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Economic Dispatch in Electric Grid Considering Demand Response using Dynamic Consensus based ADMM Approach

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Abstract

Increasing switching type and plugged in hybrid electric vehicle (PHEV) load makes the energy consumption pattern more complex. Proliferation of highly intermittent Distributed Energy Resources(DER) and complex energy consumption pattern add more complexity for the power management units. This paper proposes a dynamic consensus Alternating Direction Method of Multiplier(ADMM) based dynamic Economic Dispatch algorithm for finding optimal real time price and optimal generation/demand. In this proposed algorithm, each agent estimates their average of the total power mismatch of the network and dual variable from the dynamic average consensus, which eliminates the traditional ADMM of finding dual variable in centralized way. Two aspects of ED is taken into account. First, economic dispatch algorithmic solution for non-responsive demand units is designed considering generation limit (generation limit and ramp rate limit) as constraints. Second, economic dispatch is integrated with Demand Response (DR) and a algorithm is designed for finding the optimal real time price and optimal generation and optimal demand for responsive demand units. Finally, it is tested upon standard IEEE 30 test bus system to find the effectiveness of proposed algorithms. Also, the effect of renewable energy source (photo-voltaic energy sources) to the conventional generation units and responsive demand unit is analysed, which shows that shifting of controllable load form other time period to low energy cost renewable energy sources available time.

Keywords

ADMM, Dynamic Consensus, Economic Dispatch, Controllable load, Demand Response

1. Introduction

Economic dispatch (ED), fundamental of Demand Side Management, is the resource allocation problem in power system in which each generator unit finds their optimum strategy to ensure power balance in the network [1]. As the switching type load and Plugged in Hybrid Electric Vehicle (PHEV) load increases, the energy consumption pattern is becoming more complex [2].

Moreover, due to the world communities' increasing commitment to low carbon emission and advancement in technology, use of Distributed Energy Resources (DER) as energy source in power system is increased day by day. Proliferation of highly intermittent DER and the complex energy consumption pattern of demand units add more complexity for the power management system. As the number of player increases in market, hesitation of sharing their personal data makes economic dispatch more challenging. Also, consumers might have controllable load [3] such as PHEV, and the non-controllable load such as refrigerator and normal household load. These types of load respond to the electric price differently, so that different aspect of economic dispatch is required.

Significant number of research work are available in the literature concerning economic dispatch in different aspect. In [4], an ADMM algorithm along with model predictive control is used in a decentralized fashion in a micro-grid to schedule and control the distributed energy resources in real time. The central coordinator collects the information from all the agents to find optimal decision variable and send back to each agents. Involvement of a central leader to communicate directly with all units for the operation may vulnerable to single point failure, might have data privacy concerns. In [5] multi agent based distributed sub-gradient algorithm has been used to coordinate among multiple micro-grid to balance active power. Supply and demand is kept balance by adjusting utilization level of renewable generations based on local frequency i.e. the frequency is considered as the controlled parameter in coordination. Author in [6], has proposed an accelerated distributed gradient-based algorithm for economic dispatch, but an extra momentum term is added to ensure power balance by communicating with the all the agents. Two level Incremental cost consensus (ICC) algorithm is proposed in [7]. In lower level, average consensus algorithm is run and average mismatch in each node is found out and the ICC is run in higher level of consensus network. Through, the operation is based on distributed algorithm, more than one consensus algorithm is run and dynamic behavior of demand is not accounted. Multi parameter matrix perturbation theory and graph theory has been proposed in [8] to find the economic dispatch solution in a distributed manner, in which mismatch energy has used as feedback in the control logic. In this research, conventional generation units has been taken and the generation ramp rate limit is not considered.

Plethora of research are available in literature including responsive demand in economic dispatch.In [9], Vickrey-Clarke-Groves (VCG) mechanism for demand side management is proposed, in which each user provide their demand information to energy provider. The energy provider compute the optimal energy consumption level for each user by running centralized mechanism, and provide specific payment for individual user. For this, optimization problem is formulated to maximize aggregated utility for user and minimize the total cost imposed on energy provider. While doing so, only single energy provider is considered and it collects information from all the participating units. In [10], author have presented the distributed algorithm for optimal scheduling of resources, where the social welfare problem is formulated and solved. Gradient algorithm is used to jointly compute utility and customer equilibrium point, the effect of battery energy storage system has also analysed. However, the communication at each iteration is all-to-all and at the beginning of the day, the utility companies and customers compute their price, consumption, and charging schedule for the each period of the day in advance. In [11], incremental welfare consensus algorithm for energy management has introduced. For a single period, author tried to manage generation side and demand side simultaneously optimizing combined benefits of participants. Observer design has been proposed to approximate the generation and load mismatch. In [12], social welfare is optimized using dual decomposition methods to find distributed solution of optimal energy generation and optimal demand. In this algorithm, power balance is not guaranteed, total power consumption level always below the power generation capacity.

In this paper, two aspect of Economic Dispatch is investigated and dynamic consensus based fully distributed algorithmic solution using ADMM is designed. First aspect is to design algorithm for solving demand non-responsive economic dispatch problem with conventional generation as the energy sources and time-variant loads as demand to be fulfilled. Second is to design the distributed ED algorithm incorporating Demand Response (DR) in time-variant demands. Also, photo-voltaic energy sources as variable renewable resources (VRE) is added. Main contribution of this paper are listed below.

1. Finding economic dispatch for uncontrollable demand units in distributed manner, in which generation limit including ramp rate is taken as constraint.
2. Finding economic dispatch for responsive demand units in totally distributed manner. In this aspect, consumer can change their demand based on the energy price. For this case, optimal value of generation and demand is obtained at maximum combined social welfare.
3. The proposed algorithm maintain privacy of each agent as it share only the energy mismatch to their neighbors. Also, robustness and scalability is guaranteed in the proposed algorithm.

The rest of the paper are presented as follows. Graph theory and consensus algorithm is presented in section (2),the problem formulation model is presented in section (3), section (4) contains simulation set up and results and conclusion is drawn in section (5).

2. Graph Theory and Dynamic Consensus Algorithm

2.1 Graph Theory

Plenty of excellent literature are available in graph theory and its notation. Electric grid network is also a graph and can be denoted in a graph theory. Let ($\mathscr{V}$, $\mathscr{E}$) denote the graph in which set of vertices $\mathscr{V}$ (number of nodes in graph) and set of edges $\mathscr{E}$(line connecting from node i to node j). The cardinality of node $\mathscr{V}$ is defined by $\mathscr{N}$ and d_i is the degree of node V_i defined as the total number of neighbours. As stated in [13] Laplacian of a graph forms the basis for distributed consensus dynamics. The Laplacian matrix of a graph, G is defined in terms of the adjacency matrix, A and degree matrix with the vertex degree along its diagonal, D. The graph Laplacian matrix can be expressed in matrix form as:
$L = D - A$
Laplacian consensus dynamics is defined by the differential equation

$$\dot{x} = -Lx \tag{1}$$

And, the dynamics of individual agent can expressed as [13]:

$$\dot{x} = \sum_{j \in \mathscr{N}_i} (x_i - x_j) \tag{2}$$

Each agent need only the values of its neighbors in order to implement its own update, therefore the dynamics is completely distributed. As mentioned in [13], Laplacian matrix gives three intuitive remarks.

1. For an undirected graph G, the Laplacian is a symmetric positive-semidefinite matrix and its all eigen value are real and positive. This implies that the dynamics is stable, and must converge to steady-state.

2. Laplacian always have at least one zero eigen value, that is $Lx = 0$

3. The second smallest eigen value of Laplacian is non-zero only if the network is connected, called the algebric connectivity of the network.

Thus, the properties of *Laplacian Matrix* shows that it drives any initial condition to the consent value and summerized as:

$$\frac{1}{N}\mathbf{1}^T\mathbf{x}_0 = \frac{1}{N}\sum_i x_i^0 \tag{3}$$

2.2 Dynamic Consensus Algorithm

Initial value of the each agent of the network can be denoted as $\mathbf{x_i}^0 \in \mathbb{R}^N$ and the vector of initial value is $x(0) = (x_1(0), \cdots, x_N(0))$. As the each agent communicates only with their neighbors, the average value $\frac{1}{N}\sum_i x_i^0$ can be calculated in distributed linear iterative form [14] as

$$x_i^{k+1} = a_{ii}x_i^k + \sum_{j \in \mathscr{N}_i} a_{ij}x_j^k, \quad i = 1, \ldots, N \tag{4}$$

where $k = 0, 1, 2, \ldots$ and a_{ij} is the weight on x_j at node i, and $\mathscr{N}_i$ denotes the set of all neighbors of agent i. Setting $a_{ij} = 0$ for $j \notin \mathscr{N}_i$, this iteration can be written as

$$\mathbf{x}^{k+1} = \mathbf{A}\mathbf{x}^k \tag{5}$$

The equation (2.2) can equivalently written as

$$\mathbf{x}^k = \mathbf{A}^k x(0) \tag{6}$$

Important aspect is to choose weight matrix A so that for any initial value x(0), x converge to the average vector

$$\bar{x} = \left[\frac{\mathbf{1}^T\mathbf{x(0)1}}{N}\right] = \left[\frac{\mathbf{1}^T\mathbf{1}}{N}\right]\mathbf{x(0)} \tag{7}$$

Parameter of the coefficient matrix A i.e. the adjacency matrix depending only on the incident node and is calculated by the Metropolis-algorithm [13] and is given by:

$$a_{ij} = \begin{cases} \frac{1}{\max\{d_i, d_j\}} & \{i, j\} \in \mathscr{E} \\ 1 - \sum_{j \in \mathscr{E}} \frac{1}{\max\{d_i, d_j\}} & i = j \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

If dynamically changing signal need to be reach into consensus, some modification is required . If y be the signal and $\Delta\mathbf{y}$ is the difference in two consecutive time step, the modified as following can track the dynamically varying signal in to the common consent value

$$\mathbf{x}^{k+1} = \mathbf{A}\mathbf{x}^k - \Delta\mathbf{y} \tag{9}$$

Where, $\Delta\mathbf{y} = \mathbf{y}^{k+1} - \mathbf{y}^k$ is the bias and each agent has its own bias, so that this modification is still distributed.

3. Distrbuted Economic Dispatch

3.1 Demand Non-responsive Economic Dispatch

Economic dispatch is the resource allocation in power system in which the generation units are scheduled in such a way that the combined generated power balance the load demand in the network at marginal cost. For economic dispatch, quadratic cost function is considered for the conventional generation units. The cost function for i^{th} generating units can be expressed as:

$$C_i(P_{gi}) = a_i P_{gi}^2 + b_i P_{gi} + c_i \tag{10}$$

Where, a_i, b_i, c_i are coefficients of cost function of generating units.
Let each agent $i \in \mathscr{V} = \{1, 2, 3, \ldots\ldots, N\}$ be the bus in power system. The economic dispatch can be formulated as:

$$\min_{P_g} \sum_{i \in \mathscr{V}} C_i(P_{gi}) \tag{11a}$$

$$\text{s. t.} \sum_{i \in \mathscr{V}} P_{gi} = \sum_{i \in \mathscr{V}} P_{di} \tag{11b}$$

$$P_{gi}^{\min} \leq P_{gi} \leq P_{gi}^{\max} \forall i \in \mathscr{V} \tag{11c}$$

$$\Delta P_{gi}^{\min} \leq P_{gi}(t) - P_{gi}(t-1) \leq \Delta P_{gi}^{\max} \tag{11d}$$

Where, $P_{gi}^{\min}$ is the generation at i^{th} bus. $P_{gi}^{min} and P_{gi}^{max}$ are the minimum and maximum generating limit of generator. As the power balance in whole network is mandatory in power system, equation (11b) is the global constraint. Equation (11c) is the generation limit constraint and equation (11d) is the ramp rate limit constraint, and these are the local limit constraint of optimization. In this optimization, $P_{gi} = \{P_{g1}, P_{g2}, \ldots P_{gN}\}$ denotes the power generation of all the buses and they are the decision variables.
ADMM is a method of multiplier, in which problem is breakdown into smaler sun-problem and solution can be found out in parallel sequential fashion. Augmented Lagrangian model of ADMM in scaled form can be written as [15]

$$P_{gi}^{k+1} = \underset{p_{gi}^{min} \leq p_{gi} \leq p_{gi}^{max}}{\text{argmin}} \left\{ C_i(P_{gi}) + \frac{\rho}{2} \left\| \sum_{j \in \mathscr{N}} P_{dj}^k - (P_{gi} + \sum_{j \neq i \in \mathscr{N}} P_{gj}^k) + u^k \right\|_2^2 \right\} \tag{12}$$

$$u^{k+1} = u^k + \sum P_{di}^{k+1} - \sum P_{gi}^{k+1} \tag{13}$$

Where, u is the dual variable; ρ is the penalty parameter, $\left\|.\right\|_2^2$ is the Euclidean norm and λ is the energy price = ρu For N number of agents, average power mismatch can be written as

$$\overline{P}_{gd_mean} = \frac{1}{N} \left(\sum_{i=1}^{N} P_{gi} - \sum_{i=1}^{N} P_{di} \right). \tag{14}$$

Therefore, equation (12)-(13) can re-written as

$$P_{gi}^{k+1} = \underset{p_{gi}^{min} \leq p_{gi} \leq p_{gi}^{max}}{\text{argmin}} \left\{ C_i(P_{gi}) + \frac{\rho}{2} \left\| P_{gj}^k - \overline{P}_{gd_mean} - P_{gi} + u^k \right\|_2^2 \right\} \tag{15}$$

$$u^{k+1} = u^k - N\overline{P}_{gd_mean} \tag{16}$$

Optimal generation of each unit can be calculated using (15), in which power mismatch and the dual variable are depend on the central coordinator.

3.2 Demand Responsive Economic Dispatch

If demand response is incorporated in the economic dispatch, controllable demand units consume power in response to the energy price. Therefore, both the generating units and controllable demand units are responsible for demand management, they reach in to common operating point at the point of maximum economic efficiency for both parties. Based on their own preferences, each consumers behaves independently. The different consumption behaviors of consumers can be modeled using utility function which measure the welfare /satisfaction of consumers based on level of consumption [16]. Utility function for the consumer requires following properties [11]:

(i) Utility function is Non-decreasing

(ii) Satisfaction level of consumer should saturate with increasing power consumption.

(iii) If consumption is zero, utility of consumer should be zero

Satisfying these condition, utility function for consumers can be approximated as [11]

$$U_i(P_{di} = \begin{cases} \beta_i P_{di} - \alpha_i {P_{di}}^2 & \text{for} P_{di} \leq \frac{\beta_i}{2\alpha_i} \\ \frac{{\beta_i}^2}{4\alpha_i} & \text{for} P_{di} \geq \frac{\beta_i}{2\alpha_i} \end{cases} \tag{17}$$

Where,α and β are the coefficients which differentiate consumers from one another. For economic dispatch with responsive demand unit, optimal value of both generation and demand unit should be obtained. Therefore, optimal dispatch is found out by maximizing combined welfare of generation and demand units, called Social Welfare Maximization (SWM). Including generation limit and consumption range for adjustable load, SWM can be formulated as:

$$\min_{P_g,P_d} \sum_{i\in\mathscr{V}} U_i(P_{gi}) - \sum_{i\in\mathscr{V}} C_i(P_{di}) \tag{18a}$$

$$\text{s. t.} \sum_{i\in\mathscr{V}} P_{gi} = \sum_{i\in\mathscr{V}} P_{di} \tag{18b}$$

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \forall i \in \mathscr{V} \tag{18c}$$

$$\Delta P_{gi}^{\min} \le P_{gi}(t) - P_{gi}(t-1) \le \Delta P_{gi}^{\max} \tag{18d}$$

$$P_{di}^{\min} \le P_{di} \le P_{di}^{\max} \forall i \in \mathscr{V} \tag{18e}$$

Where, $P_{di}^{\min}$ and $P_{di}^{\max}$ are the demand limits for the demand units. Controllable demand units can adjust their consumption level based on energy price considering these limits. For equation (18), Augmented Lagrangian model of ADMM in scaled form can be written as [15].

$$\mathscr{L}(P_i^k, u^k) = \underset{p_{gi}^{min}\le p_{gi}\le p_{gi}^{max}}{\operatorname{argmin}} \Bigg\{ C_i(P_{gi}) - U_i(P_{di}) + \frac{\rho}{2} \left\| (P_{di} + \sum_{j\neq i\in\mathscr{N}} P_{dj}^k) - (P_{gi} + \sum_{j\neq i\in\mathscr{N}} P_{gj}^k) + u^k \right\|_2^2 \Bigg\} \tag{19}$$

$$u^{k+1} = u^k + \sum P_{di}^{k+1} - \sum P_{gi}^{k+1} \tag{20}$$

Power mismatch of each agent as given in equation (14). Therefore, equation (19)-(20)can be re-written as

$$\mathscr{L}(P_i^k, u^k) = \underset{p_{gi}^{min}\le p_{gi}\le p_{gi}^{max}}{\operatorname{argmin}} \Bigg\{ C_i(P_{gi}) - U_i(P_{di}) \; \frac{\rho}{2} \left\| (P_{di} - P_{di}^k) - (P_{gi} - P_{gi}^k) - N\overline{P}_{gd_mean} + u^k \right\|_2^2 \Bigg\} \tag{21}$$

$$u^{k+1} = u^k - N\overline{P}_{gd_mean} \tag{22}$$

Optimal generation and optimal demand of each unit can be calculated using (21), in which power mismatch and the dual variable are global variable and depends on the central coordinator.

The motto of this research is finding these values in a distributed way and diminish the role of central coordinator.

3.3 Distributed Approach for Finding Dual Variable and Power Mismatch

The concept of dynamic average consensus as discussed in 2.2 is used to convert the average mismatch and dual variable from global variable to local variable. For calculating distributed average mismatch, each agent share their information only to their neighboring agent and calculate average generation and demand for the network which is changing over time. Average Power mismatch, $\overline{P}_{gdi_mean}$ for i^{th} agent at iteration k, difference of average generation and average demand, can be calculated as

$$\overline{P}_{gdi_mean}^{k+1} = a_{ii}\overline{P}_{gdi}^k + \sum_{j\in\mathscr{N}_i} a_{ij}\overline{P}_{gdj}^k + (P_{gdi}^{k+1} - P_{gdi}^k) \tag{23}$$

Incorporating this average power mismatch, the dual variable of the algorithm can be obtained in distributed way as

$$u_i^{k+1} = a_{ii}u_i^k + \sum_{j\in\mathscr{N}_i} a_{ij}u_j^k - \overline{P}_{gdi_mean}^{k+1} \tag{24}$$

Dual variable u_i is the scaled variable of market price. So, the market price can be calculated as

$$\lambda_i^{k+1} = \rho u_i^{k+1} \tag{25}$$

Thus, the way of calculating average mismatch and dual variable locally as in (23)and (24) is valid for both demand non-responsive and demand responsive economic dispatch.

Demand non-responsive ED: Optimal scheduling of each generating unit can be calculated using Karush-Kuhn-Tucker optimality condition in equation (15) and is:

$$P_{gi}^{k+1} = \left[\frac{\rho(P_{gi}^k - N\overline{P}_{gdi_mean}^k + u_i^k) - b_i}{2a_i + \rho} \right] \tag{26}$$

Demand Responsive ED: Optimal generated power can be calculated using using Karush-Kuhn-Tucker optimality condition in equation (21) as

$$P_{gi}^{k+1} = \left[\frac{\rho(P_{gi}^k - N\overline{P}_{gdi_mean}^k + u_i^k) - b_i}{2a_i + \rho} \right] \tag{27}$$

Optimal power consumed by each demand units can be calculated using Karush-Kuhn-Tucker optimality condition in equation (21). There are two cases based of the limit of consumed power

Case I: $U_i(P)_{di} = \beta_i P_{di} - \alpha_i {P_{di}}^2$ for $P_{di} \le \frac{\beta_i}{2\alpha_i}$
For case I, optimal power consumption for i^{th} demand unit is

$$P_{gi}^{k+1} = \left[\frac{-\rho(P_{gi}^k - N\overline{P}_{gdi_mean}^k + u_i^k) - \beta_i}{2\alpha_i + \rho}\right] \tag{28}$$

Case II: $U_i(P)_{di} = \frac{\beta_i^2}{4\alpha_i}$ for $P_{di} \ge \frac{\beta_i}{2\alpha_i}$
For case II, optimal power consumption for i^{th} demand unit is

$$P_{gi}^{k+1} = (P_{gi}^k - N\overline{P}_{gdi_mean}^k + u_i^k) \tag{29}$$

4. Simulation Setup and Result

4.1 Demand Non-responsive Demand

Economic Dispatch simulation is executed in MATLAB R2017b platform to find effectiveness of proposed algorithm. For this simulation, standard IEEE 30 bus test case network is used. Cost coefficients, generator limits, and initial value of power demand at each bus are taken as specified in [17]. In the process of simulation, the load demand is varied with the expense of time to mimic the unpredictable changes in load and to verify the efficacy of proposed algorithm for varying load which would be the real scenario of power system. To randomize the load demand, uniform distribution function is used in MATLAB.

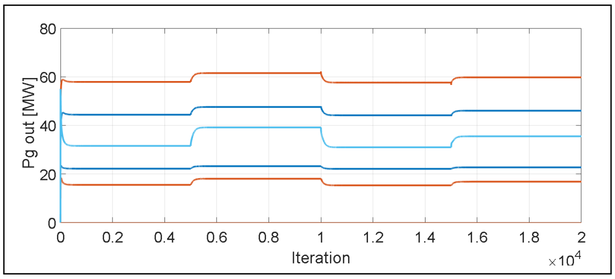

Figure 1: display the economic generation of each generating units

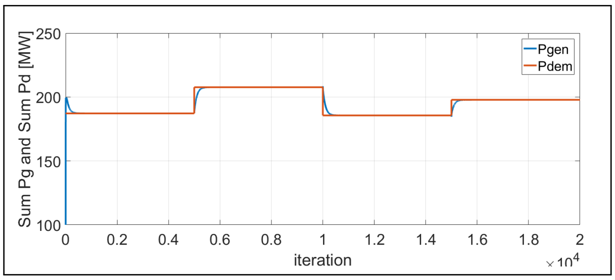

Figure 2: Display the sum of total energy generation and sum of demand

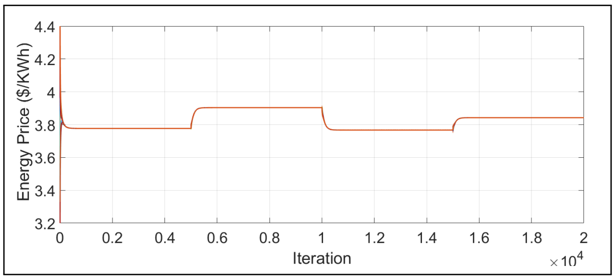

Figure 3: Display the convergence process of energy price, *lambda*

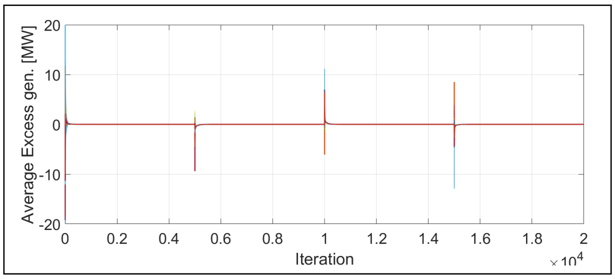

Figure 4: Display the Average Energy Mismatch

Figure (1) shows the individual optimal generation profile for each generating units. Figure (3) depicts the common consent market price for every agents in the network. And, figure (2) and (4) signify the generation and load demand is perfectly balanced, having zero power mismatch after reached in to the convergence. This shows that the algorithm is scalable. In all cases, algorithm drive any initial guesses to convergence and the algorithm seems robust enough for Economic Dispatch.

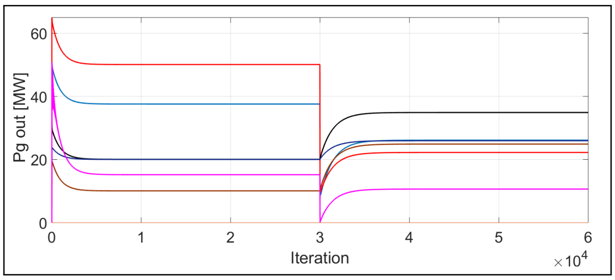

Figure 5: Display economic generation with generation cost increment

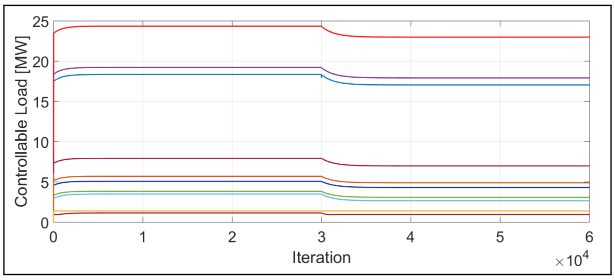

Figure 6: Display the optimal consumption of controllable load

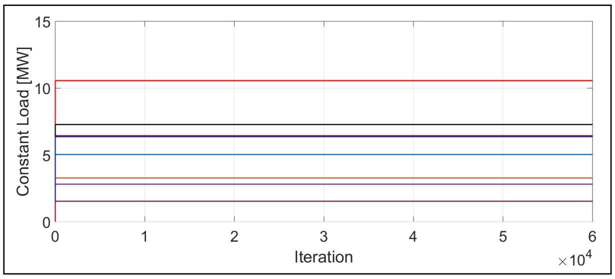

Figure 7: Display the consumption of fixed load

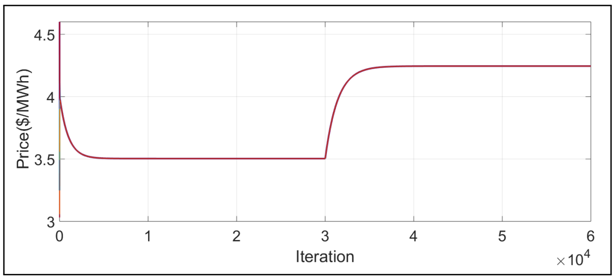

Figure 8: Display the energy price with generation cost increment

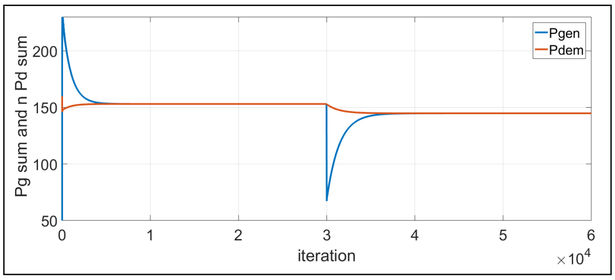

Figure 9: Display the sum of generation and demand

Figure (5) to (9) shows the results associated with increment of generation cost of some units. Figure (5) shows the optimal generation of each generating units. After 30000 iteration, generation cost for units 1, 2 and 4 increased. As the generation cost increased, the consumption of controllable load decreased as shown in figure (6) and corresponding energy price is shown in figure (8) and balancing of generation and demand is shown in figure (9).

Figure (10) to (13) shows the results associated with addition of photo-voltaic (PV) energy sources in the system. Here, it is assumed that the PV sources provide free of cost energy to the system during its available time. After 30000 iteration, two PV sources are added in bus 6 and bus 10. When PV is added, the overall price of energy decreased as shown in figure (12). As the energy cost decreases, the power consumption level of controllable load is increased, as shown in figure (11). Figure 10 shows the optimal generation with PV addition and (13) shows the balancing of generation and demand in real time.

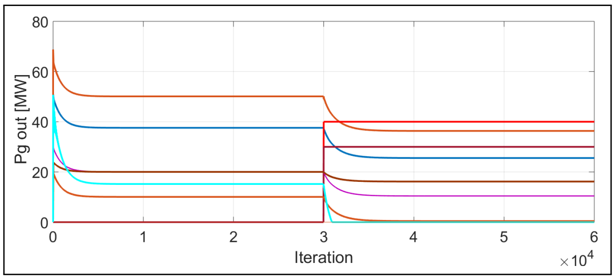

Figure 10: Display the economic generation with PV added after sometimes

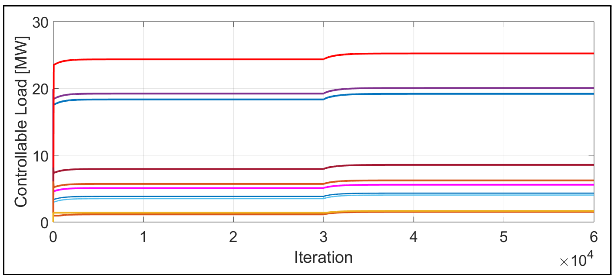

Figure 11: Display the optimal consumption of controllable load with PV

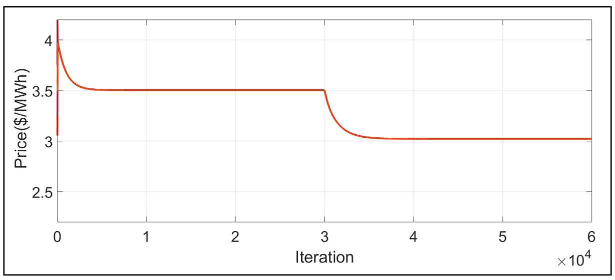

Figure 12: Display the energy price with PV

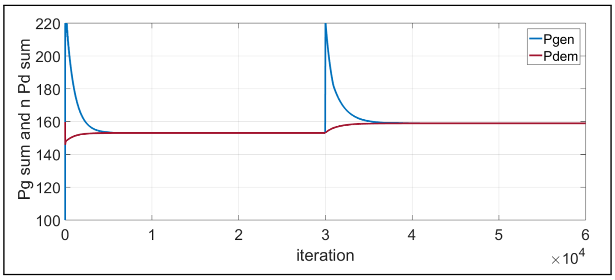

Figure 13: Display the sum of generation and demand with PV

5. Conclusion

In this paper, ADMM based fully distributed economic dispatch algorithm have been proposed by removing the concept of central coordinator for the computation of global decision variable. Two aspect of dispatch algorithm have been designed and tested upon the standard IEEE 30 bus system. Firstly, normal economic dispatch algorithm for uncontrollable load is designed and executed, where each agent only share their energy mismatch to their neighbors as control variable instead of sharing their decision variables and cost variables. As a result the privacy of each agent has well maintained. Secondly, the concept of demand response has been included in which social welfare maximization problem is formulated to find the optimal generation and optimal demand of controllable load, which respond based on the energy prices in the market. In this case, photo-voltaic energy sources has been also added. Simulation results demonstrates the promising results of the proposed algorithm for finding real time economic dispatch in both non-responsive and responsive demand units.

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