APPLICATION OF DISTRIBUTED ALGORITHM IN A MICROGRID FOR OPTIMAL ENERGY MANAGEMENT AND RAPID CONVERGENCE

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(Received 11th October 2024; revised 26th January 2025; accepted 02nd February 2025)

Abstract. An intelligent energy management system is used as a powerful tool for energy management on the demand side and production units. Optimal energy management in microgrids is usually formulated as a nonlinear optimization problem. Due to the nonlinear and discrete nature of the problem, solving it centrally requires a high volume of computations in the central microgrid controller. This paper proposes the distributed energy management strategy in the microgrid with two distributed methods, the alternating direction method of multiplier and the predictor-corrector proximal multiplier so that the central controller and local controllers jointly optimize a single program. The proposed distributed algorithms on the sample microgrid are investigated and the performance of the algorithms is compared through a case study. The results show that the proposed distributed methods reduce operating costs. The simulation results show better efficiency and faster convergence of the distributed methods than the centralized method. Also, the alternating direction method of the multiplier method with less repetition and lower operating cost than the predictor-corrector proximal multiplier method has optimized the main problem.
Keywords: *optimal energy management, distributed algorithm, convex optimization, microgrid, optimal load distribution*

Introduction

Microgrids are low-voltage distribution systems consisting of distributed energy sources (DERs) and controllable loads that can be connected to the grid and disconnected from the grid. Dispersed energy sources include distributed generation units such as wind turbines, photovoltaic systems, and energy storage units such as batteries (Shi et al., 2014b). The energy management problem in the microgrid is modeled as a nonlinear optimization problem. Solving it centrally requires a lot of computational capabilities in the Microgrid Central Controller (MGCC). Amouzad (2022) has been optimized by the KKT method with the help of DC load distribution and through the connection of adjacent rails. Various centralized methods for solving it have been proposed in various articles, including mixed-integer programming (Mahdiraji, 2022), quadratic programming (Mahdiraji, 2022), particle aggregation optimization (Mahdiraji and Shariatmada, 2023), and neural networks (Siano et al., 2012). A centralized energy management (EMS) strategy has limitations for gathering information from DERs as input and for optimizing production costs and controlling loads. DERs may belong to different individuals and entities who want to keep their information private (Mahdiraji, 2023). Therefore, in this study, we are interested in developing a distributed EMS that is efficient, scalable, and privacy-friendly.

Several distributed algorithms for exploiting microgrids have been proposed in the articles. In Dominguez-Garcia and Hadjicostis (2011), the distributed algorithm is modeled for the allocation of distributed energy sources. A convex optimization

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.190

problem with the double decomposition method is presented in Amouzad Mahdiraji and Khodadadi Zarini (2024) to develop distributed EMS to maintain supply and demand balance in the microgrid. Algorithm for energy planning with privacy in the microgrid is proposed in which the privacy constraints with linear programming method and distributed algorithms are developed. The increase/decrease algorithm adopted to optimize DER operation in distributed mode is stated. The problem with distributed methods for managing microgrid energy (Amouzad Mahdiraji and Khodadadi Zarini, 2024; Mahdiraji, 2023; Dominguez-Garcia and Hadjicostis, 2011) is that the amount of demand is simply assumed to be equal to production. Also, it is assumed that the output sources and loads are connected to a common bus and ignore issues such as load distribution effect and system operating limitations (voltage droop). As a result, the program generated by these algorithms may violate that limitation and be impractical in practice. Therefore, the idea of integrating distribution networks with distributed energy management in the microgrid, in which both production and demand-side management (DSM) are considered, has not been seen. Shi et al. (2014a), the distributed PCPM algorithm is used for optimal energy management in a sample microgrid, and Shi et al. (2014a), the mentioned method is used for optimal load response.

Shi et al. (2014a; 2014b) have optimized their main problem by proving the condition of convexity of the load distribution problem in the radial distribution network (Crisostomi et al., 2014; Low, 2014a; 2014b; Shi et al., 2014a; Gan et al., 2013) and with the help of the proposed PCPM algorithm. Various distributed algorithms are described in Pourmousavi et al. (2010). These methods have been the basis of many types of research in electricity and telecommunications (Shen et al., 2016; Gan et al., 2012; Li et al., 2012). In Zhang and Giannakis (2014), the ADMM method is used to distribute the economic load in a microgrid. Shen et al. (2016) has also divided the non-convex problem into several convex sub-problems and solved it by the ADMM method. The researchers' approach in Cai et al. (2016) is to find the marginal cost of power systems by considering wind power plants. In this study, the uncertainty related to the predicted amount of wind power in the problem of economic power distribution is considered and the problem is solved in the form of random planning. A large number of scenarios have been generated to simulate the amount of wind energy, and a number of them are considered using scenario reduction methods. The simulation results showed that the introduced method, while having the desired estimation quality, also has good stability and speed.

Due to the high complexity and computational load, various sources of load response and other renewable energies have been neglected. Researchers Siano et al. (2012) have solved the problem of economic load distribution in multi-zone power systems by considering the constraints related to pollution and using the cuckoo optimization algorithm. The introduced algorithm has been evaluated in different modes of one-zone and two-zone performance and the results have been more optimal compared to previous studies. In this study, the uncertainties of the power system have been ignored. A new method based on port decomposition for the planning of hydropower and thermal power plants is presented. The objective function used is limited to alternating load distribution, safety constraints as well as voltage stability. In the main problem, the way of participation of the units, and in the sub-problem, the production capacity of the units will be obtained. The numerical results of the paper indicate that the analysis method provides the final answers with very good accuracy and low solution time.

However, the manner of participation has not been seen many times as well as its uncertainty in the issue.

In this paper, in particular, a microgrid consisting of multiple DERs and controllable loads will be considered. The focus of this research is on designing a distributed energy management strategy for the optimal use of microgrids, taking into account the limitations of the distribution network. Also, the management of distributed generation resources in the microgrid with the problem of optimal load distribution as a distributed energy management system has been proposed, so that the central controller and local controllers are jointly programmed. Optimize unit layout by preserving unit privacy information. The innovations and features of this paper in comparison with other papers are presented: (1) Using the distributed ADMM method for optimal energy planning (management) in the microgrid; (2) Development of a load response program in a distributed method with the aim of reducing costs; (3) Protecting the private information of owners of dispersed production units and responsive loads. In the following, the modeling of microgrid components is explained; then, by adding the distributed methods to the sample model, the optimal microgrid programming with the proposed algorithms is discussed. The algorithms are fully implemented in MATLAB software and Open DSS software that exchanges information with MATLAB is used to calculate losses. The simulation outputs are discussed below and a comparison table between the methods is provided at the end.

Materials and Methods

Mathematical relations of the problem

The low-voltage distribution system usually has a radial structure and the microgrid consists of renewable DGs (such as PV) and conventional DGs (such as diesel generators) and controllable loads.

Renewable resources

Renewable PV DG units are uncontrollable in terms of the distribution system and vary according to weather conditions (such as sunlight, wind). Therefore, predicting their output power is necessary to optimize energy management. This article does not cover the cost of producing and maintaining these resources. Each ordinary DG unit, such as a diesel generator, is an adjustable and distributable source. For each DG unit, we consider the mixed power $s_g(t) = p_g(t) + ig_g(t)$, where T is the time interval in hours. The output power of a diesel generator is a variable with the following limitations:

$$0 \le p_g(t) \le \bar{p}_g, \qquad \forall t \in T \qquad \text{Eq. (1)}$$

$$p_g(t) \le \bar{p}_g(t-1)\Big| \le r_g \bar{p}_g, \qquad \forall t \in T \qquad \text{Eq. (2)}$$

The production cost for each DG unit in time is modeled using the order 2 function (Shi et al., 2014b):

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.190

$$c_{Gen}\left(p_{Gen}\right)=a_{Gen}.p_{Gen}^{2}+b_{Gen}.p_{Gen}+c_{Gen} \quad \text{Eq. (3)}$$

$$c'_{Gen}\left(q_{Gen}\right)=a'_{Gen}.q_{Gen}^{2}+b'_{Gen}.p_{Gen}+c'_{Gen} \quad \text{Eq. (4)}$$

$$q_{Gen}^{min}\leq p_{Gen}\leq p_{Gen}^{min} \quad \text{Eq. (5)}$$

$$q_{Gen}^{min}\leq q_{Gen}\leq q_{Gen}^{min} \quad \text{Eq. (6)}$$

$$p_{Gen}\left(t\right)-p_{Gen}\left(t-1\right)\leq p_{Gen}^{RU-max} \quad \text{Eq. (7)}$$

$$p_{Gen}\left(t-1\right)-p_{Gen}\left(t\right)\leq p_{Gen}^{RD-max} \quad \text{Eq. (8)}$$

Battery modeling

In the microgrid, mixed power for each battery (ES) is obtained from Eq. (9):

$$S_{ES}\left(t\right)=p_{ES}\left(t\right)+iq_{ES}\left(t\right) \quad \text{Eq. (9)}$$

Which $p_{ES}\left(t\right)$ is the active power of the battery, $q_{ES}\left(t\right)$ the reactive power of the battery, and $S_{ES}\left(t\right)$ the energy stored in the battery at time t. The production and consumption capacity of each battery has the following limitations:

$$\underline{p}_{ES}\leq p_{ES}\left(t\right)\leq \overline{p}_{ES} \qquad \forall t\in T \quad \text{Eq. (10)}$$

$$p_{ES}\left(t\right)^{2}+q_{ES}\left(t\right)^{2}\leq s_{ES}^{2} \qquad \forall t\in T \quad \text{Eq. (11)}$$

$$H_{ES}\left(t+1\right)=\eta_{ES}H_{ES}\left(t\right)+p_{ES}\left(t\right)\Delta t, \qquad \forall t\in T \quad \text{Eq. (12)}$$

$$\underline{H}_{ES}\leq H_{ES}\left(t\right)\leq \overline{H}_{ES}, \quad \forall t\in T \quad \text{Eq. (13)}$$

$$H_{ES}\left(t\right)\geq H_{ES}^{e} \quad \text{Eq. (14)}$$

Cost function model for each battery unit (Shi et al., 2014b):

$$c_{ES}\left(p_{ES}\right)=a_{ES}\sum_{t\in T}p_{ES}\left(t\right)^{2}-b_{ES}\sum_{t=0}^{T-2}p_{ES}\left(t+1\right)p_{ES}\left(t\right)+c_{ES}\sum_{t\in T}\left(\min\left(H_{ES}\left(t\right)-d_{ES}\overline{H}_{ES,0}\right)\right)^{2} \quad \text{Eq. (15)}$$

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.190

$$c'_{ES}\left(q_{ES}\right)=a'_{ES}\sum_{t\in T}q_{ES}\left(t\right)^{2}-b'_{ES}\sum_{t=0}q_{ES}\left(t+1\right)q_{ES}\left(t\right)+c'_{ES}\sum_{t\in T}\left(\min\left(H'_{ES}\left(t\right)-d_{ES}\overline{H'}_{ES},0\right)\right)^{2}$$
Eq. (16)

$d_{ES},c_{ES},b_{ES},a_{ES}$ The coefficients are fixed. For example, when d_{ES} is selected equal to 0.2, ie the energy stored in the battery ($H_{ES}\left(t\right)$) is less than 20% of the battery capacity, it is subject to a cost charge.

Loud modeling

In this microgrid, intermittent load (control) is considered. For each time the mixed power is as follows:

$$s_{RLD}\left(t\right)=p_{RLD}\left(t\right)+iq_{RLD}\left(t\right)$$
Eq. (17)

For breakable loads, the cost function depends on the load shedding, which can be described as follows:

$$c_{RLD}\left(p_{RLD}\right)\square\sum_{i=1}^{n}\alpha_{RLD}\left(p_{RLD}\left(t\right)-p_{RLD}^{forecast}\left(t\right)\right)^{2}+c_{RLD}$$
Eq. (18)

$$c'_{RLD}\left(q_{RLD}\right)\square\sum_{i=1}^{n}\alpha_{RLD}\left(q_{RLD}\left(t\right)-q_{RLD}^{forecast}\left(t\right)\right)^{2}+c'_{RLD}$$
Eq. (19)

Where $q_{RLD}^{forecast}$ and $p_{RLD}^{forecast}$ are the predicted reactive power, respectively, c'_{RLD}, c_{RLD}, and α_{RLD} are constant coefficients, and n is the number of units of charge that can be cut in the microgrid. Its cost function has the following limitations:

$$p_{RLD}^{min}\left(t\right)\le p_{RLD}\left(t\right)\le p_{RLD}^{max}\left(t\right),\quad\forall t\in T$$
Eq. (20)

$$q_{RLD}^{min}\left(t\right)\le q_{RLD}\left(t\right)\le q_{RLD}^{max}\left(t\right),\quad\forall t\in T$$
Eq. (21)

p_{RLD}^{min}, p_{RLD}^{max} are the maximum and minimum reactive power consumption frequently, respectively, q_{RLD}^{max}, q_{RLD}^{min} are the maximum and minimum reactive power consumption, respectively.

Distribution network model

The distribution network can be defined as the graph $G=\left(N,\varepsilon\right)$, where j and i are denoted by blue, N represents the group and ε represents the branch (path). The distribution network is usually radial and the graph represents a three-phase radial network. For each path $Z_{ij} = r_{ij} + ix_{i,j}, (i,j) \in \varepsilon$, the mixed current from bus i to j, the mixed power transmitted from bus i to j is equal to $V_i(t), S_{ij}(t) = P_{ij}(t) + iq_{ij}(t)$ the voltage belongs to bus i, $S_i(t) = p_i(t) + iq_i(t)$ is the net power in bus i. Each bus is a set of $G_i, i \in N$, $\{0\}$ DG units, a set of ES units and L_i a set of breakable loads. Therefore, the net power of the network is obtained as follows:

$$s_i(t) = s_{RLDi}(t) + s_{ESi}(t) - s_{DGi}(t), \forall i \in N/\{0\}, \forall t \in T$$
$$s_{RLDi}(t) = \sum_{RLD \in L_i} s_{RLD}(t), s_{DGi}(t) = \sum_{DG \in G_i} s_{DG}(t)$$
$$s_{ESi}(t) = \sum_{ES \in B_i} s_{ES}(t) \quad \text{Eq. (22)}$$

$$V_i(t) - V_j(t) = z_{ij} I_{ij}(t) \quad \text{Eq. (23)}$$

$$S_{ij}(t) = V_i(t) I_{ij}^*(t) \quad \text{Eq. (24)}$$

$$S_{ij}(t) - z_{ij} \left|I_{ij}(t)\right|^2 - \sum\nolimits_{k:(j,k)\in\varepsilon} S_{ik}(t) = S_j(t) \quad \text{Eq. (25)}$$

Using Eq. (23) to Eq. (25) and in real variable conditions, the steady state power distribution in the distribution network can be obtained $\mathcal{G}$:

$$\forall (i,j) \in \forall t \in T \quad \text{Eq. (26)}$$

$$p_j = P_{ij} - r_{ij} l_{ij} - \sum_{k:(j,k)\in E} p_{jk}, j = 1,...,n \quad \text{Eq. (27)}$$

$$q_j = q_{ij} - x_{ij} l_{ij} - \sum_{k:(j,k)\in E} q_{jk}, j = 1,...,n \quad \text{Eq. (28)}$$

$$v_j = v_i - 2\left(r_{ij} p_{ij} - x_{ij} q_{ij}\right) + \left(r_{ij}^2 - x_{ij}^2\right) l_{ij}, (i,j) \in E \quad \text{Eq. (29)}$$

$$l_{ij} = \frac{p_{ij}^2 + q_{ij}^2}{v_i}, \quad (i,j) \in E \quad \text{Eq. (30)}$$

$$\ell_{ij}(t) = \left|I_{ij}(t)\right|^2 \quad \text{Eq. (31)}$$

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.190

$$v_i(t) = |V_i(t)|^2 \qquad \text{Eq. (32)}$$

Optimal network load distribution

Eq. (26) to Eq. (32) define a system of equations with variables. The central controller has two main parts, including energy management and microgrid protection coordination. The energy management department is responsible for providing a certain amount of active and reactive power, voltage and frequency of each LC. To apply voltage limits to the microgrid we have:

$$\underline{V}_i \leq |V_i(t)| \leq \overline{V}_i, \quad \forall_i \in N, \quad \{0\}, \forall t \in T \qquad \text{Eq. (33)}$$

$$C_{Grid}(t, p_{Grid}) \square \pi(t) p_{Grid}(t) \qquad \text{Eq. (34)}$$

$$C'_{Grid}(t, q_{Grid}) \square \pi'(t) q_{Grid}(t) \qquad \text{Eq. (35)}$$

$p_{Grid}(t)$, $q_{Grid}(t)$: Is the active and reactive power exchanged between the microgrid and the distribution network at time t. If its value is negative, it means that the microgrid is selling its excess energy to the main grid. $\pi(t)$, $\pi'(t)$: Is the price of active and reactive power exchanged at time t, respectively.

$$\begin{aligned} &OPF_{min} P, Q, l, v, p, q \sum\nolimits_{i=1}^{n} C^{Gen}\left(p^{Gen}\right) \Big| + \sum\nolimits_{i=1}^{n} C^{RLD}\left(p^{RLD}\right) \\ &+ \sum_{(i,j)\in E} r_{i,j} l_{i,j} + \sum_{i=1}^{n} c^{ES}\left(p^{ES}\right) + \sum_{i=1}^{n} c^{Grid}\left(p^{Grid}\right) \\ &+ \sum_{i=1}^{n} c'^{Gen}\left(q^{Gen}\right) + \sum_{i=1}^{n} c'^{RLD}\left(q^{RLD}\right) + \sum_{i=1}^{n} c'^{ES}\left(q^{ES}\right) + \sum_{i=1}^{n} c'^{Grid}\left(q^{Grid}\right) \end{aligned} \qquad \text{Eq. (36)}$$

To solve the problem, the following condition has been used for convex optimization (Crisostomi et al., 2014):

$$l_{ij} \geq \frac{P_{ij}^2 + Q_{ij}^2}{v_i}, \quad (i,j) \in E \qquad \text{Eq. (37)}$$

Distributed algorithms

The above OPF problem is a centralized optimization problem. To design the optimal and controllable EMS, the distributed method for solving the OPF problem called PCPM and ADMM is used. Local controllers first send their initial programming to MGCC, while MGCC also randomly sends its control program to them first. Which include $S_i^k(t) \square P_i^k(t)+iq_i^k(t)$ and $\{\mu_i^k(t)\}_{t\in T},\{\lambda_i^k(t)\}_{t\in T}$ two control signals for each local unit. $\lambda_i^k(t)$ and $\mu_i^k(t)$ the optimization coefficients are related to active and reactive power, respectively.

Distributed PCPM algorithm

The distributed algorithm is based on the correction of prediction values, the working method of the algorithm is fully explained in Shi et al. (2014b). Optimal energy management in controllers will be as follows. The local controller for the diesel generator solves its problem as follows:

$$\underset{\min}{\mathrm{EMS}}-\mathrm{LC}(\mathrm{DG})$$

$$S_{Gen}C_{Gen}(p_{Gen})+(\hat{\mu}_i^k)^T p_{Gen}+(\hat{\lambda}_i^k)^T q_{Gen}$$

$$+\frac{1}{2\gamma}\left\|p_{Gen}-p_{Gen}^k\right\|^2+\frac{1}{2\gamma}\left\|q_{Gen}-q_{Gen}^k\right\|^2 \qquad \text{Eq. (38)}$$

The local battery controller solves the problem as follows:

$$\underset{\min}{\mathrm{EMS}}-\mathrm{LC}(\mathrm{ES})$$

$$S_{ES}C_{ES}(p_{ES})+(\hat{\mu}_i^k)^T p_{ES}+(\hat{\lambda}_i^k)^T q_{ES}$$

$$+\frac{1}{2\gamma}\left\|p_{ES}-p_{ES}^k\right\|^2+\frac{1}{2\gamma}\left\|q_{ES}-q_{ES}^k\right\|^2 \qquad \text{Eq. (39)}$$

The local controller for the cut-off load solves its problem as follows:

$$\underset{\min}{\mathrm{EMS}}-\mathrm{LC}(\mathrm{Load})$$

$$S_{RLD}C_{RLD}(p_{RLD})+(\hat{\mu}_i^k)^T p_{RLD}+(\hat{\lambda}_i^k)^T q_{RLD}$$

$$+\frac{1}{2\gamma}\left\|p_{RLD}-p_{RLD}^k\right\|^2+\frac{1}{2\gamma}\left\|q_{RLD}-q_{RLD}^k\right\|^2 \qquad \text{Eq. (40)}$$

The central controller solves its problem for each time as follows:

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.190

$$\underset{\min}{\mathrm{EMS}} - \mathrm{MGCC}$$

$$P(t),Q(t),V(t),I(t),S(t)$$

$$C_{Grid}\left(t,p_{Grid}(t)\right)+C'_{Grid}\left(t,q_{Grid}(t)\right)+\sum_{(i,j)\in\varepsilon} r_{ij}\ell_{ij}(t)$$

$$-\left(\hat{\mu}^{k}\right)^{T}p(t)-\left(\hat{\lambda}^{k}\right)^{T}q(t)$$

$$+\frac{1}{2\gamma}\left\|p(t)-p^{k}(t)\right\|^{2}+\frac{1}{2\gamma}\left\|q(t)-q^{k}(t)\right\|^{2} \qquad \text{Eq. (41)}$$

Distributed ADMM algorithm

It is a powerful algorithm that is suitable for solving convex problems in a decentralized manner. Instead of solving the main problem, this algorithm turns it into several smaller problems and by solving them separately and combining the results, it reaches an acceptable answer, which is fully explained in the appendix. The local controller of the diesel generator unit solves its problem as follows:

$$\mathrm{EMS}-\mathrm{LC(DG)}$$

$$p_{Gen}^{k+1}=\arg\min_{p_{Gen}} L_{\rho}\left(C_{Gen}\left(p_{Gen}\right),C'_{Gen}\left(q_{Gen}^{k}\right),\hat{\mu}_{i}^{k}\right)$$

$$q_{Gen}^{k+1}=\arg\min_{q_{Gen}} L_{\rho}\left(C_{Gen}\left(p_{Gen}^{k+1}\right),C'_{Gen}\left(q_{Gen}\right),\hat{\lambda}_{i}^{k}\right) \qquad \text{Eq. (42)}$$

The local controller of the battery unit solves its problem as follows:

$$\mathrm{EMS}-\mathrm{LC(ES)}$$

$$p_{ES}^{k+1}=\arg\min_{p_{ES}} L_{\rho}\left(C_{ES}\left(p_{ES}\right),C'_{ES}\left(q_{ES}^{k}\right),\hat{\mu}_{i}^{k}\right)$$

$$q_{ES}^{k+1}=\arg\min_{q_{ES}} L_{\rho}\left(C_{ES}\left(p_{ES}^{k+1}\right),C'_{ES}\left(q_{ES}\right),\hat{\lambda}_{i}^{k}\right) \qquad \text{Eq. (43)}$$

The local controller of the cut-off load unit solves its problem as follows:

$$\mathrm{EMS}-\mathrm{LC(RLD)}$$

$$p_{RLD}^{k+1}=\arg\min_{p_{RLD}} L_{\rho}\left(C_{RLD}\left(p_{RLD}\right),C'_{RLD}\left(q_{RLD}^{k}\right)\right)$$

$$q_{RLD}^{k+1}=\arg\min_{q_{RLD}} L_{\rho}\left(C_{RLD}\left(p_{RLD}^{k+1}\right),C'_{RLD}\left(q_{RLD}\right)\right) \qquad \text{Eq. (44)}$$

The Central Controller (MGCC) solves its problem for each time as follows:

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.190

$$\min_{P(t),Q(t),V(t),I(t),S(t)} \quad C_{Grid}\left(t,p_{Grid}(t)\right)+C'_{Grid}\left(t,q_{Grid}(t)\right)+\sum_{(i,j)\in\varepsilon} r_{ij}\ell_{ij}(t)$$

$$-\left(\hat{\mu}^{k}\right)^{T}\left(p(t)-p(t)^{k}\right)+\left(\hat{\lambda}^{k}\right)^{T}\left(q(t)-q(t)^{k}\right)+\frac{\rho}{2}\left\|p(t)-p(t)^{k}\right\|^{2}+\frac{\rho}{2}\left\|q(t)-q(t)^{k}\right\|^{2}$$

$$\hat{\mu}_{i}^{k+1}(t) \,\square\, \hat{\mu}_{i}^{k+1}(t)+\gamma\left(p_{RLDi}^{k+1}(t)+p_{ESi}^{k+1}(t)-p_{Geni}^{k+1}(t)-p_{i}^{k+1}(t)\right)$$

$$\hat{\lambda}_{i}^{k+1}(t) \,\square\, \hat{\lambda}_{i}^{k+1}(t)+\gamma\left(q_{RLDi}^{k+1}(t)+q_{ESi}^{k+1}(t)-q_{Geni}^{k+1}(t)-q_{i}^{k+1}(t)\right)$$

Eq. (45)

Results and Discussion

Case study

MATLAB-CVX and OPENDSS software have been used to solve the problem. The proposed distributed algorithms are implemented on the sample microgrid in *Figure 1*. As it is known, diesel generators are located in bus bars 1, 8 and 13, the parameters of their cost function are determined according to *Table 1*. Two similar battery units are placed on pins 4 and 12. The values of the coefficients of their cost function are given in *Table 2*. All times are controllable and α_{RLD} is assumed to be equal to 0.001. Predictive values for controllable loads and PVs are assumed to be ideal. The daily energy price is shown in *Figure 2*, which is derived from the California Electricity Market (CAISO) (Shen et al., 2016). Information about hourly intervals is used as input to the algorithm. The microgrid was connected to the global network. The daily scheduling generated by PCPM and ADMM algorithms is shown in *Figure 3* and *Figure 4*, respectively. In both methods, the total power output of diesel generators plays a greater role in feeding the overall microgrid load, and the batteries are being charged during the hours when photovoltaic systems play an effective role in production. As a result, feeding the batteries, which are themselves consumers at this time, has been done at a lower cost.

Table 1. *Values of diesel generator cost function parameters*.

Production unit	a_{Geni} (\$/kwh^2)	b_{Geni} (\$/kwh)	c_{Geni} (\$)	a'_{Geni} (\$/kwh^2)	b'_{Geni} (\$/kwh)	c'Geni (\$/kwh)
DG1	0.00009	5.49	3.48	0.0000088	0.54	0.34
DG2,3	0.00008	5.41	3.41	0.0000079	0.53	0.31

Table 2. *Values of the battery charge function parameters*.

η_{ES}	0.95
H^{e}_{ES}	1
$H_{ES}(0)$	1.2
$\underline{H}_{ES}$	0.15
$\overline{H}_{ES}$	2.5
d_{ES}	0.2
c_{ES}	0.5
b_{ES}	0.75
a_{ES}	1
H'^{e}_{ES}	0.1
$H'_{ES}(0)$	0.12

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.190

$\underline{H}'_{ES}$	0.01
$\overline{H}'_{ES}$	0.25
d'_{ES}	0.02
c'_{ES}	0.05
b'_{ES}	0.07
a'_{ES}	0.1

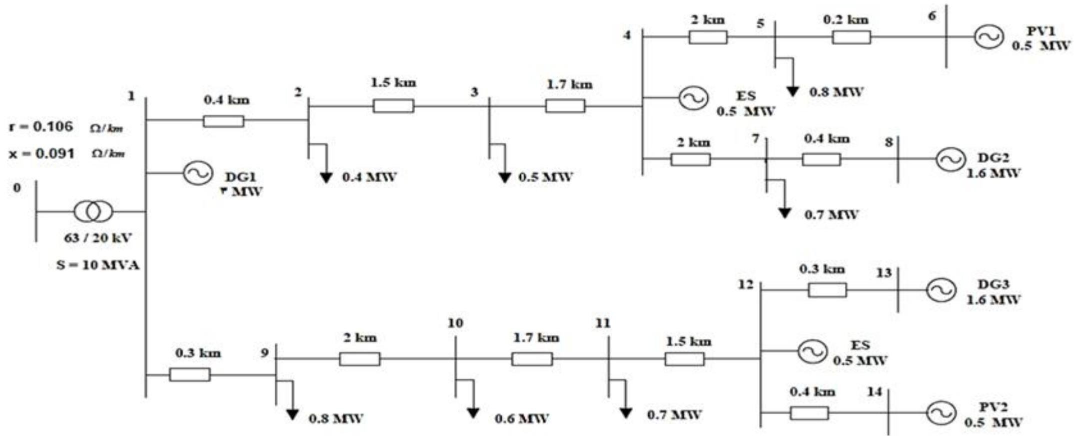

Figure 1. *Proposed distributed algorithms on the sample microgrid.*

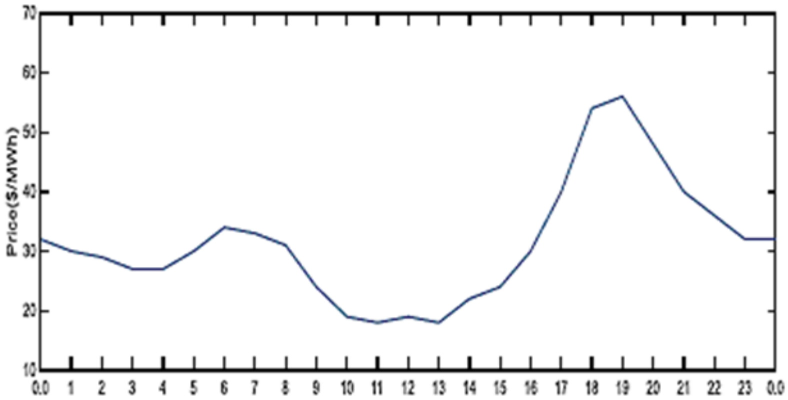

Figure 2. *Daily energy prices.*

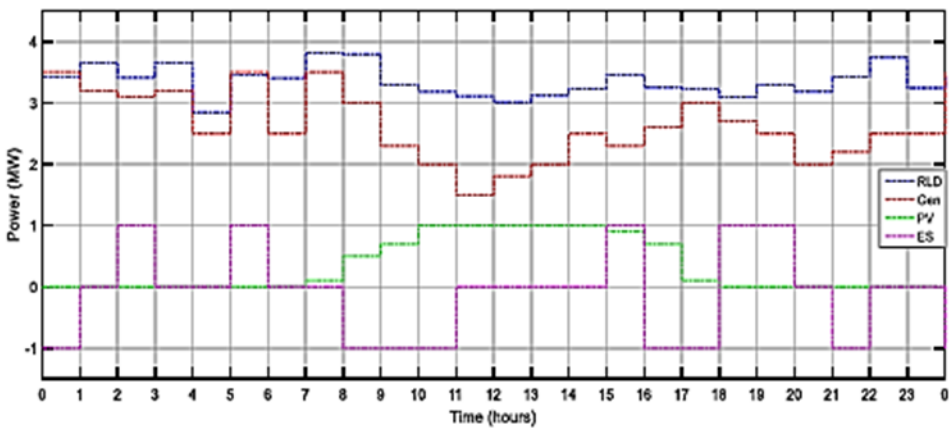

Figure 3. *Daily scheduling generated by PCPM algorithm in network connection mode.*

eISSN: 2716-6341
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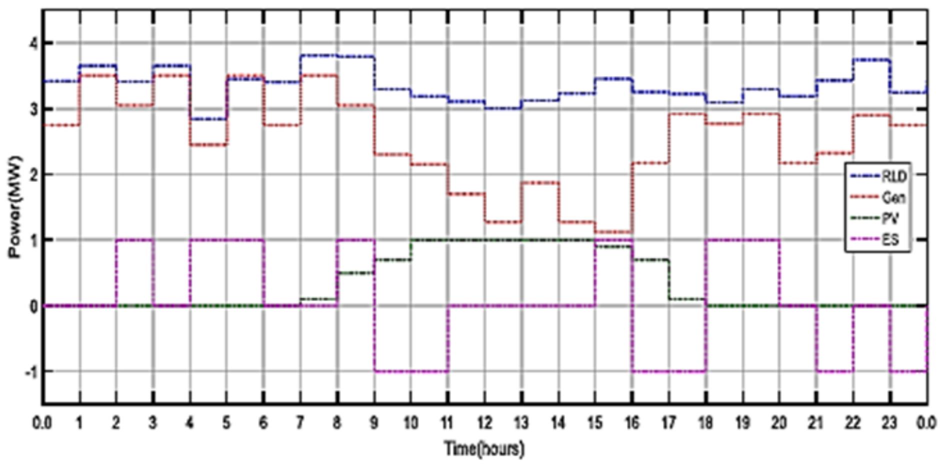
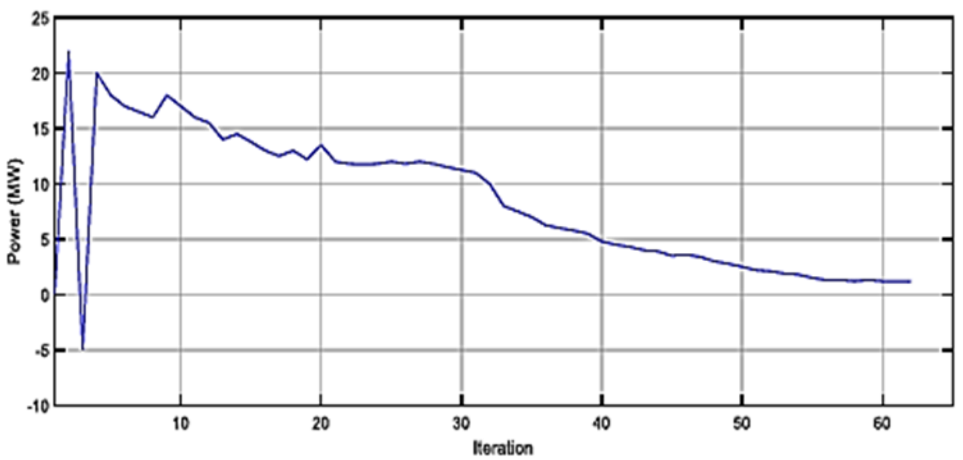


Figure 4. *Daily scheduling generated by ADMM algorithm in network connection mode.*

Figure 5 shows the convergence diagram with the PCPM method in the central controller at 14 o'clock. With this method, the algorithm has reached the optimal answer in 45 repetitions. The convergence of the algorithm with the ADMM method is shown in *Figure 6*. The algorithm has reached the optimal answer with 40 iterations. The energy exchanged between the global grid and the microgrid by PCPM and ADMM methods are shown in *Figure 7* and *Figure 8*, respectively. The microgrid imports energy from the main grid during hours when the energy price is low, and tries to export energy to the national grid by generating more during the hours when the energy price is high. The proposed distributed algorithms in network-independent mode are also examined. *Figure 9* and *Figure 10* show the daily microgrid scheduling using the PCPM and ADMM methods, respectively. The results showed a ten percent increase in the cost of operating the microgrid compared to the network-connected state. A general comparison of the two methods is shown in *Table 3*.

Table 3*. General comparison of PCPM and ADMM methods.*

Micro-grid connection mode to the network	Problem solving method	Number of repetitions in convergence	Operating cost (dollars)
Connected to the main network	ADMM	40	4025
Connected to the main network	PCPM	63	4225
Seperate from the main network	ADMM	42	4213
Seperate from the main network	PCPM	65	4513



eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.190

Figure 5. *Convergence with PCPM method in the central controller at 14 o'clock.*

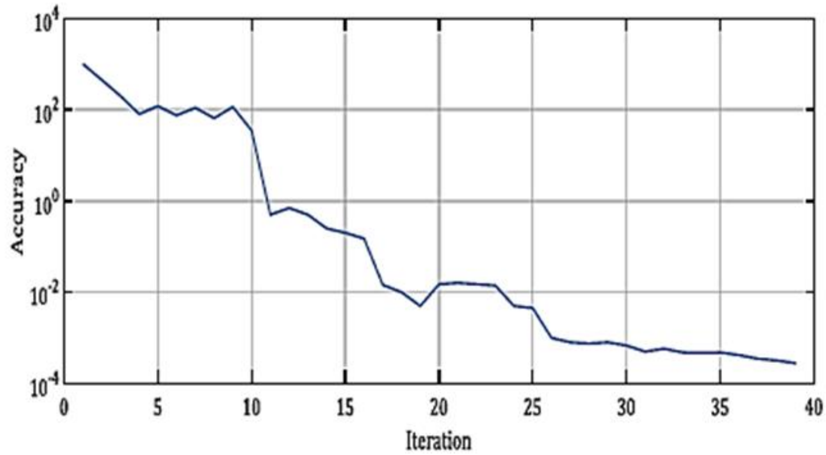


Figure 6. *Convergence of the algorithm with ADMM method.*

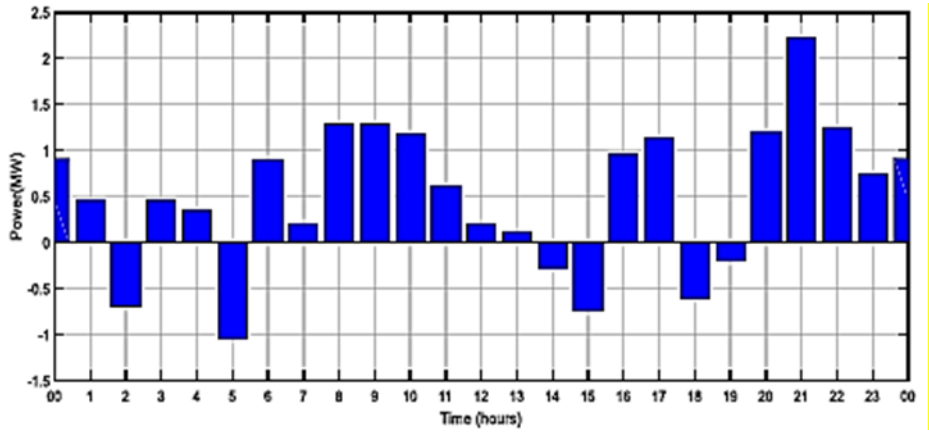


Figure 7. *Energy exchanged between the global grid and the microgrid by PCPM method.*

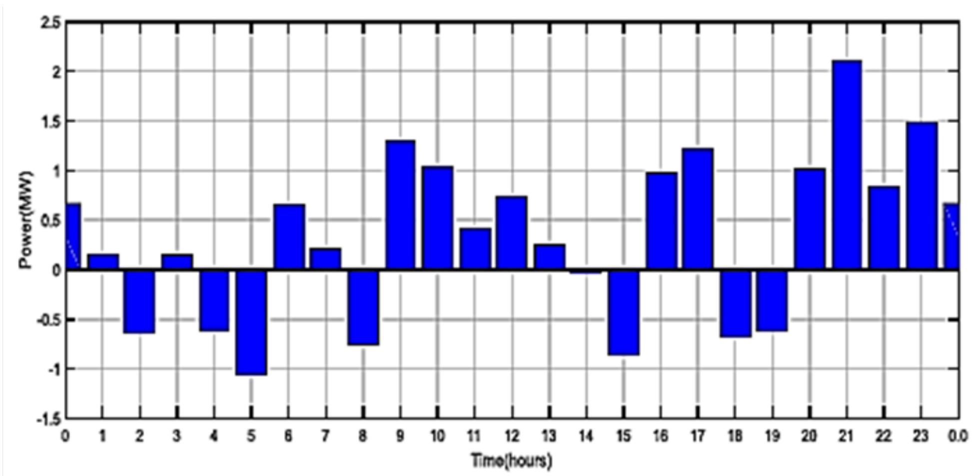


Figure 8. *Energy exchanged between the global grid and the microgrid by the ADMM method.*

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.190

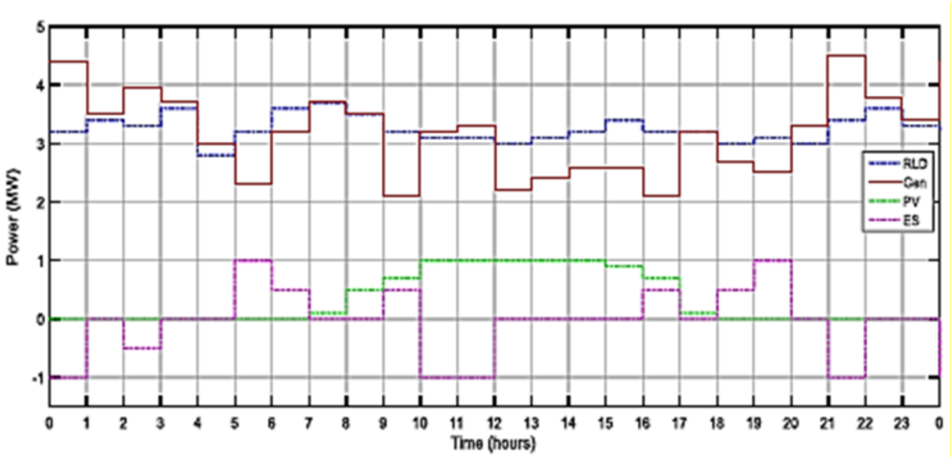


Figure 9. *Daily scheduling generated by PCPM algorithm in network independent mode.*

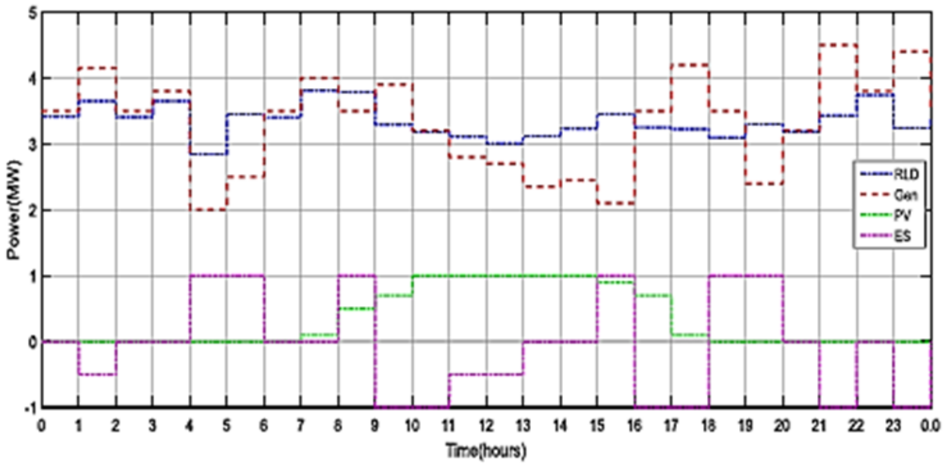


Figure 10. *Daily scheduling generated by the ADMM algorithm in network-independent mode.*

Conclusion

In this paper, a distributed energy management strategy with two methods, PCPM and ADMM, is proposed. In this method, the central controller and the local controllers jointly optimize a single program. The mentioned methods have been investigated on a sample microgrid and in network-connected and network-independent modes. The simulation results show better efficiency and faster convergence of the distributed methods than the centralized method. Also, the ADMM method with less repetition and lower operating cost than the PCPM method has optimized the main problem.

Acknowledgement

This research is self-funded.

Conflict of interest

The authors confirm that there is no conflict of interest involve with any parties in this research study.

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