Optimal Power Scheduling in Multi-Microgrid System Using Particle Swarm Optimization

Sen Pisei *, Jin-Young Choi**, Won-Poong Lee** and Dong-Jun Won†

Abstract – This paper presents the power scheduling of a multi-microgrid (MMG) system using an optimization technique called particle swarm optimization (PSO). The PSO technique has been shown to be most effective at solving the various problems of the economic load dispatch (ELD) in a power system. In addition, a new MMG system configuration is proposed in this paper, through which the optimal power flow is achieved. Both optimization and power trading methods within an MMG are studied. The results of implementing PSO in an MMG system for optimal power flow and cost minimization were obtained and compared with another attractive and efficient optimization technique called the genetic algorithm (GA). The comparison between these two effective methods provided very competitive results, and their operating costs also appear to be comparable. Finally, in this study, power scheduling and a power trading method were obtained using the MATLAB program.

Keywords: Microgrid, Multi-Microgrid, Power flow, Power scheduling, Optimization, Economic load dispatch, Particle swarm optimization, Genetic algorithm

1. Introduction

The decentralized operation of power systems has recently become crucial for replacing the older traditional power system model, i.e., the so-called centralized power system, owing to the inevitability of natural disasters, blackouts, or unexpected events.

A microgrid (MG) has proven to be a successful solution to the problems of a centralized power system and the implementation of a renewable energy source (RES) integrated into a utility grid, with a maximum possible operation scale and the keys to broaden RES availability to customers, for example, within a 10-MW operation scale around a 30 to 50-km radius [1]. An MG is very useful for small- or medium-scale areas, including business parks, hospitals, or small towns, and can be operated in remote areas or on islands where a main utility grid cannot yet be supplied. We can expect many advantages for implementing an MG, such as reliable power delivery (islanding), efficiency and sustainability (increasing the penetration of RESs), scalability and holding off making a decision for investment of new facilities, and the provisioning of ancillary services. An MG is capable of producing, transmitting, and distributing power within a local area. A single MG can generate a sufficient amount of power to satisfy the local electrical loads, and some grid-connected MGs can be used to generate power for selling back to the main utility grid when the price of electricity from the main grid is high according to the time-of-use (TOU). An MG generally consists of a distributed generation (DG) and loads, and can be connected with the main utility grid at a point of common coupling (PCC) (grid-connected mode), or disconnected from the main grid intentionally (island mode) or through a fault occurrence. MG central controller (MGCC) which can operate as the unit is one of the main parts for controlling or dispatching any generators required.

A multi-microgrid (MMG) system is built by integrating MGs having the same or different characteristics within a specific area. An MG plays an important role as a mid-range operating system between an MG and a Smart Grid. In recent years, MMG systems have been highlighted as a strategy of operation for medium- or large-scale grid-connected or islanded microgrids, such as at the community or campus scale. Several studies have been conducted on MMG strategies [2-6]. The basic concept of an MMG described in this paper is related to power sharing or exchange, and is based on the assumptions that the internal energy in a specific MG is preferably transferred or exchanged with another MG within an MMG system, rather than exchanged with the main utility grid. By doing so, both MGs, one having an energy surplus and the other having an energy shortage, can import or export power within the MMG, and will benefit from this process because the price for exchanging energy is low compared to that of the main utility grid. Thus, to achieve the most beneficial result, an optimal power flow has to be implemented within the system [6].

For further details of the MMG system proposed in this paper, we applied a cluster of three distinctive MGs in...
which the following hold:
- Each DG in an MG shares its own cost for power generation.
- Each MG has an electric demand that needs to be satisfied and generation from DGs.
- Each MG grid (represented as Grid 1, Grid 2, and Grid 3) has its own unique cost of importing and/or exporting power within the MMG.
- Each MG has a limitation in terms of power trading among the MGs.
- Because the present paper is focused on power exchanges within the MMG system, each MG does not consider functions for islanded mode such as load shedding.

By considering these points, we can cope with the power trading by searching for the optimal amount of power possible for importing and exporting among the MGs within the MMG so as to optimize the total operational costs of the entire system. To solve the problems of optimization, two main types of techniques can be applied [7]: 1) analytical (conventional) methods, such as mixed-integer linear or nonlinear programming (MILP/MINLP), and 2) heuristic (artificial intelligent, or AI) methods, such as particle swarm optimization (PSO) or a genetic algorithm (GA). Some research tasks have been discussed and compared between these two main methods [8–10]. Although a heuristic method is basically more complex than an analytical method, it can handle complex problems. For an analytical method, the optimization problem is solved using a mathematical model, so that it is obvious. However, using an analytical method to solve the problem of optimization is impractical if the prediction of the data, such as demand data or weather data for RESs, in the power system has any uncertainty influencing the results. In addition, depending on the setting for the objective function and the constraint condition of the problem, solving the optimization problem will require a long calculation time, and may reach the local optimum, and not the global optimum. In contrast to an analytical method, a heuristic method provides a better result for more complex problems. For example, PSO, described as one of the heuristic methods in section 3, uses a number of iterations for calculating the position and velocity of a particle, and it is thus quite probable that the solution to the problem will reach the near optimum. For these reasons, for a more complex and practical optimization problem, a heuristic method such as PSO or a GA can be applied with more credibility. In this paper, we implement PSO for solving the power scheduling among MGs within an island MMG such that the MMG system, including the MGs, can reach the optimal solution through power exchanges. The proposed operation strategy can contribute to medium- and large-scale microgrid operations.

The process of exporting and importing power within an MMG is achieved through some critical steps. First, each MG calculates the possible amount of power generated from the DGs with some certain power limitation. The prices for selling or buying the generated power are determined, and each MG may or may not optimally fulfill its demand in advance prior to computing the amount of surplus or shortage to be used for power trading within the grid. The proposed MMG system is shown in Fig. 1. In this figure, the MMG is composed of N- MGs connected together and centrally controlled by a microgrid central controller (MGCC), and can be operated as an island MMG or grid-connected MMG. In this paper, an island MMG system is implemented. For each MG, some DGs, including an RES such as Photovoltaic (PV) and Wind Turbine (WT), battery energy storage system (BESS), diesel engine (DE), and electrical load, are combined together. Each MG is capable of producing more or less energy depending on the possibility of exporting or importing power among the MGs, respectively, and its generation costs differ based on the type and scale. After the power generation, power trading among the MGs is implemented and the minimum operating cost is then calculated by referring to the optimal power generation.

### 2. Multi-Microgrid and System Configuration

#### 2.1 Multi-microgrid

An MMG is a combination of MGs within a specific area. Fig. 2 shows the MMG system proposed in this paper. The system mainly consists of three different MGs connected together to build one independent MMG. Some assigned DGs are included in each MG, each of which has
its own MGCC to control the output power for trading power. The costs of generating, importing, and exporting power are set uniquely for each MG. The proposed MMG system is composed of generators including a BESS, DE, WT, and PV for each MG, the rated capacities of which are listed in Table 1.

In addition to implementing the optimization problem, power trading among the three MG systems is also applied, and is described graphically in Fig. 3.

It is clear that, after optimizing the MMG system, the DG of each MG is capable of generating power at maximum profitability because the cost of fuel consumption within each DG may differ. For a single MG, this can be applied directly for the minimum fuel consumption cost; however, for multiple MGs or MMGs, certain conditions have to be considered. In addition to the power maximization based on the fuel consumption cost, each DG should share a sufficient amount of power for trading within the MMG for earning additional profits. An MG with surplus power can export to an MG with a shortage of power, and vice versa. In this way, the entire MMG system can be maintained in equilibrium mode with all balanced MGs.

### 2.2 System configuration

As described earlier, the proposed system consists of an RES (WT and PV), BESS, DE, and electrical load located in each MG. Because an RES is already used to fulfill the load, only a BESS and DE remain, which are used for the optimization. For a BESS, a Li-ion battery is used, and its state of charge (SOC) is calculated as in (1).

\[
SOC_{i}^{t+1} = SOC_{i}^{t} + \frac{Cap_{i}^{t}}{E_{i}^{acc}} \cdot \Delta t
\]

where

- \(Cap_{i}^{t}\): Output Capacity of BESS at time \(t\) in MG \(i\) [kWh]
- \(E_{i}^{acc}\): Total capacity of BESS in MG \(i\) [kWh]

For a DE, the fuel cost function is generally considered a quadratic function, which can be represented as in Table 2.

#### 2.3 Objective function

The main objective function of the proposed system, which is minimizing the operating cost, can be written as in (2), or can be basically simplified as (3). It is necessary to solve economic load dispatch (ELD) using an AI method. Each DG shares its own unique output power through each MG. Because an RES, including PV and WT, are set to operate at their maximum power point tracking (MPPT) point without any curtailment, the RES of an MMG system first satisfies the loads of each MG in advance. Hence, only a DE and BESS appear to be used for cost minimization.

\[
\text{Min}\left( \sum_{t}^{24} \text{Cost}_{\text{MG}}^{t} \right)
\]

\[
\text{Min}\left( \sum_{i}^{I} \sum_{t}^{24} \text{Cost}_{i}^{t} \right)
\]

where

- \(i\): Index for Microgrids, \(i = 1,2,3,...,I\)
- \(I\): Number of Microgrids
- \(t\): Time-step, \(t = 1,2,3,...,24\) [hour]
- \(\text{Cost}_{\text{MG}}^{t}\): Operational cost of MMG at time \(t\)
- \(\text{Cost}_{i}^{t}\): Operational cost of MG \(i\) at time \(t\)

\[
\text{Cost}_{i}^{t} = \text{Cost}_{DE}^{t} + \text{Cost}_{BESS}^{t}
\]

where

- \(\text{Cost}_{\text{MG}}^{t}\): Total cost of MG \(i\) at time \(t\)
- \(\text{Cost}_{DE}^{t}\): Total cost of DE in MG \(i\) at time \(t\)
- \(\text{Cost}_{BESS}^{t}\): Total cost of BESS in MG \(i\) at time \(t\)

\[
\text{Cost}_{DE}^{t} = a(p_{DE}^{t})^2 + b p_{DE}^{t} + c
\]

<table>
<thead>
<tr>
<th>#DE</th>
<th>Fuel Cost Coefficient</th>
<th>Pmin (kW)</th>
<th>Pmax (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.00008</td>
<td>0.007</td>
<td>0.2</td>
</tr>
<tr>
<td>2</td>
<td>0.00009</td>
<td>0.0063</td>
<td>0.18</td>
</tr>
<tr>
<td>3</td>
<td>0.00007</td>
<td>0.0068</td>
<td>0.14</td>
</tr>
</tbody>
</table>
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\[ P_{DE}^{j,t} : \text{Output power from DE in MG at time } t \text{ [kW]} \]
\[ a, b, c : \text{Cost coefficient} \]

\[ \text{Cost}_{\text{BESS}}^{j,t} = P_{\text{BESS}}^{j,t} \cdot \beta_{\text{BESS}}^{j} \]

where

\[ P_{\text{BESS}}^{j,t} : \text{Charging/Discharging power of BESS [kW]} \]
\[ \beta_{\text{BESS}}^{j} : \text{Charging/Discharging cost of BESS [$/Wh]} \]

2.4 Equality constraint

For system stability between the supply and demand of the entire proposed MMG system, the generators have to generate sufficient output power to satisfy the entire demand. The output power generated by the generators should generally provide a sufficient amount of power to support the load demand that is curtailed in advance using an RES and the system transmission loss, which can be written as follows:

\[ \sum_{i=1}^{I} P_{\text{Gen}}^{j,t} = \sum_{i=1}^{I} (P_{\text{Load}}^{j,t} - P_{\text{RES}}^{j,t}) + P_{\text{Loss}} \]

where

\[ P_{\text{Gen}}^{j,t} : \text{Output power from Diesel & BESS in MG at time } t \text{ [kW]} \]
\[ P_{\text{Load}}^{j,t} : \text{Power demand by load in MG at time } t \text{ [kW]} \]
\[ P_{\text{RES}}^{j,t} : \text{Output power from RES in MG at time } t \text{ [kW]} \]

where \( P_{\text{Loss}} \) is the total transmission loss in the system. In this study, the transmission loss is not considered, and thus (7) can be re-written as (8).

\[ \sum_{i=1}^{I} P_{\text{Gen}}^{j,t} = \sum_{i=1}^{I} (P_{\text{Load}}^{j,t} - P_{\text{RES}}^{j,t}) \]

2.5 Inequality Constraint

For the system stability in each MG, the output power from every generator must be equal to the power needed based on the demand at that particular MG. Moreover, one MG may produce more additional power that is needed for a nearby MG experiencing a power shortage. A limitation in the buying and/or selling of power for each MG within an acceptable range is proposed in this section, and is shown in (9). The possible limitation output power for both importing and exporting power for an MG is also shown in Table 3.

\[ P_{\text{Load}}^{j,t} - P_{\text{in}}^{j,t} \leq P_{\text{Gen}}^{j,t} \leq P_{\text{Load}}^{j,t} - P_{\text{out}}^{j,t} \]

where

| Table 3. Possible limited importing/exporting power |
|-----------------|-----------------|-----------------|
| #MG        | \( P_{\text{in}}^{j,t} \) (import) | \( P_{\text{out}}^{j,t} \) (export) |
| MG1        | 30              | 30              |
| MG2        | 50              | 25              |
| MG3        | 25              | 50              |

Each DG has its own operating power constraints. A DG cannot operate over its power limit because doing so could seriously damage it. As a result, a PV, WT, DE, and BESS must be operated within the lower and upper power bounds, shown in (10) through (13), where a DE is operated within its lower 10% until reaching its higher bound of 100%. In addition, the charging and discharging power for a BESS is set to operate within its limited constraint.

- Power constraint for PV:

\[ 0 \leq P_{\text{PV}}^{j,t} \leq P_{\text{PV,max}}^{j} \]

- Power constraint for WT:

\[ 0 \leq P_{\text{WT}}^{j,t} \leq P_{\text{WT,max}}^{j} \]

- Power constraint for DE:

\[ P_{\text{DE,min}}^{j} \leq P_{\text{DE}}^{j,t} \leq P_{\text{DE,max}}^{j} \]

- Power constraint for BESS:

\[ -P_{\text{BESS,min}}^{j} \leq P_{\text{BESS}}^{j,t} \leq P_{\text{BESS,max}}^{j} \]

where

\[ P_{\text{PV,max}}^{j} \] : Maximum generated power from PV of MG i
\[ P_{\text{WT,max}}^{j} \] : Maximum generated power from WT of MG i
\[ P_{\text{DE,min}}^{j} \] : Minimum generated power of DE in MG i
\[ P_{\text{DE,max}}^{j} \] : Maximum generated power of DE in MG i
\[ P_{\text{BESS,min}}^{j} \] : Minimum power for BESS in MG i during step i
\[ P_{\text{BESS,max}}^{j} \] : Maximum power for BESS in MG i during step i

3. Particle Swarm Optimization

Particle Swarm Optimization (PSO) was originally introduced by Kennedy and Eberhart in 1995, and imitates the behaviors of flocks of birds or schools of fish optimally finding food [11]. PSO is an effective, reliable, and evolutionary-based approach used for solving the constraint ELD problem. It has been applied to various fields of power system optimization, such as reactive power and voltage.
control, and power system designs [12]. PSO works closely with the fitness function to minimize the given objective function. This optimization technique has been recently gaining more and more popularity from most researchers owing to its structural simplicity and highly robust performance compared to other optimization techniques. In this context, PSO is mainly used to solve the optimization problem within the following form [13]:

\[ \min(x) = f(x) \]  \hspace{1cm} (14)  

Subject to  
\[ A \cdot x \leq B \cdot x \]  
\[ A_{eq} \cdot x = B_{eq} \cdot x \]  
\[ c(x) \leq 0 \]  
\[ c_{eq}(x) = 0 \]  
\[ l_{b} \leq x \leq u_{b} \]  

where \( A, b \) is the inequality constraints matrix, \( A_{eq} \) and \( B_{eq} \) are the equality constraints, \( c \) and \( c_{eq} \) represents the nonlinear constraints, \( l_{b} \) for lower bound, and \( u_{b} \) indicates the upper bound. Thus the fitness function \( f(x) \) can be obtained based on the performance of variable \( x \).

There are some steps for applying a PSO algorithm, which are described in more detail in the following section. The PSO is implemented using Matlab [14].

The movement of a particle mainly depends on the social and cognitive parameters, which are represented as \( c_{1} \) and \( c_{2} \), respectively. In (15), the first term represents the current velocity of the particle, whereas the second term indicates its change in velocity based on its thought and memory (cognitive term), and the final part represents the changes in the particle velocity based on the social-psychological adaption of knowledge (social term) [15]. In addition, the inertia weight factor \( (w) \) shall be selected carefully because it can provide a balance between global and local exploration and exploitation. While running a PSO, the initial weight factor decreases linearly from around 0.9 \( (w_{\text{max}}) \) to 0.4 \( (w_{\text{min}}) \), which can be written as in (17).

\[ w = w_{\text{max}} - \frac{w_{\text{max}} - w_{\text{min}}}{k_{\text{max}}} \cdot k \]  \hspace{1cm} (17)

where  
\( w_{\text{max}} \) : The initial weight  
\( w_{\text{min}} \) : The final weight  
\( k_{\text{max}} \) : The maximum iteration number  
\( k \) : The current iteration number

Fig. 4 shows a graphical updating of the velocity and position in the PSO algorithm in a two-dimensional space. The particle memory influence and swarm influence represent a cognitive attraction and social attraction, respectively. A cognitive attraction is used for attracting a personal-best position, whereas a social attraction is mainly used for a global-best position of the entire swarm. As shown here, \( v_{k+1} \), representing a new velocity, keeps the particle on its current path, and is then attracted to the personal-best position \( P_{\text{best}} \) through a cognitive attraction, and to the global-best position \( G_{\text{best}} \) through social attraction. Finally, a new position, \( x_{k+1} \), is obtained through a combination of the current position, \( x_{k} \), and the updated velocity, \( v_{k+1} \).

To implement a PSO, some parameters are needed, as

**Table 4. PSO and GA Parameters**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
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<tr>
<td>Population Size</td>
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<td>Population Size</td>
<td>240</td>
</tr>
<tr>
<td>Generation</td>
<td>150</td>
<td>Generation</td>
<td>100</td>
</tr>
<tr>
<td>Cognitive Attraction</td>
<td>1.9</td>
<td>SelectionFct</td>
<td>[@selectiontournament, 8]</td>
</tr>
<tr>
<td>Social Attraction</td>
<td>1.9</td>
<td>MutationFct</td>
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<tr>
<td>Wmax, Wmin</td>
<td>0.9, 0.4</td>
<td>CrossoverFct</td>
<td>@crossoverheuristic</td>
</tr>
<tr>
<td>TolFun, TolCon</td>
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<td>Penalty Factor</td>
<td>1000</td>
</tr>
<tr>
<td>StallGenLimit</td>
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<td>EliteCount</td>
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</tr>
<tr>
<td>Nvars</td>
<td>144</td>
<td>StallGenLimit</td>
<td>150</td>
</tr>
<tr>
<td>The number of Iteration</td>
<td>100</td>
<td>StallNvar</td>
<td>144</td>
</tr>
</tbody>
</table>
shown in Table 4. The size of the studied population is 120 with 150 iterations, and the attraction parameters are set to 1.9 for both cognitive and social attractions. For the PSO, it generally appeared to set the social attraction parameter larger than the cognitive attraction parameter. In addition, and are also provided, and TolFun indicates that the PSO will terminate if the global value reaches this minimum, which is similar to TolCon for the minimum acceptable constraint violation. Moreover, without the development of a better solution, the algorithm will also stop if StallGenLimit reaches its limited value of 150. Nvars represents the number of variables used in this algorithm.

4. Case Study and Result

For a better understanding and verification of the use of these methods, some case studies were developed:

1) Case 1: All DGs are under a normal operation status. The DGs (BESS and DE) in each MG within an MMG share the same price for both a PSO and GA method, but different among MGs of MMG.

2) Case 2: A critical study on the time for the maintenance of some DGs in an MG is applied, i.e., a DE and/or BESS in MG1 is not operated owing to certain maintenance tasks that have to be conducted from 15:00 p.m. to 18:00 p.m., by implementing both a PSO and GA respectively. (MG2, MG3, and the other remaining DG in MG1 will generate more output power during this time for additional satisfaction of load 1 in MG1 in addition to their own load demand for maintaining the entire system balance.) In addition, the operating costs for a BESS and DE in this case are set the same as in Case 1.

In these cases, both optimization and power trading among the MGs within the system are implemented. We are going to analyze the effectiveness of the results obtained from the simulation using PSO, and then compare the results with those of the GA for our proposed MMG system.

4.1 Case 1

In the first case, the charging and discharging costs of a BESS for each MG are set to be equal to those of a DE because the cost of buying or importing power for each MG is fixed in each time-step. Hence, (6) above can be modified into (18). After implementing these optimizations separately using the Matlab program, the output power, possible import and/or export power, and optimal operating cost results are obtained. Note that the operational cost of each MG is varied depending on the location, fuel consumption cost, and other related aspects. Because there is no curtailment for an RES, all output power from the RES is directly absorbed through the load demand in each MG. Hence, the loads shown in the following are already supplied by the RES, and are marked as Load-RES. As a result, the optimization of the DGs in each MG is accomplished only though the BESS and DE, and the generation cost is set the same for the DGs in an MG.

\[
Cost_{BESS}^{k,i} = \beta P_{BESS}^{k,i} = P_{BESS}^{k,i} \left( \frac{a(P_{DE}^{k,i})^2 + bP_{DE}^{k,i} + c}{P_{DE}^{k,i}} \right)
\]

where

\[
\beta = \frac{a(P_{DE}^{k,i})^2 + bP_{DE}^{k,i} + c}{P_{DE}^{k,i}}
\]

A simulation was conducted, the results of which are shown in Fig. 5. MG1 occasionally generates more power (especially during the morning shift), but sometimes does not generate sufficient power for its domestic demand (particularly for a period of high demand) owing to the high fuel consumption cost. As shown in Fig. 5(a), the combination of DG generation is much higher than the local load from midnight to early morning, and is almost lower than the load demands all other times after 06:00 a.m. for the PSO method; in addition, the GA shows a similar output with a shortage or surplus of power compared to its local load. MG2 has the largest amount of load demand among the three studied MGs of the MMG system, followed by MG1 and MG3 in order. Moreover, the operating fuel price of MG2 is also higher than that of MG1 and MG3. Because of the high price of fuel consumption, it appears that DGs including DE2 and BESS2 in the MGs can only generate a limited amount,
and an insufficient amount of power to satisfy its local demand in certain MGs (MG1 and MG2) at a particular time. The simulation results indicate that the DGs in MG2 generate an amount of power satisfying the local load by priority. Thus, in Fig. 5(b), the output power from DE2 for PSO produces an amount between 40 and 60 kW on average. From this figure, we noticed three points, that is, midnight, noon, and 22:00 p.m., at which DE3 fluctuates more than normal, and we present two of these three points in detail. During the first hour of the time-step, as shown in more detail in Table 5, DE2 provides 50.7848 kW of power with some benefit from BESS2 charging 5.2266 kW to its large load demand, and it needed 16.0418 kW to satisfy its local demand.

Thus, this import amount was taken from MG3 at the lowest fuel consumption cost. In addition, as shown in Fig. 5(c), MG3, which has the lowest fuel consumption cost, appears to generate drastically more power than its local demand, and hence the shortage/surplus curve in MG3 is mainly in the surplus power position above zero (representing a surplus of produced power). The surplus power in MG3 is stored, and made ready for any circumstances of exportation to a closer MG that needs power to satisfy its demand. For the first hour, MG2 is capable of producing power sufficient to its own needs (21.89 kW), and provides an additional power surplus of 38.7237 kW to the system, which can be sold or exported to any MGs experiencing a power shortage (in this case, MG1=22.682 kW and MG2=16.0418 kW). In addition, at noon, the power generated from DE3 (68.4314 kW) is higher than that of DE1 and DE2 because of its lowest fuel consumption cost. Thus, in addition to charging BESS3 at this hour (26.868 kW), the remaining power is sold to MG2 for both profitability and balance of the MMG system.

Table 5 provides detailed data for the power trading during the first hour and noon after implementing PSO and the GA.

In this table, the balance among MGs and that of the entire MMG, are clearly verified during each time-step, and all the import and export powers marked in Grid are between the power trading limitation constraints. (Generated power = Demand power ± P_{limit}).

Furthermore, the SOC of the BESS in each MG for each optimization method is shown in Fig. 6. Apparently, the SOC using PSO fluctuate more than that using the GA because the BESS is shown to be more active for PSO than for the GA. The boundary of the SOC ranges from 10% to 90%, and therefore the SOCs of BESS fluctuate only within the assigned boundary range.

Power trading among MGs within an island MMG is conducted as shown in Fig. 7. The (+) axis represents surplus generated power, and (-) refers to a power shortage. For both PSO and the GA, the surplus in MG3 and shortages in MG1 and MG2 are simply characterized.

The final results for the proposed MMG when implementing PSO and the GA are shown in Fig. 8.

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Table 5. Import/export power calculations in Case 1

(a) - PSO

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>At 1st hour of the day</td>
<td>52.048</td>
<td>45.082</td>
<td>38.727</td>
<td>22.682</td>
<td>16.042</td>
<td>21.890</td>
<td>68.431</td>
<td>22.682</td>
<td>16.042</td>
</tr>
<tr>
<td>DE</td>
<td>27.987</td>
<td>38.756</td>
<td>60.352</td>
<td>18.411</td>
<td>71.782</td>
<td>55.806</td>
<td>68.401</td>
<td>170.502</td>
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<tr>
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<td>128.11</td>
<td>54.18</td>
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<td>19.18</td>
<td>122.57</td>
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<tr>
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<td>Shortage MG</td>
<td>Surplus MG</td>
<td>Surplus MG</td>
<td>Surplus MG</td>
<td>Surplus MG</td>
<td>Surplus MG</td>
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<td>Yes</td>
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(b) - GA

<table>
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<tr>
<td>Time</td>
<td>At 1st hour of the day</td>
<td>39.67</td>
<td>39.562</td>
<td>39.756</td>
<td>39.582</td>
<td>32.36</td>
<td>25.804</td>
<td>32.769</td>
<td>28.004</td>
<td>30.015</td>
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<td>DE</td>
<td>45.982</td>
<td>45.321</td>
<td>39.756</td>
<td>39.582</td>
<td>32.36</td>
<td>25.804</td>
<td>32.769</td>
<td>28.004</td>
<td>30.015</td>
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<td>Load</td>
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<td>43.00</td>
<td>21.89</td>
<td>128.11</td>
<td>54.18</td>
<td>54.9</td>
<td>19.18</td>
<td>122.57</td>
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<td>Grid</td>
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<td>-16.418</td>
<td>38.727</td>
<td>-25.44</td>
<td>6.033</td>
<td>-31.676</td>
<td>38.801</td>
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<td>Shortage MG</td>
<td>Surplus MG</td>
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<tr>
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<td>Yes</td>
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Fig. 6. SOC comparisons between PSO and GA of each BESS in MMG

Fig. 7. Power Trading among MGs using PSO and GA
The results show that the minimum operating cost using PSO ($213.4017 USD) is lower than that using the GA ($235.2854 USD) at many time steps of the entire study day. In total, a benefit was obtained when using PSO for the proposed MMG system through a daily accumulation of $21.884 USD. Another perspective of such optimizations is the speed of the result search (convergence) and the stopping conditions, which are illustrated graphically in Fig. 9. In (a), the PSO method can reach the global minimum at around ten iterations with a minimum daily cost of $213.402 USD.

4.2 Case 2

In this case, one BESS (BESS1) is set to be down for maintenance for three consecutive hours during the afternoon shift, from 15:00 p.m. to 18:00 p.m. In addition, an operator can shut down one or more DGs at any time. This is the time period when the remaining energy is scheduled to be supplied to the system, as shown in Case 1, and when the demand increases. All necessary equations and constraints from Case 1 are also applied.

Looking at Fig. 10 (a), we can see that from 15:00 p.m. to 18:00 p.m., BESS1 apparently does not operate as scheduled. For this reason, other available DGs are urged to generate more output power to balance the system during this time interval. For this case, we focus more on the power obtained during this time period. At every other time step, we found a smooth operation when applying
PSO. During this stage, MG3 appears to fluctuate greatly because it has the lowest generation cost, as shown in (c). Because BESS1 is down, DE1 generates more power, and mainly for MG3 during this time period, DE3 generates significant power following its incremental cost, and supplies this power to both its local load and the other power-shortage loads. In addition, during the first hour of the day and at 19:00 p.m., MG3 also produces significant power because the power generated from MG1 and MG2 is insufficient to serve their loads.

The SOC of each BESS during this time period appears to be fixed, which can be seen in Fig. 11. The stability of the SOC during the maintenance time of BESS1 for both PSO and the GA is shown. Hence, re-scheduling to balance the whole system is conducted with support from the remaining DGs. DE3 operates at its peak output capacity to fulfill the remaining power shortage. Thus, based on the order of the generation operation, we can obtain the power surplus and shortage amounts from each DG by referring to its fuel consumption cost, as shown in Fig. 12. MG3 generates sufficient output power to satisfy the power shortages of MG1 and MG2.

For both methods, MG3 appears to have more surplus energy than the other MGs, whereas MG1 and MG2 mainly require power to balancing their own system. A power calculation during the selected hours of maintenance (during the first time step, and at 09:00 a.m. and 15:00 p.m.) is briefly given in Table 6.

It can also be seen that each MG is in balance. Grid 1, Grid 2, and Grid 3 are generating -30 kW, -20 kW, and 50 kW of power when applying PSO, and -33.7767 kW, -51.9015 kW, and 85.6782 kW when applying the GA, respectively; these values indicate the balance of each MG after power trading among the MGs during the absence of BESS1. It was found that some of the grids have a surplus of power, and others have a shortage; however, these amounts show a balance because there is also a limited amount of power going through each Grid as shown in Table 3.

Also for this case, we found that in addition to achieving better optimal results than the GA, applying PSO also shows a better and faster convergence. Thus, the minimum solution can be obtained more quickly within around ten or fewer iterations with a daily optimal cost of $220.8264 USD, whereas the GA result appears to be obtained within around 30 iterations at a cost of $233.3795 USD.

Table 6. Import/export power calculations in Case 2

<table>
<thead>
<tr>
<th>Time</th>
<th>PSO</th>
<th>MG1 (MW)</th>
<th>MG2 (MW)</th>
<th>MG3 (MW)</th>
<th>MG1 (MW)</th>
<th>MG2 (MW)</th>
<th>MG3 (MW)</th>
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</thead>
<tbody>
<tr>
<td>00:00</td>
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<td>09:00</td>
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<tr>
<td>15:00</td>
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</table>

Fig. 11. SOC of each BESS using PSO and GA

Fig. 12. Power Trading among MGs using PSO and GA in Case 2
5. Conclusion

In this paper, we coped with the problem of optimization for optimal power scheduling in an MMG system using the most appropriate PSO techniques. The results of the proposed MMG system with PSO implementation are good, and were shown to be more suitable than when applying the GA. Moreover, the convergence using PSO is noticeably fast and provides higher efficiency for the ELD problem. PSO is mainly used here and for clarifying the effectiveness, GA is also applied along with PSO. Both of these optimization techniques have recently attracted significant interests from researchers with regard to any problem of optimization; that is why, we use PSO and then use these two methods to compare for better results for our MMG system. The results can provide some ideas for power system operators to decide for the most optimal solution for power system scheduling. According to the result from case 1, the differential optimum cost of both techniques is 21.3387$, which indicates the advantage of PSO. Also, when one or more DG in a certain MG are not operating or when a certain MG is unbalanced due to any expected or unexpected events, other MG can provide additional power to MG with power shortage and by means of this, the power balance of the whole MMG system is accurately maintained. This procedure implies the benefit of power sharing/trading among MGs in the whole system that was implemented in this paper. Finally, we note that PSO is a more appropriate and effective method than others for solving this kind of optimization problem because of its fast convergence ability.

Acknowledgements

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References


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