm for the ISO to determine the unique solution of problem (14).

B. Energy Market Competition

In practice, the ISO has no direct control over the suppliers' and consumers' behaviour. Instead, the ISO may only influence the BSEs by using some control signals. The ISO provides the BSE at each bus with an access to the energy market to determine its optimal generation and load demand. In this case, the flexible active BSEs compete with each other, such that the costs of their supplier and demand are minimized. In the energy market, the decision vector of BSE_i is $(\mathbf{P}_i^G, \mathbf{x}_i)$.

In the energy market, each BSE_i will purchase electricity from the ISO with price $\rho_{i,h}^{\rm cons}$ and sell electricity to the market with price $\rho_{i,h}^{\rm gen}$ in time slot $h \in \mathcal{H}$. We define the row vectors of prices as $\boldsymbol{\rho}_i^{\rm cons} = (\rho_{i,h}^{\rm cons},\, h \in \mathcal{H})$ and $\boldsymbol{\rho}_i^{\rm cons} = (\rho_{i,h}^{\rm gen},\, h \in \mathcal{H})$. The BSE_i aims to determine the optimal decision vector $\mathbf{d}_i = (\mathbf{P}_i^G, \mathbf{x}_i)$ to jointly minimize the generation cost of its supplier, the discomfort cost of its controllable demands, and the profit from trading in the market. The objective function of the BSE_i can be expressed as

$$\begin{aligned} f_i^{\rm BSE}\left(\mathbf{P}_i^G, \mathbf{x}_i\right) = &\ \Upsilon_i(\mathbf{x}_i) + C_i(\mathbf{P}_i^G) \\ &+ \boldsymbol{\rho}_i^{\rm cons} \bullet (\mathbf{l}_i)^{\rm T} - \boldsymbol{\rho}_i^{\rm gen} \bullet (\mathbf{P}_i^G)^{\rm T}, \end{aligned} \quad (15)$$

where $\bullet$ is the inner-product operation. In (15), the term $\boldsymbol{\rho}_i^{\rm cons} \bullet (\mathbf{l}_i)^{\rm T}$ is equal to the total payment of BSE_i to the ISO to purchase electricity with amounts of $\mathbf{l}_i = (l_{i,h},\, h \in \mathcal{H})$. The term $\boldsymbol{\rho}_i^{\rm gen} \bullet (\mathbf{P}_i^G)^{\rm T}$ is equal to the total revenue of BSE_i from selling electricity with amounts of $\mathbf{P}_i^G = (P_{i,h}^G,\, h \in \mathcal{H})$. The local optimization problem of BSE_i is

$$\begin{aligned} &\underset{\mathbf{P}_i^G, \mathbf{x}_i}{\text{minimize}} \ f_i^{\rm BSE}\left(\mathbf{P}_i^G, \mathbf{x}_i\right) \\ &\text{subject to constraints (8) and (9).} \end{aligned} \quad (16)$$

From (16), the optimization problem for each BSE_i does not directly include any signal from other BSEs' decision variables. Furthermore, the BSEs do not care about these constraints in their optimization problem and only cares about minimizing the cost of supplier and demand in their corresponding buses. On the other hand, the ISO is responsible for meeting the network constraints (3)–(5). The ISO is able to set the prices $\boldsymbol{\rho}_i^{\rm cons}$ and $\boldsymbol{\rho}_i^{\rm gen}$ for all buses $i \in \mathcal{N}$ to motivate the BSEs towards the unique solution of the centralized problem (14). One possible technique is to use the *dual decomposition* method. Let $\lambda_{i,h},\, h \in \mathcal{H}, i \in \mathcal{N}$ denote the Lagrange multiplier associated with the equality constraint (3). We define vector $\boldsymbol{\lambda} = (\lambda_{i,h},\, i \in \mathcal{N},\, h \in \mathcal{H})$. Using the defined Lagrange multipliers, we can rewrite the Lagrangian of the objective function (13) as follows:

$$\begin{aligned} &f_{\rm Lag}^{\rm ISO}\left(\mathbf{P}^G, \mathbf{x}, \boldsymbol{\lambda}\right) = \\ &\sum_{i \in \mathcal{N}} \Big(\theta_i \Upsilon_i(\mathbf{x}_i) + (1-\theta_i) C_i(\mathbf{P}_i^G)\Big) \\ &+ \sum_{i \in \mathcal{N}} \sum_{h \in \mathcal{H}} \lambda_{i,h} \big(P_{i,h}^G - l_{i,h} - \sum_{j:(i,j) \in \mathcal{L}} b_{i,j}(\delta_{i,h} - \delta_{j,h})\big). \end{aligned} \quad (17)$$

The dual function is obtained as the minimum of $f_{\rm lag}^{\rm ISO}(\cdot)$ over the variables $\mathbf{P}^G$ and $\mathbf{x}$. That is, we have

$$\begin{aligned} &f_{\rm Dual}^{\rm ISO}(\boldsymbol{\delta}, \boldsymbol{\lambda}) = \\ &\sum_{i \in \mathcal{N}} \min_{\mathbf{P}_i^G, \boldsymbol{x}_i} \Big\{\theta_i \Upsilon_i(\mathbf{x}_i) + (1-\theta_i) C_i(\mathbf{P}_i^G) + \sum_{h \in \mathcal{H}} \lambda_{i,h} \big(P_{i,h}^G - l_{i,h}\big)\Big\} \\ &- \sum_{i \in \mathcal{N}} \sum_{h \in \mathcal{H}} \lambda_{i,h} \big(\sum_{j:(i,j) \in \mathcal{L}} b_{i,j}(\delta_{i,h} - \delta_{j,h})\big). \end{aligned} \quad (18)$$

The dual problem of the ISO's centralized problem is

$$\underset{\boldsymbol{\delta}, \boldsymbol{\lambda}}{\text{maximize}} \ f_{\rm Dual}^{\rm ISO}(\boldsymbol{\delta}, \boldsymbol{\lambda}) \quad (19a)$$

$$\text{subject to constraints (4) and (5).} \quad (19b)$$

The centralized problem (14) is convex and the constraints are linear. Thus, the strong duality gap condition (Slater's

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TPWRS.2017.2771279, IEEE Transactions on Power Systems

condition) is satisfied if a feasible solution exists (see [26, Proposition 5.2.1]). That is, the optimal solution to the dual problem (19) is equal to the optimal solution to the ISO's centralized problem (14) [26, Ch. 6]. We can write the Karush–Kuhn–Tucker (KKT) conditions for the the dual problem (19) and the BSEs local problems in (16) and if they become then the solution to the BSEs local problems coincides with the unique solution to the ISO's centralized problem in (14). By performing some algebraic manipulations, we have

$$\rho_{i,h}^{\text{cons}} = \frac{-\lambda_{i,h}}{\theta_i}, \quad \rho_{i,h}^{\text{gen}} = \frac{-\lambda_{i,h}}{1-\theta_i}, \tag{20}$$

The nodal prices $\boldsymbol{\rho}_i^{\text{cons}}$ and $\boldsymbol{\rho}_i^{\text{gen}}$ are the control signals sent by the ISO to the BSEs. Then, the BSEs communicate this nodal prices to the consumers and suppliers in their corresponding bus. Now, we develop a *decentralized* algorithm to model the interactions among the BSEs and ISO. Fig. 1 shows the interactions among ISO and BSEs in the energy market. Let k denote the iteration index. The superscript k for an arbitrary variable represents its value in iteration k. Our algorithm involves the *initiation phase* and *trading phase*.

Initiation phase: Set iteration index k to 1. The BSE_i initializes the consumers' controllable load profile $\mathbf{x}_i^1$ and the supplier's generation $\mathbf{P}_i^{G,1}$. The ISO initializes the voltage angles $\boldsymbol{\delta}^1$ and Lagrange multipliers $\boldsymbol{\lambda}^1$.

Trading phase: In iteration k, the BSEs and ISO update their decision variables. This phase includes the following parts:

- *Information exchange:* It involves the information exchange between the BSEs and ISO about the consumption profile and the generation levels. BSE_i sends the total load demand $\mathbf{l}_i^k = (l_{i,h}^k,\, h \in \mathcal{H})$ of its consumers and the generation profile $\mathbf{P}_i^{G,k} = (P_{i,h}^{G,k},\, h \in \mathcal{H})$ of its suppliers in iteration k to the ISO via the communication network.
- *ISO update:* When the ISO receives the information from all BSEs, it updates the voltage angles $\delta_{i,h}^k$ for $i \in \mathcal{N}$, $h \in \mathcal{H}$ and the Lagrange multipliers $\boldsymbol{\lambda}^k$ according to the following projected gradient-based update process:

$$\boldsymbol{\delta}^{k+1} = \left[\boldsymbol{\delta}^k + \alpha^k \nabla_{\boldsymbol{\delta}^k} f_{\text{Dual}}^{\text{ISO}}(\boldsymbol{\delta}^k, \boldsymbol{\lambda}^k)\right]^+, \tag{21a}$$

$$\boldsymbol{\lambda}^{k+1} = \boldsymbol{\lambda}^k + \alpha^k \nabla_{\boldsymbol{\lambda}^k} f_{\text{Dual}}^{\text{ISO}}(\boldsymbol{\delta}^k, \boldsymbol{\lambda}^k), \tag{21b}$$

where ∇ is the gradient operator, and $[\cdot]^+$ is the projection onto the feasible set defined by constraint (19b). By updating vector $\boldsymbol{\lambda}^{k+1}$, the ISO determines the updated values of the nodal prices $\rho_{i,h}^{k+1}$, $h \in \mathcal{H}$ as

$$\rho_{i,h}^{\text{cons},k+1} = \frac{-\lambda_{i,h}^{k+1}}{\theta_i}, \quad \rho_{i,h}^{\text{gen},k+1} = \frac{-\lambda_{i,h}^{k+1}}{1-\theta_i}, \tag{22}$$

The ISO sends the updated control signals $\rho_{i,h}^{\text{cons},k+1}$ and $\rho_{i,h}^{\text{gen},k+1}$, $h \in \mathcal{H}$ to BSE_i.
- *BSE update:* When BSE_i receives the trading nodal prices from the ISO, it updates its objective function in (15) as

$$\begin{aligned} f_i^{\text{BSE},k+1}\left(\mathbf{P}_i^G, \mathbf{x}_i\right) = \; & \Upsilon_i(\mathbf{x}_i) + C_i(\mathbf{P}_i^G) \\ & + \boldsymbol{\rho}_i^{\text{cons},k+1} \bullet (\mathbf{l}_i)^{\text{T}} - \boldsymbol{\rho}_i^{\text{gen},k+1} \bullet (\mathbf{P}_i^G)^{\text{T}}, \end{aligned} \tag{23}$$

and then, it solves the following convex problem to obtain

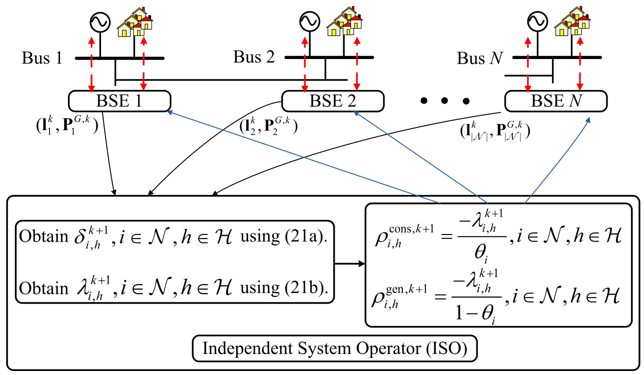

Fig. 1. Interactions of the consumers and suppliers with the ISO.

the updated profiles $\mathbf{x}_i^{k+1}$ and $\mathbf{P}_i^{G,k+1}$:

$$(\mathbf{P}_i^{G,k+1}, \mathbf{x}_i^{k+1}) = \underset{(8) \text{ and } (9)}{\text{argmin}} \; f_i^{\text{BSE},k+1}\left(\mathbf{P}_i^G, \mathbf{x}_i\right) \tag{24}$$

- *Step size update:* We use a nonsummable diminishing step size for the ISO with conditions $\lim_{k\to\infty} \alpha^k = 0$, $\sum_{k=1}^{\infty} \alpha^k = \infty$, and $\sum_{k=1}^{\infty} \left(\alpha^k\right)^2 = \infty$. One example is $\alpha^k = \frac{1}{a+bk}$, where a and b are positive constant coefficients.
- Update the iteration number; $k := k+1$.

Remark 1: For the stopping criterion, we use the convergence of the voltage angles for tolerance ξ, i.e., $||\delta_{i,h}^k - \delta_{i,h}^{k-1}|| \le \xi$, $h \in \mathcal{H}, i \in \mathcal{N}$, since they depend on the generation and load level at all buses. Hence, the convergence of the voltage angles implies the convergence of all BSEs' decision variables.

Remark 2: Our algorithm is based on the projected gradient method and it is guaranteed to converge for the above-defined diminishing step size. In Section IV, we show that our proposed algorithm can converge to the optimal solution of centralized problem (14) in a reasonable number of iterations. The proposed Lagrange relaxation-based algorithm works well for the underlying ISO's centralized problem (14) with convex objective function and linear constraints.

Remark 3: The proposed decentralized framework is designed for day-ahead electricity markets. Hence, it is not necessary for the algorithm to be feasible in all iterations. Nevertheless, when the algorithm converges, the solution is feasible and satisfies the network constraints.

IV. Performance Evaluation

In this section, we evaluate the performance of our proposed distributed algorithm.

A. Simulation Setup

We divide a day into $H = 24$ one-hour time slots. We simulate our approach on the IEEE 14-bus test system with 5 suppliers serving the loads scattered in different buses. The topology of the test system is shown in Fig. 2. The test system data can be found in [27]. To obtain different baseload patterns for the consumers, we use a load pattern for about 5 million consumers (which includes residential, commercial,

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and industrial consumers) from Ontario, Canada power grid database [28] from June 1 to June 21, 2016. Without loss of generality, we scale the load pattern for each bus, such that the average baseload becomes equal to 60% of the load demand of that bus in [27]. To simulate the controllable load demand of each bus, we randomly generate the *desirable* load profile of 50 to 100 controllable loads of types 1 and 2 with average demand of 2 to 25 kW at each bus. Limits $x^{\max}_{a,i,h}$ and $x^{\min}_{a,i,h}$ for a controllable load a in bus i are set to $\pm 30\%$ of the desirable demand of that load in time slot h. Limits $X^{\max}_{a,i}$ and $X^{\min}_{a,i}$ for a controllable load a in bus i are set to $\pm 5\%$ of the desirable total energy demand of that load. The discomfort coefficients $\omega_{a,i}$ and $\omega_{a,i,h}$, $h \in \mathcal{H}$ for each controllable load a are randomly chosen from a truncated normal distribution, which is lower bounded by zero and has a mean value of $\omega_i^{\text{avg}} = 15\,\$/(\text{kWh})^2$ and a standard deviation of $0.5\,\$/(\text{kWh})^2$. The discomfort coefficients $\omega'_{a,i,h}$, $h \in \mathcal{H}$ for each controllable load a of type 2 are set to $0.5\,\$/(\text{kWh})^2$. The step size is $\alpha^k = \frac{1}{10+0.2k}$. The weight coefficients θ_i are set to 0.5. We perform simulations using Matlab R2016b in a PC with processor Intel(R) Core(TM) i7-3770K CPU@3.5 GHz.

B. Algorithm Convergence

To evaluate the convergence of our proposed algorithm, we study the required number of iterations to converge, which can be interpreted as the number of message exchange among the BSEs and ISO over the communication infrastructure. We consider the convergence of the voltage angles in different buses. As an concrete example, we provide the values of voltage angles of buses 6, 10, 11, and 12 in Figs. 3 and 4 that require the highest number of iterations to converge. Notice that by solving the power flow problem, the values of the voltage angles of all buses can be added by a constant without changing the flow of the lines, and thus, the difference between the voltage angles are important. Hence, we also show the difference between the voltage angles of the connected buses $\delta_{12} - \delta_6$ and $\delta_{11} - \delta_{10}$. We can observe that 50 iterations are sufficient for the convergence of the algorithm. Our proposed algorithm is based on the projected gradient method and has $O(\xi)$ running time for diminishing step size. We set $\xi = 10^{-2}$. The average CPU time of the algorithm is 10.7 seconds.

We use MOSEK to solve the ISO's centralized problem (14). The solution is the same as the decentralized approach, but the CPU time is 30 seconds. To further elaborate the comparison, we provide the average CPU time of our proposed algorithm and the centralized approach for six test systems [27] in Fig. 5. The significant lower CPU time of the decentralized approach is due to the BSEs' parallel update and smaller number of decision variables in their local problems.

Finally, we use the approach in [29] that applies semidefinite programming (SDP) to obtain the global optimal point in a grid with AC power flow model. In addition to comparing the algorithm running time, the global optimality of the solution to the full AC power flow enables us to quantify the approximation in using the DC power flow in our decentralized algorithm. The main difference is that the AC power flow includes the network losses. Furthermore, the SDP approach

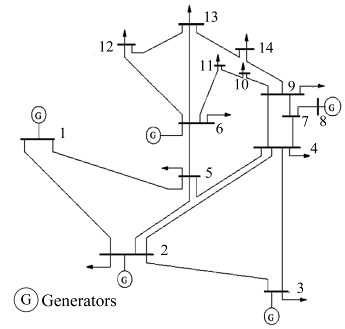

Fig. 2. IEEE 14-bus test system used for simulations.

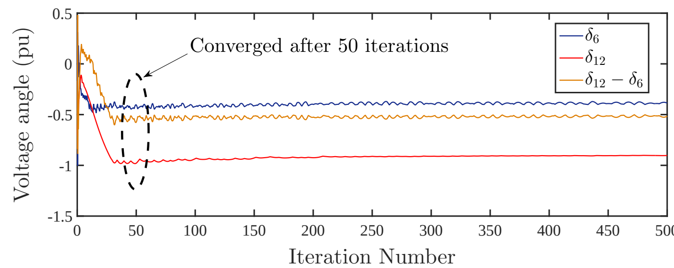

Fig. 3. The convergence of δ_6, δ_{12}, and $\delta_{12} - \delta_6$.

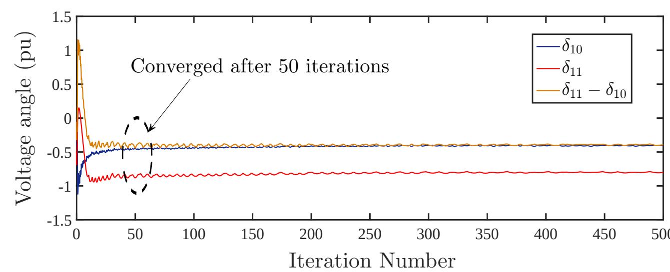

Fig. 4. The convergence of δ_{10}, δ_{11}, and $\delta_{11} - \delta_{10}$.

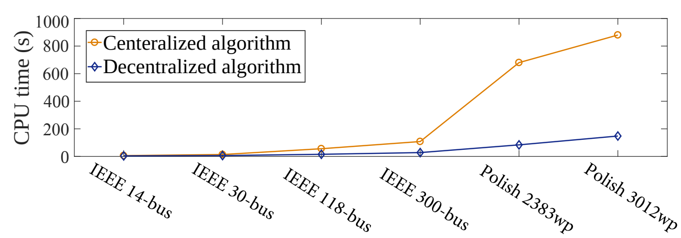

Fig. 5. The CPU time of the centralized and decentralized algorithms.

in [29] returns the global optimal solution to the AC OPF. We consider the constant power factor of 0.5 for the loads. The calculation results show that the values of the ISO's objective using our algorithm with DC OPF are lower by 3% (in Polish 2383wp) to 8% (in IEEE 300-bus system) than the centralized method with AC OPF and SDP approach due to the inclusion of losses and optimality of the SDP method. Whereas, the computation time is much lower in our proposed algorithm.

C. BSE's Benefit from the Proposed Algorithm

The consumers of an arbitrary BSE can respond to the control signals communicated by the ISO and decide to modify their controllable load demand during the day. Fig. 6 shows the

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TABLE I
THE OPTIMAL VALUE AND AVERAGE CPU TIME FOR THE DETERMINISTIC MULTI-STAGE ALGORITHM AND OUR PROPOSED ALGORITHM.

	The proposed Algorithm		Centralized algorithm with AC OPF	
Test system	f^{ISO} (\$)	CPU time (s)	f^{ISO} (\$)	CPU time (s)
IEEE 14-bus	315,140.2	10.7	331,897.2	38.5
IEEE 30-bus	682,142.8	16.8	723,081.7	82.8
IEEE 118-bus	3,180,223.7	25.6	3,282,715.7	240.2
IEEE 300-bus	18,272,124.8	42.5	19,733,892.8	320.5
Polish 2383wp	42,167,127.1	136.3	43,432,562.4	1,512.5
Polish 3012wp	63,222,649.1	182.4	71,338,462.4	1,836.8

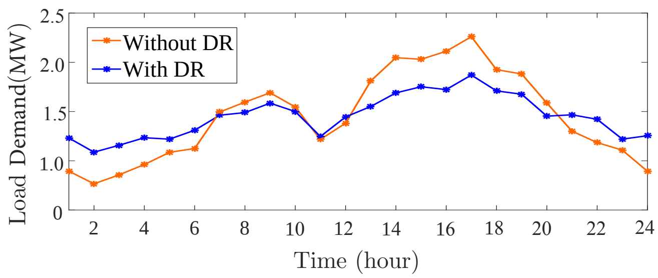

Fig. 6. The daily load profile for bus 2 with and without DR.

aggregate load profile in bus 2 with and without DR. We can observe that the consumers reduce their load demand during peak hours (from 13 pm to 20 pm) in order to reduce their payment to the ISO. We study the impact of the discomfort cost coefficients on the load shifting of the consumers in different buses. Fig. 7 shows the load shift percentage (i.e., the percentage of shifted load demand) in all buses for different values of coefficients ω_i^{avg}, $i \in \mathcal{N}$. We can observe that when ω_i^{avg} tends to ∞, the consumers will prefer not to change their load pattern as its discomfort cost increases significantly. By decreasing the value of ω_i^{avg}, the consumers will shift larger portion of their load demand from peak to off peak hours. Load shifting helps consumers to reduce their total cost. Fig. 8 shows that the total cost of the consumers in different buses with DR is lower by about 13.5% compared with their total cost without DR.

The suppliers of the BSEs also update their generation levels based on the received price signals from the ISO. Fig. 9 represents the generation of the suppliers in different buses. We can observe that using the proposed DR strategy makes the generation profiles of the suppliers smoother. In order to quantify the impact of the proposed DR algorithm on the generation profile, we consider the peak-to-average ratio, PAR_i, for the suppliers. Table II presents the value of PAR_i with and without demand response, as well as the percentage of reduction of this metric. The results shows 15.74% reduction in the PAR on average.

In addition to reducing the PAR in the generation, the suppliers can benefit from DR program by reducing their total cost (the generation cost minus the revenue from selling

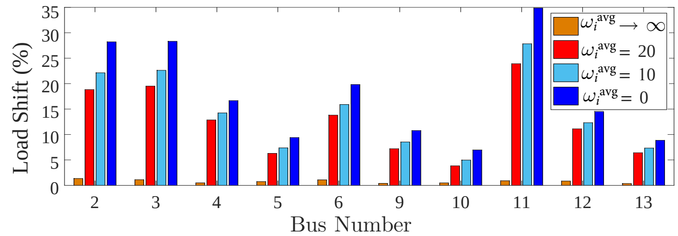

Fig. 7. Load shift percentage at all load buses with DR for different average coefficients ω_i^{avg}, $i \in \mathcal{N}$.

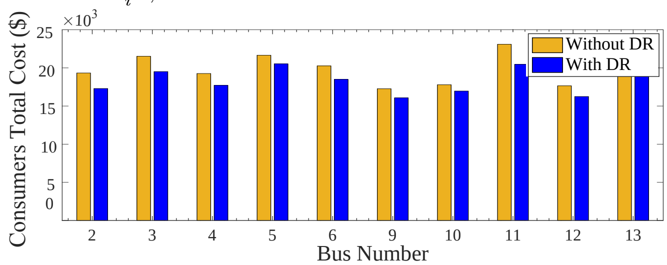

Fig. 8. Total cost of the consumers in different buses with and without DR program.

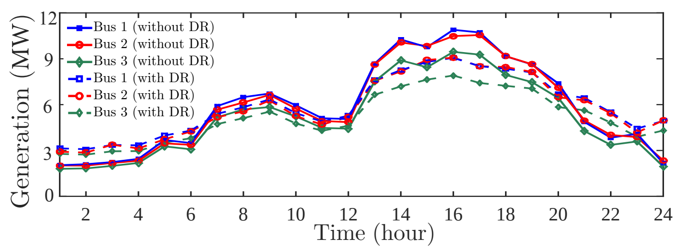

Fig. 9. Generation levels at buses 1, 2, and 3 with and without DR.

electricity). Generally, the revenue of the suppliers decreases due to the reduction in the peak load demand and the electricity price in most of the buses. However, the generation cost of the suppliers will also decrease during the peak hours. Considering both factors, Fig. 10 shows that the total cost of the suppliers will decreases with the DR program by about 18.8%. Notice that we have used the cost data available for the IEEE 14-bus test system to determine the generation cost of the suppliers. Here, revenue of suppliers were smaller than their generation cost, and thus their total cost is positive.

D. ISO's Benefit from the Proposed Algorithm

The DR program can lead to a smoother demand and generation profiles during the day. Hence, DR program can reduce the peak demand and generation, and thus prevent the congestion of the transmission lines during peak-hours by reducing the loading index. We define the branch loading index of line (i, j) as the calculated power flow divided by the maximum flow limit of the line. We have $\zeta_{i,j} = \frac{P_{i,j}}{P_{i,j}^{max}}$, $h \in \mathcal{H}$, $(i, j) \in \mathcal{L}$, where $\zeta_{i,j}$ denotes the branch loading index of line (i, j). In order to compare the branch loading index improvement, $\zeta_{i,j}$ for lines $(1, 5)$, $(3, 4)$, $(10, 11)$, and $(12, 13)$ with and without DR, at $h = 16$, are given in Table III. We can observe that the proposed DR algorithm benefits the ISO

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TABLE II
PAR$_i$ VALUES FOR DIFFERENT SUPPLIERS WITH AND WITHOUT DR

Bus Number	1	2	3	6	8
PAR$_i$ Without DR	1.875	1.802	1.562	1.611	1.721
PAR$_i$ With DR	1.512	1.509	1.325	1.385	1.474
PAR$_i$ Improvement	19.3%	16.2%	15.1%	14%	14.1%

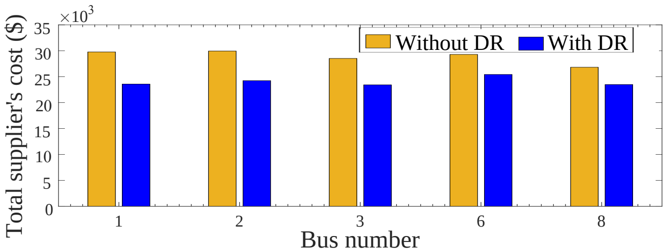

Fig. 10. Total cost of the suppliers with and without DR program.

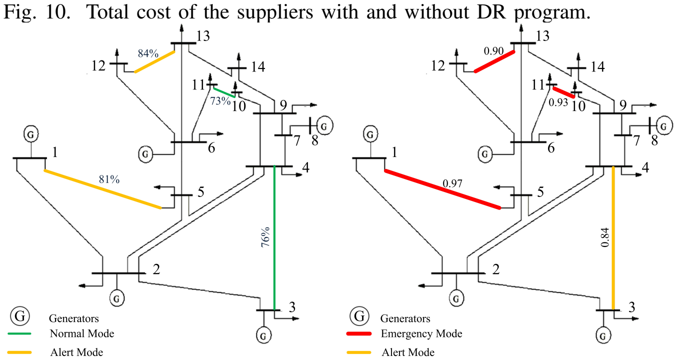

Fig. 11. Branch loading index in four lines at $h = 16$ with and without DR.

by reducing the loading of the lines; and thereby improving the load capability of the system. Fig. 11 shows the loading condition of the selected lines before and after implementing the DR algorithm. We use green color for lines with branch loading index lower than 80% operation mode, dark yellow for lines with branch loading index between 80% to 90%, and red color for the 91% to 100% loaded lines. Hereafter, these three modes are referred to as normal, alert, and emergency modes, respectively.

E. Comparing with the ADMM-based Algorithm

One can also propose an alternating direction method of multipliers (ADMM)-based algorithm [30] that still works with the partial Lagrange relaxation of the objective function (13) given in (17), but with an additional penalty term, namely the *augmentation*. Details on implementing the ADMM-based decentralized algorithm can be found in [30]. In a nutshell, for the ADMM-based algorithm, the ISO, broadcasts both the price signals and the generation and load levels of each BSE to other BSEs; hence, the privacy of the BSEs may not be protected. Furthermore, the ISO should broadcast information in series to the BSEs in each iteration, which increases the communication delay significantly. These two drawbacks are important, especially in practical implementation of a decentralized algorithm. However, in general, the ADMM-based algorithm can converge in a smaller number of iterations.

We provide the average CPU time in Table IV. We emphasize that the ADMM algorithm converges to the solution of the centralized problem due to the convexity of the centralized problem and satisfying the Slater's conditions [30]. We can observe that the CPU time with the ADMM-based algorithm is lower than our proposed algorithm. Using the ADMM algorithm, however, the ISO needs to provide each BSE with some additional information about other BSEs' decisions. This feature is not suitable for the energy markets, since the BSEs usually do not prefer to reveal their strategies.

TABLE III
BRANCH LOADING INDEX VALUES IN DIFFERENT LINES WITH AND WITHOUT DR

Line (i, j)	$(1, 5)$	$(3, 4)$	$(12, 13)$	$(10, 11)$
$\zeta_{i,j}$ Without DR	97%	84%	93%	90%
$\zeta_{i,j}$ With DR	81%	76%	73%	84%
$\zeta_{i,j}$ Improvement	16.4%	9.5%	21.5%	6.6%

TABLE IV
THE AVERAGE CPU TIME FOR OUR PROPOSED DECENTRALIZED ALGORITHM AND THE ADMM-BASED ALGORITHM.

	Our proposed algorithm	ADMM-based algorithm
Test System	CPU time (s)	CPU time (s)
IEEE 14-bus	10.7	7.9
IEEE 30-bus	16.8	12.1
IEEE 118-bus	25.6	18.5
IEEE 300-bus	42.5	27.6
Polish 2383wp	136.3	104.1
Polish 3012wp	182.4	134.8

V. CONCLUSION

In this paper, we introduced a decentralized algorithm to solve a DR-based DCOPF problem. In our model, the ISO sent control signals to BSEs to incentivize them towards optimizing their objectives independently, while considering the received control signals from the ISO. The main goal of the ISO was to minimize the aggregated generation cost of the suppliers and the discomfort cost of the consumers simultaneously. We evaluated the performance of the proposed decentralized algorithm on an IEEE 14-bus test system. Simulation results confirmed that the algorithm converges after reasonable number of iterations (about 50 iterations in less than 11 seconds). The proposed decentralized algorithm could benefit the consumers by reducing their payment due to load shifting from peak to off-peak hours, and the suppliers by reducing the peak-to-average generation ratio. Finally, we evaluated the effect of our proposed DR strategy on the branch loading. The results confirmed the effect of our method on reducing the loading of the transmission lines. For future work, we plan to extend our proposed day-ahead decentralized algorithm to real-time energy trading markets by taking into account the uncertainties in the load and generation levels.

ACKNOWLEDGEMENT

J.P.S. Catalão and M. Shafie-khah acknowledge the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under Projects SAICT−PAC/0004/2015−POCI−01−0145−FEDER−016434, POCI−01−0145−FEDER-006961, UID/EEA/50014/2013, UID/CEC/50021/2013, and UID/EMS/00151/2013, and also funding from the EU 7th Framework Programme FP7/2007−2013 under GA no. 309048.

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