Simultaneous dynamic optimal control of active and reactive power of microgrids in real-time market considering losses

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Hierarchical control, which includes centralized and decentralized control systems, is a convenient method to control microgrids. The optimal operation of a microgrid from an economic point of view is the duty of the third level of hierarchical control. In the market model with a uniform payment method, the optimal economic dispatch of active power is based on the equality of marginal utility of the microgrid controllable resources. A dynamic population dispatch is applied to a real-time market to implement this equality. The share of each source from the demand is proportional to the value of its fitness. The fitness of each source depends on its rated power, the cost factor, and penalty factor. To calculate the penalty factor, Jacobian and numerical methods are compared. By calculating the marginal utility using a dynamic power dispatch approach and knowledge of the market price of the main power grid (MPG), the path of energy exchange between the microgrid and the MPG is specified. The microgrid participation in the ancillary services market and the profit of microgrid in active or reactive power sales are also investigated. A 14-bus radial network with resistive lines and five different controllable sources are chosen in this paper. A real-time approach is presented for optimal economic control of microgrids with the objective of maximizing their profit in the real-time market.

keywords: *Microgrid, Dynamic optimal control, Real-time market, Losses.*

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NOMENCLATURE

i, j Bus or habitat number.

$p_{gi}(t)$ Instantaneous population of habitat (source) i for active power in kW.

$q_{gi}(t)$ Instantaneous population of habitat (source) i for reactive power in KVar.

$f_{pgi}(t)$ Fitness function of habitat (source) i for active power.

$f_{qgi}(t)$ Fitness function of habitat (source) i for reactive power.

$\bar{f}_{pgi}(t)$ Average fitness function for active power.

u_{pi} Utility function of habitat (source) i for active power in \$/h.

u_{qi} Utility function of habitat (source) i for reactive power in \$/h.

m_p^{mg} Marginal utility of habitat (source) i for active power in \$/MWh.

m_q^{mg} Marginal utility of habitat (source) i for reactive power in \$/MVarh.

m_p^{mg-mdf} Modified marginal utility of habitat (source) i for active power in \$/MWh.

m_p^{ub} The buying price of energy offered by the MO in \$/MWh.

m_p^{us} The selling price of energy offered by the MO in \$/MWh.

m_q^{ub} The buying price of reactive power offered by the MO in \$/MVarh.

a_i, b_i, c_i Coefficients of fuel and pollution cost function of source i.

c_{fpi} Cost coefficient of habitat (source) i for active power in \$/h.

p_d Population of active power demand in kW.

n Number of controllable sources.

p_{loss} Microgrid losses in kW.

c_{qi} Costs of generating reactive power of source i in \$/h.

mc_{qi} Marginal cost of generating reactive power in region m_2 in \$/MVarh.

ρ_{0i} Availability price for generator i in \$.

ρ_{1i} Price of losses in the under-excitation region (m_1) for generator i in \$/MVar.

ρ_{2i} Price of losses in the over-excitation region (m_2) for generator i in \$/MVar.

ρ_{3i} Loss of opportunity price for the generator i in $\$/MVar^2$.

Q_{Gbi}^{lead} Base leading reactive power of the generator i.

Q_{Gbi}^{lag} Base lagging reactive power of the generator i.

Q_{GAi} Maximum reactive power limit of the generator i without a reduction in real power generation.

1. INTRODUCTION

From the economic point of view, considering the amount of internal demand of the microgrid and the purchase price of active and reactive power by the market operator (MO) of the main power grid (MPG), how much the share of distributed energy resources (DERs) of microgrids can be in the generation of active and reactive power? Different factors, such as an increase in the share of microgrids in the production of electrical energy, ever-increasing expansion of renewable sources within microgrids, and the presence of the private sector in the production of electrical energy, enhance the importance of answering the above question.

Microgrids can be operated in both grid-connected and islanded modes. The voltage and frequency of microgrids in grid-connected mode are adjusted by the MPG. In this case, the extra active and reactive power of a microgrid can be injected into the MPG, considering the purchase price of the MPG and the cost-effective economic condition of the microgrid. In the islanded mode, there must be a balance between the active and reactive power generation of the microgrid and its demand. Moreover, in this case, the voltage and frequency of the microgrid must be adjusted by DERs [1]. The IEEE 1547 standard expresses the requirements of connecting the DERs together and to the MPG [2]. Energy management and optimal economic control of the microgrid are more important in grid-connected mode compared to the islanded mode of operation. This is due to the fact that there are more options for the microgrid to exchange energy with the MPG and the neighboring microgrids in the grid-connected mode to maximize the profit of the microgrid.

Suppose that in a real-time market, the microgrid acts as a small grid and follows the prices that are announced by the MO. The microgrid can determine the level of its participation in supplying active and reactive power of the MPG with the aim of maximizing its profit. This is done by receiving the purchase price of active and reactive power from the MO in the MPG, in addition to using a suitable optimization algorithm and prompt control system. Therefore, the main issue in this paper is simultaneous and real-time optimal economic control of both active and reactive power in a grid-connected microgrid, with the aim of maximizing the profit of the microgrid in the real-time market. Various algorithms and control approaches have been proposed so far to control microgrids; these approaches are mostly based on centralized control, decentralized control or a combination of them. Some of these approaches are reported in the following.

In the centralized control method, all DERs and load information are sent to the central controller. After processing and calculating, the required control commands are sent to the controllable DERs and loads. In contrast, in the decentralized method, each unit is controlled merely by a local controller and does not communicate with other controllers or system variables. The first method is not an appropriate control method due to the need for reliable and extensive communication between the central and local controllers. The second method is also inappropriate because of the incapability of making any coordination between

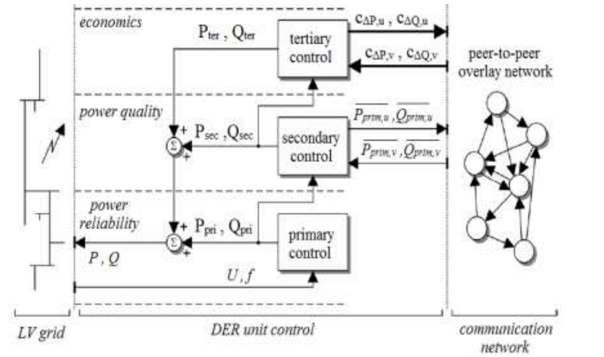

Fig. 1. The block diagram of hierarchical control of microgrids [7].

units in the microgrid. A combination of these methods in the form of a hierarchical control with three levels, i.e., primary, secondary, and tertiary controls, is a suitable method for the control of microgrids [1–3]. These levels are independent of each other since they have different time responses. Controlling the voltage and frequency of the microgrid and preventing the circulating current between the sources are done by the local controller in each source as the primary control and has the fastest response time. Permanent voltage and frequency deviations due to active and reactive power imbalances and the performance of the primary control are restored by the secondary control. Economically optimal operation of the microgrid in both grid-connected and islanded modes and the control of power flow with the MPG are considered to be the responsibilities of the tertiary control, which has the lowest speed compared to the other control levels [4, 5].

Since the subject of this article is related to the economic problems of the microgrid and the tertiary control, some researches in this field are reviewed and discussed in depth. In [6], two optimal economic control mechanisms of the market are compared using an educational algorithm. One of these mechanisms considers a uniform payment based on the equality of the marginal cost or marginal utility of fuel, while the other mechanism considers a pay-as-bid payment rule. It is proved that the profit of the bidder is maximized by implementing a uniform payment mechanism.

The complete schematic diagram of a hierarchical control system including primary, secondary, and tertiary levels as well as their interrelationships with each other, a low voltage distribution network and the communication network is shown in Fig. 1. In [7], a distributed control system and the gossiping algorithm are used for planning the generation in the day-ahead market. In this algorithm, the optimal power is calculated peer to peer, based on equality of the marginal cost of sources such that all sources are operated in the optimum economic condition.

Two control approaches for optimal power dispatch are presented in [8]; one of them is based on market theory and the other on evolutionary game theory. These approaches are implemented by multi-agent systems (MASs). In a MAS, which is a distributed and hierarchical control system, each of the controllable sources and loads in the microgrid (real agents) communicate with a microgrid central controller (MGCC) (virtual agent); the MGCC, in turn, communicates with the MO for the optimal dispatch of power between the generation sources and the MPG. The market theory approach is based on taking the first derivative of the utility (profit) functions of the generation sources, which is equal to a certain value (i.e., the minimum bid price). In this approach, either numerical or analytical methods can be used to solve the problem. In the analytical market theory approach, it is possible to get a negative result for optimal economic power generation under some conditions, such as low demand and high generation cost coefficients. In these conditions, we must impose more constraints, particularly for the power generated by the sources ($p_{gi} \geq 0$), which makes it hard to solve the problem analytically.

The numerical approach for solving the market theory that is considered to be in the form of a non-linear constrained optimization is implemented in the structure of MAS. However, since this optimization problem may be solved using iterative techniques such as Newton-Raphson, there is a heavy computational burden if it is used for microgrids with a large number of DERs.

In the evolutionary game theory approach, a fitness function is defined for each DER (according to the dynamic population dispatch model) by taking the derivative of the utility function. In this model, each unit of the microgrid demand is allocated to a source with the highest fitness. Thus, all units of demand will find their dedicated sources. The fitness function is designed by assuming that all DERs are connected to a single node and that the effect of losses in the microgrid is negligible.

From the researches mentioned above, it can be concluded that using a hierarchical control in the form of MAS and applying a dynamic population dispatch method to it seems to be a suitable candidate for a precise, fast and optimal control of the microgrid in the real-time market. In the following, we review the works conducted in the field, for an understanding of definitions and economic limitations of the electricity market.

Energy management of a network consisting of several microgrids owned by various owners, which can be operated in the grid-connected mode of operation, has been implemented on the basis of MAS [9–11]. The architecture of this system includes three markets, microgrid, an association of the microgrids, and the MPG. For a larger number of microgrids with more versatile sources, there will be lower costs, compensation for uncertainties and contingencies and a higher reliability index. However, if it is possible for a microgrid to purchase its required energy from the MPG or the neighboring microgrids at a lower price, it must reduce its generation and obtain its needs from external sources. The authors of [10] convert the functions and constraints of a nonlinear energy management optimization problem into a set of linear functions and binary variables and then solve the optimization problem using mixed integer linear programming (MILP) by using YALMIP toolbox in MATLAB. The authors of [11] propose a decentralized control system and use MAS architecture for the energy management of the market. They divide the ahead market into two stages of day-ahead and hour-ahead markets and express that the hierarchical structure is an appropriate option for the energy management of a microgrid.

In [12], a daily risk-based optimal scheduling of reconfigurable smart microgrids (RSMGs) in the presence of wind turbines for microgrid operator profit maximization is presented. As a reward scheme for further use of wind, the price of selling power is considered different and more than the price of purchasing power. The wind speed, price of selling and purchasing power are considered as uncertain parameters and scenario generation based on ARMA model is used for simulation. To find the best combination of microgrid switches in each hour, TVAC-PSO algorithm is used and a new constraint called the maximum number of optimal topology constraint is added to limit the number of changes in the structure. Moreover, a risk measure is based on condition value-at-risk (CVaR) is formulated. Numerical results show that by assessing the risk, the expected profit of optimal scheduling problem will be improved and RSMG can achieve the greater revenue by selling power to the upstream network in a long time. Also, in [13], a new optimal strategy for scheduling of RSMGs considering islanding capability constraints is presented. To demonstrate the successful islanding operation, the islanding capability is considered as a probability of islanding operation (PIO) index, which shows the probability, that the microgrid has an adequate level of spinning reserve to meet the local load. The scheduling of RSMGs with islanding operation constraints is formulated as a chance-constrained goal optimization problem, where the objective is defined as minimizing the total operation cost of microgrid in terms of fuel cost, reliability cost, cost of purchasing power from the mains, and switching cost. The numerical results show the effectiveness of the proposed scheduling method.

In the energy management problem of a microgrid, not only we should analyze and determine the objective function and choose the proper optimization approach, but we also should define an implementable market model considering the MPG market operator's policies. The inequality $c^{bg} > c^{bl} > c^{sl} > c^{sg}$ is presented in [14], where c^{bg}, c^{bl}, c^{sl}, and c^{sg} are the purchase rate of energy from the MPG, the purchase rate of energy from the microgrid, selling rate of energy to the microgrid and selling rate of energy to the MPG, respectively. Insertion of the energy exchange rates of the microgrid (c^{bl} and c^{sl}) between the rates of energy exchange of the MPG (c^{bg} and c^{sg}) results in encouraging the local grids (microgrids) to seek independence from the MPG. The results of this policy will be energy exchange among the microgrids and a reduction in their costs. In [15], all DER units and loads are connected by a two-way real-time communication infrastructure linking the microgrid central controller (MGCC) to the local controllers (LCs). The MGCC is able to gather real-time information from the LCs, perform energy management and send control commands to the LCs. It uses a discrete-time model, assuming that the system operates in discrete time for a 24-hour study period.

An ancillary services market for reactive power is defined in a way similar to the active power market. The microgrid can participate in the ancillary services market of the MPG considering its constraints and profits after meeting its own local reactive power demands. The ancillary services market for reactive power is divided into two levels of purchasing reactive power on a seasonal long-term basis and the real-time reactive power dispatch [16]. In [17], for real-time dispatch of reactive power, the reactive power payment function for DERs or microgrid is defined with the goal of its minimization.

In the presented methods for active and reactive power dispatch in the power market, first, the active power dispatch is considered. Moreover, in order to generate more reactive power, it may be required to reduce the active power of DERs (due to field or armature heating limit of synchronous generators); therefore, in this case, an active power re-dispatch is necessary. Indeed, the duration of active and reactive power dispatch will increase in this way. Similarly, the authors of [18] solve the minimization problem of the payment function for reactive power using a genetic algorithm. It should be noted that the DERs with no participation in the economic dispatch of active power cannot also participate in the reactive power market.

It is assumed that the microgrid used in this paper is a low-voltage radial network with resistive lines that can connect to the MPG through a bus at the point of common coupling (PCC). The aforementioned bus is also assumed to have sometimes a weak voltage level. Therefore, in addition to selling active power to the MPG, in accordance with the rules governing the electricity market, the microgrid is also able to participate in the ancillary services market and sell reactive power to improve the voltage at PCC. Moreover, microgrids follow the price announced by the MPG and are not able to change the market price because they have less production than medium and large power plants. Therefore, by taking into account the buying and selling price of active and reactive power from the MO in different time periods throughout the day, the microgrid makes a decision on the amount of active or reactive power purchase or sale to maximize its profits.

We mention the following items as the innovations of this study:

- Presenting an algorithm for economic power dispatch in the real-time market using simultaneous dynamic dispatch of both active and reactive power, according to Fig. 5 by considering the purchase or sale price of active and reactive power by the MO in the real-time market for the next 10 minutes.
- Applying the effects of the injection of active and reactive power of each source to the losses of the microgrid and considering the active limitations such as thermal limitation of apparent power in synchronous generators according to the relations of 12, 22, 23 and 25.
- Reduce the time of optimization, because the three-stage process of active power dispatch, reactive power dispatch, and active power re-dispatch in the previous researches have changed to the one-stage process of simultaneous dispatch of active and reactive power.
- Accurate approximation of the numerical method to calculate the losses penalty factor compared to the analytical method, and the use of the numerical method to reduce the runtime of the dynamic power dispatch algorithm according to the results of Tables 4 and 5.
- Investigating the impact of losses penalty factor on the competitive price of the microgrid in the electricity market according to Fig. 7.
- The possibility of responding to the spike price fluctuations in the real-time market due to the desired speed of simultaneous management of active and reactive power of the microgrid in the proposed method.

The precise definition of a dynamic population model and its implementation method for dynamic dispatch of the active and reactive power of microgrid are presented in Section 2. The effect of microgrid losses on the fitness function of dynamic power dispatch is studied in Section 3. The microgrid model in the real-time market is discussed in Section 4. The radial model of the microgrid with resistive lines is introduced in Section 5; the fuel cost functions of DERs and their pollution costs plus the microgrid energy management flowchart are discussed and simulated. Moreover, the competitive price is determined for active and reactive power in this section. Finally, conclusions are drawn in Section 6.

2. DYNAMIC POWER DISPATCH STRATEGY

A. Definition of dynamic model

A dynamic population model is proposed for solving important issues in smart grids, including power dispatch and demand response. An optimal power dispatch in this model is called the replicator dynamic (RD). In this model, it is assumed that members of a finite population can choose one of the n habitats for their own lives. A fitness function is defined for each habitat based on its capacity and cost of maintenance of the population. Naturally, at each instant, any member of the population is attracted to a habitat with the best fitness. The fitness of each habitat decreases as it reaches closer to its ultimate (nominal) capacity, and the fitness becomes zero when the habitat reaches the ultimate capacity. In this model, the membership process of the habitats in each period is done, assuming that the number of members and habitats are fixed. When either all members of the population find their proper habitats or the capacity of the habitats is full, the process is terminated. The dynamic model for membership of habitat i for population p_d is given as follows:

$$\frac{\dot{p}_{gi}(t)}{p_{gi}(t)} = f_{pgi}(p_{gi}(t)) - \overline{f}_{pg}(t) \quad \textbf{(1)}$$

where $p_{gi}(t)$ is the instantaneous population of habitat i, $\dot{p}_{gi}(t)$ is the time derivative of $p_{gi}(t)$, $f_{gi}(t)$ is the fitness function of habitat i and $\bar{f}_{pg}(t)$ is the average fitness function defined as follows:

$$\overline{f}_{pg}(t) = \frac{1}{p_d}\sum_{j=1}^{n} p_{gj}(t).f_{pgj}(p_{gj}(t)) \quad \textbf{(2)}$$

From this definition, the following constraint is also met:

$$\sum_{i=1}^{n} p_{gi}(t) = p_d \quad \textbf{(3)}$$

The dynamic model (1) reaches a stable state when $\dot{p}_{gi}(t) = 0$. Therefore, we can write the following relation for all units from $1: n$:

$$f_{pgi}(p_{gi}{}^*) = \overline{f^*}_{pg} \quad \textbf{(4)}$$

where $p_{gi}{}^*$ is the optimal population for unit i [8].

B. Implementation of dynamic population dispatch model in microgrid active power dispatch

According to the definition presented in section A, for implementing the dynamic population dispatch model in active power dispatch of microgrids, the amount of active power demand is denoted by p_d, n is the number of controllable sources in the microgrid and p_{gi} is the active power generated by the ith unit in the microgrid. The fitness function is descending since it drops as more members are added to the habitat (source). Furthermore, for optimal economic dispatch of active power amongst the sources, the equality of their marginal utility is required according to relation (5).

$$\frac{du_{p1}}{dp_{g1}} = \frac{du_{p2}}{dp_{g2}} = ... = \frac{du_{pn}}{dp_{gn}} = m_p^{mg} \quad \textbf{(5)}$$

where u_{pi} is the utility function of source i and m_p^{mg} is its marginal utility, which serves as a bidding price for the active power generation of the microgrid.

The utility function (income minus cost) and the fitness function of each source (that is derived from its marginal utility) are defined according to Eqs. (6) and (7) as follows [8, 9]:

$$u_{pi}(p_{gi}) = m_p^{mg} p_{gi} - (c_i p_{gi}^2 + b_i p_{gi} + a_i) \tag{6}$$

$$f_{pi}(p_{gi}) = \frac{du_{pi}(p_{gi})}{dp_{gi}} = m_p^{mg} - 2c_i p_{gi} - b_i \tag{7}$$

The parameters a_i, b_i, and c_i in (6) are related to the coefficients of fuel and pollution cost function of source i. In (7), the marginal utility m_p^{mg} can be omitted from the fitness function of source i for the production of rated power (p_{gnomi}) as a boundary condition because the fitness function is zero.

$$\begin{aligned} & f_{pi}(p_{gi}) = 0 \; when \; p_{gi} = p_{gnomi} \;\Rightarrow\; m_p^{mg} - \mathrm{b_i} = 2\mathrm{c_i} p_{gnomi} \\ & f_{pi}(p_{gi}) = 2\mathrm{c_i p_{gnomi}} - 2\mathrm{c_i p_{gi}} = 2\mathrm{c_i} p_{gnomi}(1 - \tfrac{p_{gi}}{p_{gnomi}}) \\ & c_{fpi} = \tfrac{1}{2c_i p_{gnomi}} \\ & f_{pi}(p_{gi}) = \tfrac{1}{c_{fpi}}(1 - \tfrac{p_{gi}}{p_{gnomi}}) \end{aligned} \tag{8}$$

where c_{fpi} is the cost coefficient of source i. The utility function is redefined by integrating Eq. (8) as follows:

$$u_{pi}(p_{gi}) = \frac{1}{c_{fpi}}(p_{gi} - \frac{0.5p_{gi}^2}{p_{gnomi}}) \tag{9}$$

Lagrange equation can be used to study the effect of network losses on the active power fitness function as follows:

$$\ell_p = \sum_{i=1}^{n} u_{pi} + m_p^{mg-mdf}(\sum_{i=1}^{n} p_{gi} - p_d - p_{loss}) \tag{10}$$

The modified marginal utility (m_p^{mg-mdf}) may be obtained by taking derivative of Eq. (10) with respect to the power generation of unit i as follows:

$$\begin{aligned} & \tfrac{\partial \ell_p}{\partial p_{gi}} = \tfrac{du_{pi}}{dp_{gi}} + m_p^{mg-mdf}(1 - \tfrac{\partial p_{loss}}{\partial p_{gi}}) = 0 \\ & m_p^{mg-mdf} = \tfrac{1}{1-\frac{\partial p_{loss}}{\partial p_{gi}}} \; \tfrac{du_{pi}}{dp_{gi}} \end{aligned} \tag{11}$$

The condition for the optimal economic power dispatch is the equality of marginal utility for the DERs. After defining the marginal utility as the fitness function for DERs, the modified fitness function is defined considering the effect of generation of each unit on the losses of the microgrid:

$$f_{pi}^{mdf}(p_{gi}) = \frac{1}{1 - \frac{\partial p_{loss}}{\partial p_{gi}}} . \frac{1}{c_{fpi}}(1 - \frac{p_{gi}}{p_{gnomi}}) \tag{12}$$

According to Eq. (12), the modified fitness function is also zero for generating the rated power. Any resource that has a greater impact on microgrid losses increases its fitness function, and according to Eq. (2), the average fitness function and minimum bid price of microgrid increase. The modified utility function for DER can be obtained by considering microgrid losses as it was done in the previous section by integrating the modified fitness function. However, first, it is better to discuss the approach of dynamic reactive power dispatch and then the parameter $\partial p_{loss}/\partial p_{gi}$ in microgrids.

In order to implement the theory of dynamic power dispatch in the MAS, the relations of this theory are expressed in a discrete manner in Fig. 2. This figure shows the type and method of

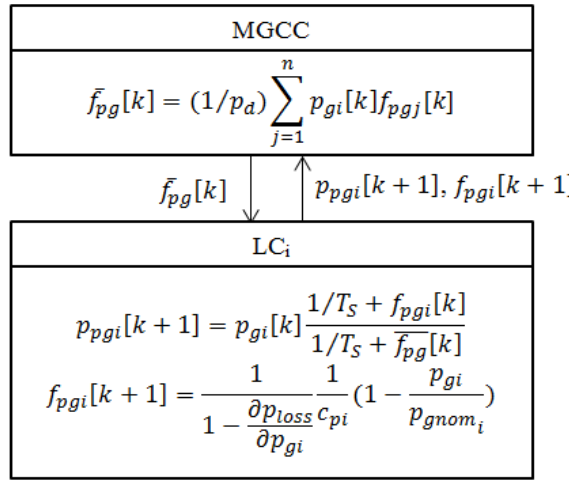

Fig. 2. Agent scheme for the RD strategy at kth iteration time.

data transmission between the local controller and the MGCC. The MGCC (third control level) calculates the average fitness function of the kth rank and sends it to the local controllers (first level control), based on the amount of demand, nominal power and cost coefficients of the DERs. This level also calculates the rank of k+1 and sends it to the MGCC. This process continues until the allocation of demand to DERs is completed [8].

C. Implementation of dynamic population dispatch model in microgrid reactive power dispatch

Similar to the relations of the previous subsection, with some other considerations for reactive power, we can obtain:

$$\frac{du_{q1}}{dq_{g1}} = \frac{du_{q2}}{dq_{g2}} = ... = \frac{du_{qn}}{dq_{gn}} = m_q^{mg} \tag{13}$$

where u_{qi} is the utility of reactive power of source i and m_q^{mg} is its marginal utility. The function u_{qi} (income minus costs) is defined as follows:

$$u_{qi}(p_{gi}) = m_q^{mg} q_{gi} - c_{qi} \tag{14}$$

Costs of generating active power and reactive power are different from each other. A survey of the literature indicates that the following relation can be used as the cost of generation for reactive power (c_{qi}) by the sources of microgrid [17]:

$$\begin{aligned} c_{qi} = {} & \rho_{0i} - m_{1i}\rho_{1i}(q_{gi} - Q_{Gbi}^{lead}) + m_{2i}\rho_{2i}(q_{gi} - Q_{Gbi}^{lag}) \\ & + m_{3i}\rho_{2i}(q_{gi} - Q_{Gbi}^{lag}) + \tfrac{1}{2}m_{3i}\rho_{3i}(q_{gi} - Q_{GAi})^2 \end{aligned} \tag{15}$$

The reactive power generated by a synchronous generator may be divided into three ranges $m1$, $m2$, and $m3$, according to Eq. (16). These parameters are described accordingly in Fig. 3.

$$\begin{aligned} & m_{1i} + m_{2i} + m_{3i} = 1; \\ & m_{1i} = 1; \;\; if\; Q_{Gi}^{\min} \le q_{gi} \le Q_{Gbi}^{lead} \\ & m_{2i} = 1; \;\; if\; Q_{GBi}^{lag} \le q_{gi} \le Q_{GAi} \\ & m_{3i} = 1; \;\; if\; Q_{GAi} \le q_{gi} \le Q_{GBi} \end{aligned} \tag{16}$$

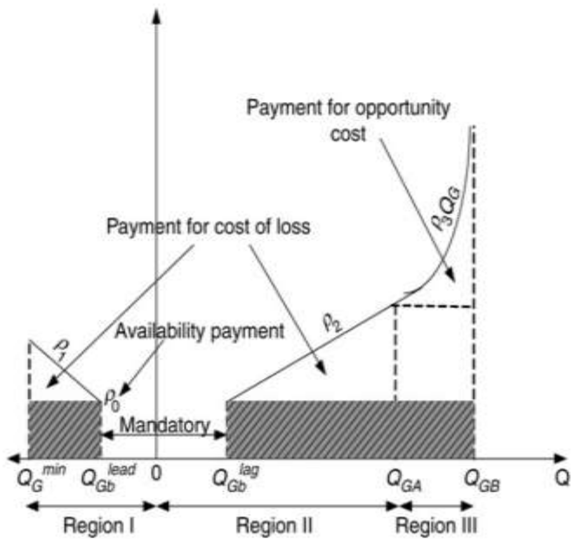

Fig. 3. Payment for reactive power [17].

Considering Eqs. (14) and (15), the fitness function for reactive power is given as:

$$f_{qi}(q_{gi}) = \frac{du_{qi}(q_{gi})}{dq_{gi}} = m_q^{mg} + m_{1i}\rho_{1i} - m_{2i}\rho_{2i} \\ -m_{3i}\rho_{2i} - m_{3i}\rho_{3i}(q_{gi} - Q_{GA\,i}) \tag{17}$$

Consequently, the fitness function is constant over ranges m_1 and m_2. Moreover, an increase in the generation of reactive power in these operating regions does not impose any restriction on the generation of active power. Therefore, the criterion for the allocation of reactive power can be obtained by comparing the reactive power marginal costs of DERs. Selling the reactive power to the MPG is economical if the purchase price of the reactive power payable by the MPG is higher than the lowest reactive power marginal cost of DERs. However, in the operating region m_3, the fitness function of reactive power is descending similar to that of active power, and for this region, we can write:

$$@m_3: \; f_{qi}(q_{gi}) = m_q^{mg} - m_{3i}(\rho_{2i} - \rho_{3i}(q_{gi} - Q_{GA\,i})) \\ if\; q_{gi} = Q_{GBi} \Rightarrow f_{qi}(q_{gi}) = 0\,,\; m_q^{mg} = m_{3i}(\rho_{2i} - \rho_{3i}(Q_{GBi} - Q_{GA\,i})) \\ f_{qi}(q_{gi}) = m_{3i}\rho_{3i}Q_{GBi}(1 - \tfrac{q_{gi}}{Q_{GBi}}) \tag{18}$$

The marginal cost of generating reactive power in region m_2 (mc_{qi}) is given by:

$$@\,m_2: \; mc_{qi} = m_{2i}\rho_{2i} \tag{19}$$

It can also be assumed that the amount of generated active power exceeds the local demand of the microgrid and the extra power can be injected into the MPG. In this situation and simultaneous dynamic dispatch of active and reactive power, the maximum economic generation of active power by the microgrid can be determined from the MO's buying bid. In other words, according to Eq. (12) and Fig. 7 in the simulation section, higher demand for generation results in a lower average fitness function and the marginal utility. It is necessary to consider the buying bid for reactive power by the MPG. It is assumed that dynamic active power dispatch is in the position of the equality of the average fitness function with the bid price of the MO. In this case, selling active power is no longer economically justified if the utility of active power is less than that of reactive power, and the dynamic dispatch of active power must stop at this point and the dynamic dispatch of reactive power must proceed up to the maximum generation capacity or a needed amount and vice versa.

In previous researches (e.g., [16]), first, active power dispatch is done before reactive power dispatch. If the reactive power is dispatched in region m3, it is necessary to perform an active power re-dispatch and compute the cost of changes in active power and losses in the microgrid. This process, in turn, increases the computational time required for economic active and reactive power dispatch. Considering the simultaneous dispatch of active and reactive power in this paper, the reactive power constraint for the synchronous generators (Q_{GA}) is computed for each unit of power being dispatched based on the field heating limit in Fig. 4 and Eq. (20). Therefore, there is no need to use the descending fitness function in region m_3. In other words, with the simultaneous dynamic dispatch of active (based on the fitness function given by (12)) and reactive power (based on the marginal cost given by relation (22)), the main goal, namely, real-time control at the third level of hierarchical control is achieved.

$$Q_{GAi} = -\frac{V_{ti}^2}{X_{si}} + \sqrt{(\frac{E_{\max i}}{X_{si}}V_{ti})^2 - P_{gi}^2} \tag{20}$$

where X_s is the synchronous reactance, E_{max} is the magnetic motive force (mmf), V_t is the terminal voltage and P_g is the instantaneous power generation of the synchronous generator [17].

The impact of microgrid losses on the marginal cost of reactive power in region m2 is obtained in a way similar to the fitness function of active power using the Lagrange equation as follows:

$$\ell_q = \sum_{i=1}^{n} c_{qi} + mc_q^{mdf} \sum_{i=1}^{n} (p_{gi} - p_d - p_{loss}) \tag{21}$$

Assuming a resistive microgrid, we can ignore reactive power losses and obtain the modified marginal cost (mc_q^{mdf}) by taking the derivative of Eq. (21) with respect to the generated reactive power as follows:

$$\frac{\partial \ell_q}{\partial q_{gi}} = \frac{dc_{qi}}{dq_{gi}} + mc_{qi}^{mdf}(1 - \frac{\partial p_{loss}}{\partial q_{gi}}) = 0 \\ @\,m_2: \; mc_{qi}^{mdf} = \frac{1}{1-\frac{\partial p_{loss}}{\partial q_{gi}}}\frac{dc_{qi}}{dq_{gi}} = \frac{1}{1-\frac{\partial p_{loss}}{\partial q_{gi}}}\rho_{2i} \tag{22}$$

3. CALCULATION OF DERIVATIVE OF LOSSES WITH RESPECT TO ACTIVE AND REACTIVE POWER

There are various methods for calculating the derivative of losses. Some of these methods are Generation Shift Distribution Factor (GSDF), Generalized Generation Shift Distribution Factor (GGDF), Z-bus Distribution Factor (ZBD), Power Transformer Distribution Factor (PTDF) and Jacobian Based Distribution Factor (JBDF). While the first four approaches mentioned above are merely applied to the derivative of losses with respect to the active power, the approach JBDF involves the derivative of losses with respect to the active and reactive power. In this paper, according to the following equations, the derivative of losses with respect to active and reactive power is calculated

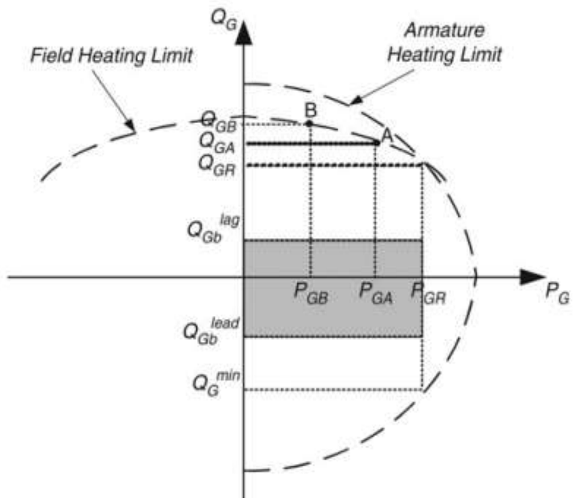

Fig. 4. The synchronous generator limitations curve [17].

using JBDF and applied to the fitness function of dynamic active and reactive power dispatch [19].

$$\frac{\Delta p_{loss}}{\Delta p_i} = \sum_{m=1}^{nbr} \frac{2}{g_m |v_p|^2}\Big[p_m\Big(\frac{\partial|v_p|}{\partial p_i}\frac{\partial p_m}{\partial|v_p|} + \frac{\partial|v_q|}{\partial p_i}\frac{\partial p_m}{\partial|v_q|} + \frac{\partial\delta_p}{\partial p_i}\frac{\partial p_m}{\partial\delta_p} + \frac{\partial\delta_q}{\partial p_i}\frac{\partial p_m}{\partial\delta_q}\Big) + q_m\Big(\frac{\partial|v_p|}{\partial p_i}\frac{\partial q_m}{\partial|v_p|} + \frac{\partial|v_q|}{\partial p_i}\frac{\partial q_m}{\partial|v_q|} + \frac{\partial\delta_p}{\partial p_i}\frac{\partial q_m}{\partial\delta_p} + \frac{\partial\delta_q}{\partial p_i}\frac{\partial q_m}{\partial\delta_q}\Big)\Big] \quad \textbf{(23)}$$

Assuming a microgrid with resistive lines, parameters g_m, v, δ, and nbr are the conductivity of line m, bus voltage, the angle of the bus voltage and the number of lines in the microgrid, respectively; p_m and q_m denote the active and reactive transmission power of line m between the nodes p and q. Some quantities such as $\partial|v_p|/\partial p_i$, $\partial|v_q|/\partial p_i$, $\partial\delta_p/\partial p_i$, and $\partial\delta_q/\partial p_i$ can be obtained from the inverse of the Jacobean matrix as follows:

$$\begin{bmatrix} \Delta\delta \\ \Delta|V| \end{bmatrix} = J^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \quad \textbf{(24)}$$

The derivative of losses with respect to reactive power can also be computed as follows:

$$\frac{\Delta p_{loss}}{\Delta q_i} = \sum_{m=1}^{nbr} \frac{2}{g_m |v_p|^2}\Big[p_m\Big(\frac{\partial|v_p|}{\partial q_i}\frac{\partial p_m}{\partial|v_p|} + \frac{\partial|v_q|}{\partial q_i}\frac{\partial p_m}{\partial|v_q|} + \frac{\partial\delta_p}{\partial q_i}\frac{\partial p_m}{\partial\delta_p} + \frac{\partial\delta_q}{\partial q_i}\frac{\partial p_m}{\partial\delta_q}\Big) + q_m\Big(\frac{\partial|v_p|}{\partial q_i}\frac{\partial q_m}{\partial|v_p|} + \frac{\partial|v_q|}{\partial q_i}\frac{\partial q_m}{\partial|v_q|} + \frac{\partial\delta_p}{\partial q_i}\frac{\partial q_m}{\partial\delta_p} + \frac{\partial\delta_q}{\partial q_i}\frac{\partial q_m}{\partial\delta_q}\Big)\Big] \quad \textbf{(25)}$$

The inverse Jacobian matrix approach might run into problems in some radial networks since the determinant of the Jacobean matrix has a high value in such networks such that it might lead to divergence in the inverse matrix computation. Another method for computing the derivative of losses is the numerical method. Accordingly, with a partial increase of active (Δp) or reactive (Δq) power in the generation nodes, the derivative of losses can be obtained at the output of the load flow. In this case and assuming fixed loads in the microgrid, some of these partial changes in active power (Δp_{gi}) will appear in microgrid losses (Δp_{losses}) and the remaining will appear as a change in the power of the node connected to the MPG (Δp_{ref}) according to Eq. (26). The results of the two methods are compared with each other in the section of simulation.

$$\Delta p_{gi} = \Delta p_{loss} + \Delta p_{ref} \rightarrow \frac{\Delta p_{loss}}{\Delta p_{gi}} = 1 - \frac{\Delta p_{ref}}{\Delta p_{gi}} \quad \textbf{(26)}$$

The following relation is obtained for the derivative of losses with respect to reactive power in a similar numerical method as follows:

$$\Delta p_{loss} + \Delta p_{ref} = 0 \rightarrow \frac{\Delta p_{loss}}{\Delta q_{gi}} = -\frac{\Delta p_{ref}}{\Delta q_{gi}} \quad \textbf{(27)}$$

From Eq. (25), it can be seen that the derivative of losses is a function of the variables in the neighborhood of node i, and it is not directly related to the amount of power injected into node i (p_{gi}). Thus, the modified fitness function of active power can be obtained by integrating Eq. (12) as follows:

$$u_{mdf\,i}(p_{gi}) = \frac{1}{1-\frac{\partial p_{loss}}{\partial p_{gi}}}.\frac{1}{c_{fpi}}.(p_{gi} - \frac{0.5p_{gi}^2}{p_{gnomi}}) \quad \textbf{(28)}$$

The modified utility function for reactive power is shown below considering the relation for the modified marginal cost function (22) as follows:

$$@m_2 : u_{mdf\,i}(q_{gi}) = \frac{1}{1-\frac{\partial p_{loss}}{\partial q_{gi}}}\,(m_{qi}^{mg} - \rho_{2i})q_{gi} \quad \textbf{(29)}$$

4. PROPOSED MICROGRID MODEL IN THE REAL-TIME MARKET

In [20], the structure of energy trading and the market model is based on a decentralized energy management system that is implemented in a discrete-timely double-sided auction capability and uniform pricing mechanism. Indeed, the implementation of a continuous-timely market model, in addition to a secure and fast communication platform, requires agile players (buyers and sellers), which is not realistic. Therefore, energy trading in a discrete-timely structure is a good environment for all players in the electricity market. Additionally, the uniform payment mechanism provides a competitive price for all market participants, regardless of their bid rate, and encourages suppliers to bid a lower price in order to increase the likelihood of selling in the market. The decision-making process in the market mechanism includes announcing the status of the buyer (seller) and the bid rate to the market plus determining the market clearing price (MCP) and announcing it to the winner players in order to plan production within the specified time frame.

The uniform payment method can also be implemented using the dynamic power dispatch in the form of a decentralized and discrete-time control system. Considering the real-time market, the proposed algorithm in this article has to receive the information required from the market players, including the conditions for production and consumption of the microgrid. Moreover, assuming that the microgrid follows the market price, the proposed algorithm determines the optimal economic production of the microgrid for the next period (10 minutes) in the grid-connected mode.

One of the inequalities in a power market indicates that the purchase price of energy offered by the MO (mp^{ub}) is always less than its selling price (mp^{us}). The marginal utility of the microgrid (mp^{mg-mdf}) is a function of the level of participation, constraints of generation, level of demand and the results of the load flow of the microgrid. On the other hand, selling to the MPG is possible if mp^{ub} is equal to or larger than mp^{mg-mdf}. It should be noted that the tariff for the purchase and sale of energy by the MO of the MPG varies during a 24-hour period. However, it may be assumed as a constant value in the same way as other parameters during a 10 minutes period for the real-time market.

The flowchart in Fig. 5 is thus used to compute the optimal active and reactive power dispatch for each unit based on a given market mechanism by considering the presented equations and data. Regarding the radial nature of the microgrid, a forward/backward sweep (FBS) load flow method is a convenient and fast way to calculate the derivative of the losses of each source in the microgrid. In this algorithm, the most suitable source is identified by Eqs. (12) and (22) at each step that the dynamic power dispatch is executed.

If no active power is requested by the MPG from the microgrid in the real-time market, the production of DERs is not economical when the marginal utility of the microgrid for supplying its own load (m_{pint}^{mg}) is higher than the selling price of the MPG (m_p^{us}). Therefore, in this situation, the power required by the microgrid is purchased from the MPG.

In the case of requesting active power from the microgrid by the MPG, the dynamic allocation of active power to the DERs has to be continued at least to the extent that the marginal utility of the microgrid (m_p^{mg-mdf}) is equal to the purchase price of the MPG (m_p^{ub}). In fact, this equality is the threshold for the minimum economic output of the microgrid to sell active power to the MPG besides supplying its internal demand. In addition, more production reduces the marginal utility to less than the purchase price of the main network, and selling of active power can be more economical. However, at the equalization point, the marginal utility of active and reactive power should also be compared.

If the utility of either active or reactive power exceeds for each step of allocation, its production will continue to a required level or the maximum production, and the production of the other one will be stopped. The output of the dynamic power dispatch algorithm in the real-time market is to decide whether to buy or sell the active and reactive from/to the MPG and determine its amount, considering the market operator prices and the costs of active and reactive power generation by the DERs. One of the advantages of dynamic power dispatch is its ability to respond to a wide variety of spike prices in the real-time market and to increase the profit for the microgrid as an active economic player from the private sector.

5. SIMULATION

A. Case study 1

The first microgrid under study is a 14-bus radial network with resistive lines connected to the MPG. Moreover, it is assumed that the microgrid has five DERs consisting of three diesel generators and two microturbines with different fuel and pollution cost functions. Data on the lines and the topology of the microgrid are presented in Table 1.

Coefficients related to the second-order fuel cost of generators (a_1, b_1, and c_1), and the coefficients of the second-order cost of NOx pollutant production of generators (a_2, b_2, and c_2) are given in Table 2. Load data of the microgrid is given in Table 3, and the single line diagram of the microgrid is shown in Fig. 6 [21–23].

Variable and uncontrollable sources (i.e., solar and wind) do not have fuel and pollution cost functions and must always inject

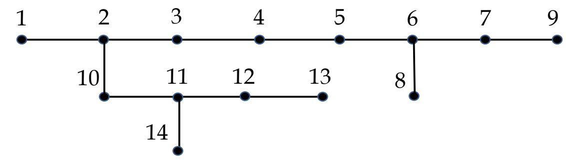

Fig. 6. single line diagram of the microgrid.

the maximum of their generated power into the grid. These sources can be modeled as negative loads at the buses where they are installed, and their presence results in a reduction in load of the microgrid and variable costs. However, they are not included in this case study.

The BFS method has been used for the load flow of microgrid as a radial network in this research study [24, 25]. Two approaches have been presented to compute the derivative of losses in Section 3. Here, we shall compare them by benefiting from an example. When generating 780 kW at the rated power of the microgrid, 311 kW is the share of microgrid's loads and the rest is the losses and possible injection into the MPGs. Under these conditions, the results of using JBDF and partial numerical methods for the derivative of losses with respect to active and reactive power are given in Table 4. These results indicate very little difference between the two methods. Thus, the numerical method could also be used given the mentioned limitations on the use of the Jacobean method in radial networks. The same procedure could be used for the derivative of losses of the buses with respect to reactive power injection.

Fig. 7 shows the fitness function of DERs for supplying the needed active loads of the microgrid plus selling its excess generation to the MPG. The solid line shows the fitness function without the losses penalty factor (mp^{mg}), while the dotted line shows the modified fitness function, considering the losses penalty factor (mp^{mg-mdf}). According to Fig. 7, at a certain point, the improved marginal utility (mp^{mg-mdf}) is greater than the normal marginal utility (mp^{mg}) due to the derivative of losses of DERs. In other words, the losses penalty factor shows its role by an increased marginal utility, that is, an increased minimum economic bid price in microgrids. When the derivative of losses in buses is larger, the minimum economic bid price (competitive) is also higher. In the assumed operating point with an improved average fitness function of 10 $/MWh, the share of buses 2, 3, 7, and 13 are 224, 89, 116, and 40 KW, respectively with a total sum of 469 KW according to Fig. 7. Indeed, the minimum value of the improved economic bid for the microgrid is 10 $/MWh in this case. The normal marginal utility is 9.61 $/MWh for generating the same amount of power (469 KW) without considering the derivative of losses (single node model). In fact, the competitive price of the microgrid has an increase of 0.39 $/MWh because of losses.

As shown in Fig. 7, the normal and improved fitness functions of the generator at bus 7 has the biggest difference, which is mainly due to the longest electrical distance to the MPG, and as a result, the highest derivative of losses compared to the other sources at other buses. In contrast, the generator at bus 2 has the smallest derivative of losses due to its proximity to the MPG. Therefore, the difference between its normal and improved fitness is less than that of other buses. The time required to get an answer for the present microgrid is about 10 seconds. In the case of a microgrid with a single-node model, the time to receive a re-

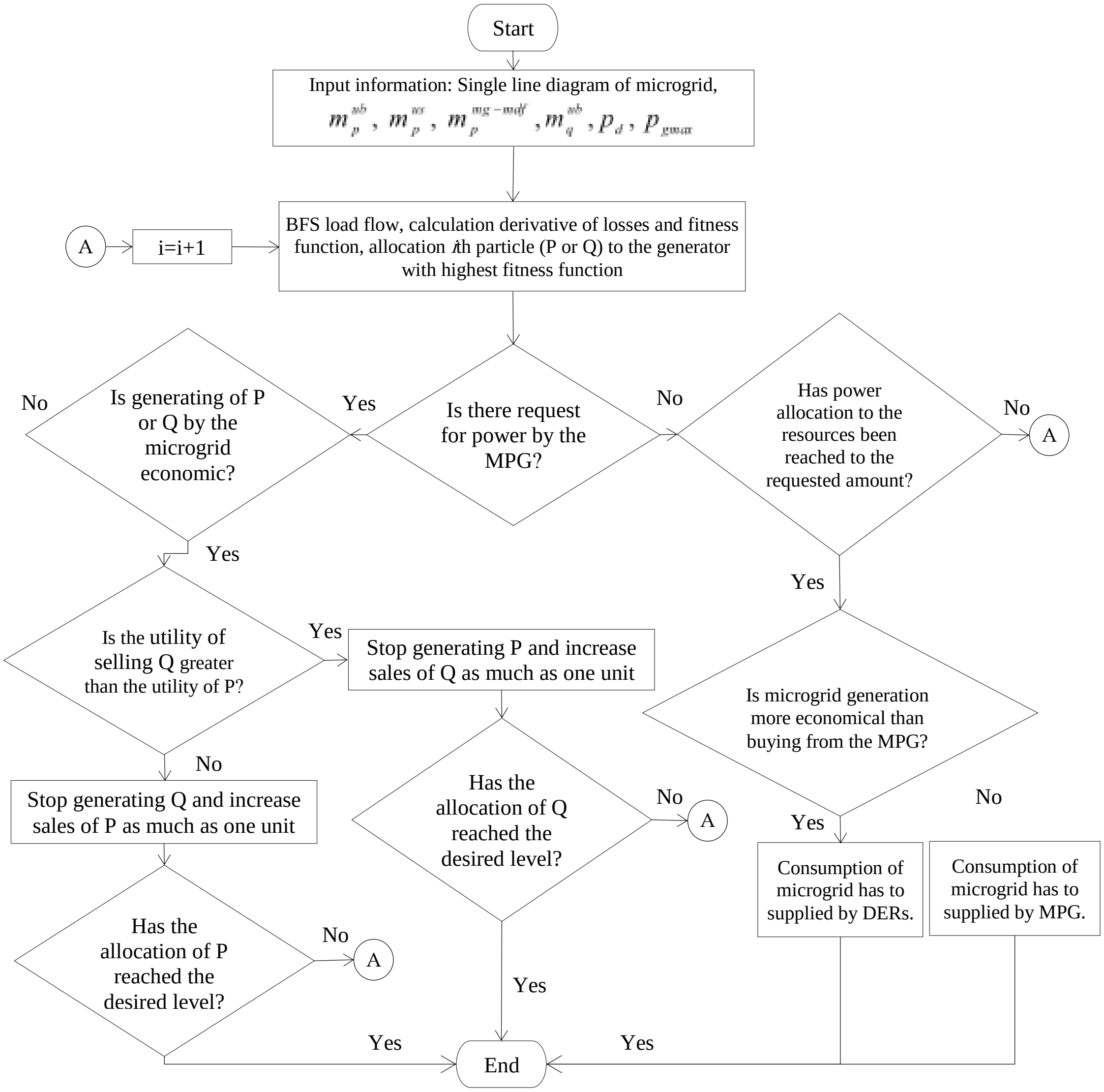

Fig. 5. Flowchart for simultaneous management of active (P) and reactive (Q) power.

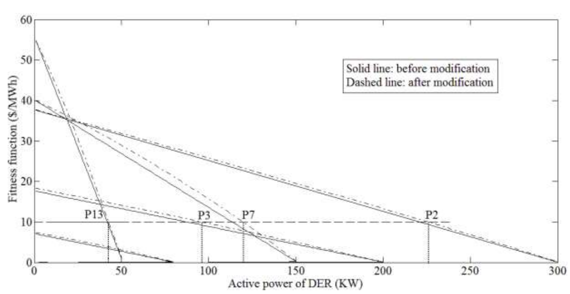

Fig. 7. The fitness function of the sources for dynamic power dispatch (case study 1).

sponse is 2.18 seconds. The main reason for this difference is the need to perform load flow and calculate the fitness function and the derivative of losses with respect to active/reactive power to allocate power to the best DER, which is one of the requirements of the proposed algorithm. However, with the implementation of simultaneous dynamic dispatch of active and reactive power using the RD strategy, as one of the innovations, the required time is reduced. Thus, while this approach is more effective for microgrids with more buses, the real-time market concerns at least 10 minutes later. Accordingly, since this approach has sufficient speed, it gives us plenty of time for real-time energy management.

In order to make a decision on whether to sell active or reactive power or both, it is necessary to consider the dynamic power dispatch in three stages. These stages are 1) active and reactive power supply to fulfill the microgrid demand, 2) determining the minimum economic amount of active power selling after passing the first stage, and 3) investigating the economic selling of active or reactive power after passing the second stage.

According to Table 5, the total power generation in the first stage is 311 kW from which the share of each generator is specified, and the DER connected to bus 12 in this stage does not participate in the dynamic economic power dispatch due to its low fitness. The three stages described above can be investigated in various steps. In the first step, which is the same as the first stage above, the total utility at the first step (u_{p1}) is 8.56 \$/h, and the total utility in the final step (u_{pf}) (supplying active and

Table 1. Line data-14 bus system [21]

Line no.	Start bus	End Bus	R (pu)
1	1	2	0.0119
2	2	3	0.0119
3	3	4	0.0135
4	4	5	0.0167
5	5	6	0.01938
6	6	7	0.0224
7	6	8	0.03181
8	7	9	0.0342
9	2	10	0.0167
10	10	11	0.01938
11	11	12	0.06701
12	12	13	0.09498
13	11	14	0.08135

Table 2. The coefficients of fuel cost, pollutants, and cost of reactive power losses of microgrids [21, 23]

Bus no.	2	3	7	12	13
Active power (kW)	300 (DG)	200 (DG)	150 (Mt)	80 (DG)	50 (Mt)
a_1	10.19	2.035	0.577	1.1825	0.338
b_1	105.18	60.28	57.78	65.34	89.15
c_1	62.56	44	133.1	44	547.6
a_2	26.55	14.43	3.036	19.38	1.035
b_2	16.18	64.15	57.34	176.7	60.38
c_2	7.051	130.4	311.6	821.7	943.2
ρ_2	0.57				

reactive power of the microgrid and selling active power to the MPG at the maximum capacity) is equal to 14.02 \$/h, i.e., there is a difference of 5.46 \$/h between the two steps. The condition for selling reactive power instead of active power (surplus of the microgrid consumption) is a profit at least equal to the profit of selling active power. Otherwise, the sale of reactive power in the first step is not economical and should be investigated in the next steps in the same way.

Equation (30) shows the rate of reactive power sale instead of active power. The derivative of losses with respect to reactive power is ignored due to its very small value according to Table 4. The parameter Δu_{pij} denotes the difference between the profit of source i from selling active power in jth step and the final step, Q_{gAij} is the floating capacity of the reactive power and Q_{gini} is the internal consumption of the microgrid (with a total of 122 kvar). In the first step, considering Eq. (30) and Table 6, the reactive power sale (for active power production in terms of microgrid consumption) is equal to 344 kvar, and the minimum offered reactive power price is equal to 16.77 \$/MVarh.

$$m_{qj} = \frac{\sum_{i=1}^{N} \Delta u_{pij}}{\sum_{i=1}^{N} \left(Q_{gAij} - Q_{\text{gini}} \right)} + \rho_2 \tag{30}$$

Similarly, in the next steps (production of 350, 400, 450, 500, 550, 600, 650, 700, 750, and 780 kW active power) the reactive power sale and its minimum rate can be considered. For example, the output of the proposed algorithm for a production of 750 kW is described in Table 7.

Table 3. Load data for 14 bus microgrid [21]

Bus no.	Active power (kW)	Reactive power (kVAr)
1	0	0
2	20	7
3	85	28
4	40	13
5	20	7
6	20	7
7	8	2
8	10	3
9	6	2
10	11	7
11	16	9
12	32	16
13	30	15
14	13	6

Table 4. Derivative of losses with respect to active and reactive power

Bus No.	$\partial p_{loss}/\partial p_i$		$\partial p_{loss}/\partial q_i$	
	Numerical method	JBDF method	Numerical method	JBDF method
2	0.091	0.094	6.43*10-5	5.33*10-5
3	0.119	0.123	-60	-60
7	0.211	0.217	-16	-17
12	0.171	0.176	-0.0212	-0.0212
13	0.196	0.201	-0.0111	-0.0112

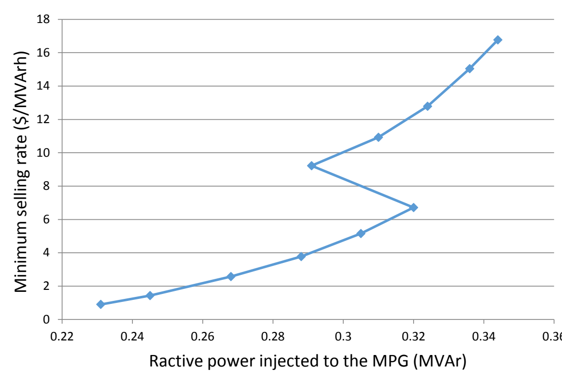

Fig. 8. Rate of microgrid reactive power sales versus production.

As shown in Fig. 8, with an increase in the reactive power demanded by the MPG, the minimum sales rate increases. The zigzag pattern on the curve results from the release of reactive power of the generator at bus 12 due to the economization of its active power generation.

Given the MPG power requirement for reactive power and from Fig. 8, the minimum reactive power sales rate can be determined. In case of acceptance of this price, the production of active power is limited and its minimum rate is determined according to its production.

B. Case study 2

The second microgrid under study is IEEE 33-bus test system radial network with resistive lines connected to the MPG. More-

Table 7. Output algorithm for dynamic reactive power dispatch at the 10th step

Active power (kW)		u_{p10i} (\$/h)	Δu_{p10i} (\$/h)	Q_{gin10i} (KVar)	Q_{gA10i} (KVar)	Q_{out10i} (KVar)	m_{q10}^{mg} (\$/MVarh)
p_{g2}	293	6.16	0.03	67	140	73	1.43
p_{g3}	190	1.98	0.02	10	96	86	
p_{g7}	147	3.75	0.04	21	69	48	
p_{g12}	70	0.33	0.01	1	39	38	
p_{g13}	50	1.67	0.03	23	23	0	
Sum	750	13.89	0.13	122	367	245	

Table 5. Output algorithm for dynamic active power dispatch at the first and final step

Active power (kW)		u_{p1i} (\$/h)	p_{nomi}	u_{pfi} (\$/h)	Δu_{p1i} (\$/h)
p_{g2}	171	4.58	300	6.19	1.61
p_{g3}	13	0.22	200	2	1.78
p_{g7}	92	2.63	150	3.79	1.16
p_{g12}	0	0	80	0.34	0.34
p_{g13}	35	1.13	50	1.7	0.57
sum	311	8.56	780	14.02	5.46

Table 6. Output algorithm for dynamic reactive power dispatch at the first step

Reactive power (KVar)	Q_{gini} (KVar)	Q_{gA1i} (KVar)	Q_{gout1i} (KVar)	m_{q1}^{mg} (\$/MVarh)
Q_g2	67	207	140	16.77
Q_g3	10	144	134	
Q_g7	21	89	68	
Q_g12	0	0	0	
Q_g13	24	26	2	
sum	122	466	344	

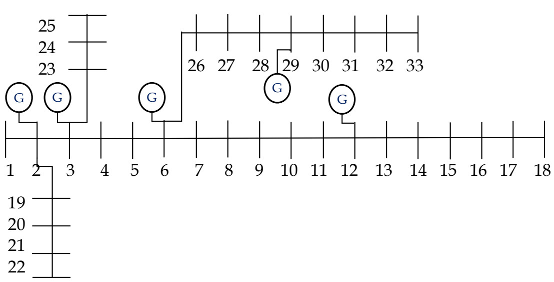

Fig. 9. single line diagram of the microgrid (Case stydy 2).

over, it is assumed that the microgrid has five DERs same as the first case study but different in the nominal power of generators as 1500, 1000, 750, 400 and 250 kW for the bus numbers of 2, 3, 6, 12 and 29 respectively with a total sum of 3900 KW. All data for the lines and loads are presented in [26]. The single line diagram of the microgrid is shown in Fig. 9.

Fig. 10 shows the fitness function of DERs for supplying the needed active loads of the microgrid plus selling its excess generation to the MPG. The line shows the modified fitness function, considering the losses penalty factor (m_p^{mg-mdf}). The time required to get an answer for the second case study is about 5 minutes. We can even reduce it with the larger steps in the dynamic population dispatch. So this method can also be used

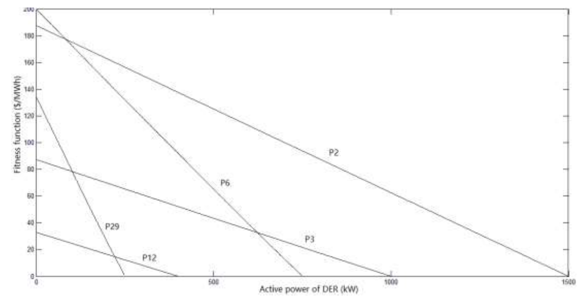

Fig. 10. The fitness function of the sources for dynamic power dispatch (case study 2).

for larger microgrids.

6. CONCLUSION

The proposed algorithm attempts to make all choices in line with increasing the speed in control of microgrids, particularly in the real-time market. This includes the elimination of the need for iterations in optimal power dispatch by using dynamic population distribution, making use of FBS load flow in radial networks, simultaneous active and reactive dynamic power dispatch, the combination of the three steps of active power dispatch, reactive power dispatch and active power re-dispatch along with using a numerical method instead of an analytical method in computing relative power losses. Moreover, another contribution of this paper is converting the single node fitness function into a distributed fitness function by adding the penalty factor.

At first, the share of losses in a microgrid might seem negligible. However, this share is considerable in the microgrids that are built within existing distribution networks. Consequently, we had to consider the share of a DER in the microgrid losses along with its cost function. The results showed the effect of microgrid losses on the minimum bid price (competitive). The more losses there are in the microgrid, the more expenses are incurred. In other words, the competitive price is increased and thereby, the chances for the participation of microgrid in the market are reduced. For simultaneous participation of the microgrid active and reactive power in the real-time market, the fitness function (marginal utility) of reactive power is defined as that of the active power. As a result, the microgrid can determine its share of the energy and ancillary services market in real-time while taking into account all existing electrical constraints with the aim of maximizing its profit.

The main difference between selling active and reactive power is in the descending slope of the minimum active power price compared to the ascending slope of the minimum reactive power price for an increase in production. New researches can be conducted in the field of energy management and ancillary services of several adjacent microgrids connected to the MPG.

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