Applied Energy 292 (2021) 116883

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Scheduling controller for microgrids energy management system using optimization algorithm in achieving cost saving and emission reduction

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HIGHLIGHTS

- Lightning search algorithm-based scheduling control for MG energy management system.
- Optimized controller to minimize cost and environmental emission in the MGs system.
- Effectiveness of the scheduling controller is executed based on uncertainty condition.
- Modelling and simulation is tested on modified version of the IEEE 14-bus test system.
- The proposed approach outperformed other techniques in solving optimization problems.

ARTICLE INFO

Keywords:
Microgrids
Scheduling
Optimization algorithm
Energy management system
Controller
Uncertainties
Distributed energy resource

ABSTRACT

This study deals with the development of an optimal power scheduling controller for energy management of distributed energy resources in the microgrid system. The developed optimized controller is implemented using lightning search algorithm to overcome the uncertainties of microgrid energy management and to provide an optimum power delivery to loads with minimum cost. The primary objectives of the proposed optimized controller are to: (i) develop an optimized controller for microgrids energy management, (ii) minimize the total operating cost of the distributed energy resources units, (iii) reduce the environmental emission, and (iv) solve the complicated constraint optimization problems. The proposed optimization algorithm is implemented in the modified IEEE 14-bus test system to optimize the microgrid power management schedule. The optimized controller is executed based on the real load varying conditions recorded in Perlis, Malaysia. It is observed that the optimized controller successfully reduced the amount of power consumption from 971.65 MW to 364.3 MW which in turn saving cost of RM 265432.06. The proposed scheduling optimized controller performance is compared with the recent reported work of backtracking search algorithm optimization for validation. Result shows that the lightning search algorithm based MG controller produced a cost-effective system with 62.5% of cost saving and 61.98% of carbon dioxide emission reduction which is much higher compared to with MG and backtracking search algorithm based MG optimization, respectively. The effectiveness of the proposed approach outperformed other techniques in terms of minimum total operating cost of distributed energy resources and solving complicated constraints in optimization problems.

1. Introduction

The development and utilization of renewable energy sources (RES) have gained great attention from society due to environmental issues. The tolerable environmental impact of clean energy, which is renewable-based power source, is considered another great solution [1]. Renewable-based power sources are essential for the power system to attain better distribution flexibility and power system quality improvements. However, the interconnection of distributed energy resource (DER) units, such as photovoltaic (PV) system, wind turbine (WT) system, and battery storage system, had brought significant

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https://doi.org/10.1016/j.apenergy.2021.116883
Received 21 October 2020; Received in revised form 19 March 2021; Accepted 25 March 2021
Available online 7 April 2021

Nomenclature and abbreviations

P_{PV}	PV power
P_{WT}	WT power
P_{nom}	Nominal power
v_{nom}	Nominal voltage
v_{max}	Maximum voltage
$SOC_{bat}^{(t)}$	State of charge of battery storage system
i_{bat}	Battery current
B_{AH}	Battery ampere hour
Q_{bat}	Maximum battery capacity
η_{charge}	Battery charging efficiency
$E_{bat}^{(t)}$	Energy of battery storage system
t	Time
$\eta_{DC/AC}$	Inverter efficiency
E_{load}	Total energy in the load
P_r	Rated capacity of DGen
$P_{DGen}^{(t)}$	Total generated power of the DGen unit
a_1, a_2	Coefficient of fuel consumption
T	Total number of hours
N_g	Total number sum of DER
$P_{Gi}^{(t)}$	Real output power of the *i*th units
$P_{Grid}^{(t)}$	Active power of utility grids
F_k	Fuel cost function of *k* DGen
$P_{k,t}$	Output power of *k* DGen at time *t*
a_k, b_k, c_k	Unit coefficient of *k* DGen
N_{DGen}	Number of DGen
$E_{(MWh/day)}$	Energy in megawatt hour per day
N_L	Total number of load demand
k	Index of the DGen units
ird	Solar irradiance
λ	Expected value of normal distribution
σ	Standard deviation value of normal distribution
$P_L^{(t)}$	Load demand power at time*t*
$P_{Gi,max}^{(t)}$	Maximum limits of real output power of the *i*th units
$P_{Gi,min}^{(t)}$	Minimum limits of real output power of the *i*th units
$P_{Grid,max}^{(t)}$	Maximum limits of the active power of grid
$P_{Grid,min}^{(t)}$	Minimum limits of the active power of grid
$P_{DGen,max}^{(t)}$	Maximum limits of the active power of DGen
$P_{DGen,min}^{(t)}$	Minimum limits of the active power of DGen
$E_{bat}^{(t)}$	Energy stored in the battery storage system
$E_{bat,max}^{(t)}$	Maximum limits of energy stored in the battery storage system
$E_{bat,min}^{(t)}$	Minimum limits of energy stored in the battery storage system
$SOC_{bat,min}^{(t)}$	Minimum state of charge
$SOC_{bat,max}^{(t)}$	Maximum state of charge
$\eta_{discharge}$	Battery discharging efficiency
$C_{grid}^{(t)}$	Energy cost per day
B_{Gi}	Bid of the *i*th units
j	Index of DGen emission pollution
i	Index of DER units
EMS	Energy management system
MGs	Microgrids
PV	Photovoltaic
WT	Wind turbine
DGen	Diesel generator
RES	Renewable energy sources
DER	Distributed energy resources
MG	Microgrid
MG	Multi-MG
DR	Demand response
BESS	Battery energy storage system
cer	Certain amount of irradiance
std	Standard amount of irradiance
$Cost^t$	Cost at time *t*

challenges to the operation of a power system. Besides, the management and controllability aspect in distributed generation (DG), which includes DER units in the power system, also need to be solved [2,3]. Hence, the microgrid (MG) has attracted increasing attention, which brings a friendly approach to this challenge nowadays. The MG contains various renewable energy resources that can deal with the high penetration of DGs in the power system.

A MG is an integration of distributed energy resources (DERs), including RESs, energy storage and loads that can operate locally in single controllable entity [4,5]. MG is founded in low and medium voltage distribution grid typically operating ranges from 400 V to 69 kV. It also provides the operation in two different operating modes, including islanded from distribution network in a remote area or the grid-connected mode [1,6]. The MG is also considered an alternative approach to fulfil energy demands in such a reliable and efficient way in the future power grid system. The size of generation and energy storage is limited in a single MG that gradually forms in large grid system. A MGs system that contains an individual MG, which is connected to the same distribution network, improves the efficiency, stability, and reliability of the entire grid system [7]. Therefore, interconnecting an MG to form an MGs system in the distribution network system has received great attention among researchers. An optimum coordinated operation of MGs can reduce the system operating costs while enhancing the reliability and environmental performance [3]. This condition is attributed to the controllability of an MGs as its main characteristic, which is regarded as a challenging issue. To achieve this goal, scheduling an energy management system (EMS) adjusts the power imported from or exported to the main grids while meeting the operation and dispatch of DER to fulfil the load demands [8,9]. The two most crucial tasks in the energy management problems in MGs are the day-ahead and real-time scheduling [10–12]. To date, various studies have been published to address the management and scheduling of MGs. In [13], a deterministic optimization method solved the scheduling optimization problem, which includes storage batteries, wind power generation, fuel cells, and solar unit, while minimizing the active power losses.

A decentralized economic dispatch for a MGs scheduling management considering the high uncertainties of the renewable energy sources and load demands is presented in [14]. The robust optimization can maximize the economic benefits of the whole system. Zhao et al. [15] presented a decentralized economic dispatch approach for an active distribution network to optimize the energy management of the MGs system. Tamer et al. [16] introduced an optimization-based hybrid iterative/genetic algorithm system for MGs to find the optimal sizing of the PV array, WT, and battery system to minimize configuration cost. In [17], a double deep Q-learning method is proposed to manage the operation of the community battery energy storage system in the MG system. The proposed operation strategy can deal with uncertainties in the system for both modes of MG operation. In the previously published

Table 1
Comparison of methodology with related literature.

Ref.	Methods	Renewable sources	Contribution	Supervisory control	Limitations
[40]	Particle swarm optimization (PSO)	PV/WT/Battery	Provide an optimal allocation and capacity of non-dispatchable renewable DER and grid-scale energy storage units in a spatially dispersed hybrid power system under an imperfect grid connection by combining the dynamic optimal power flow and PSO optimization.	Centralized	Long time, reduced particle numbers and iterations have lead premature convergences and falling local optima of PSO algorithm.
[41]	Multi-objective PSO	PV/WT/Battery	Provide operational value factor (OPF), reduce the system operational cost, and maximize the revenue of MG.	Centralized	Bidirectional operation is necessary to provide a high level of reliability.
[42]	Genetic algorithm (GA)	PV/WT/combine heat and power	The memory-based GA improved the intensification capability of GA in EMS to determine the optimum scheduling of the MG.	Centralized	A huge set of parameters is needed for the GA.
[36]	Multi-period GSA	PV/WT/Battery	The EMS-based multi-period GSA solved the optimal operating point within the isolated MG system. The GSA optimization minimized the production cost and increase system efficiency.	Centralized	High depth of discharge leads to fast degradation of the battery storage lifetime.
[1]	Modified bat Algorithm (BAT)	PV/WT/Fuel cell/Battery/Micro Turbine	EMS for the grid-connected MG at different seasons of irradiance in the PV system to obtain optimal scheduling of the MG. Modified BAT provides lesser computation time than PSO and GA in the EMS.	Centralized	The emission cost of the diesel generator (DGen) is not considered. Only single loads are considered.
[3]	Chance constraints programming	PV/WT/Battery/DGen	A day ahead scheduling with a three-stage hierarchical structure for the multi-microgrid system considering the battery degradation cost based on the CCP operator system for EMS.	Decentralized	The emission cost of DGen and load uncertainty condition are not considered.
[43]	Modified PSO	PV/WT/CHP	An optimum power sharing in the MG system based on the modified PSO algorithm to minimize the cost of energy production considering load uncertainty conditions.	Centralized	The battery storage system and DGen are not considered.
[38]	Binary BSA	PV/WT/DGen/battery/fuel cell	Optimal scheduling of each MG system in the IEEE 14-bus based on the binary BSA in control, coordinate the power flows to reduce generation cost and power losses, improving power saving, and increase the reliability.	Centralized	Charging/discharging status of the battery storage system is not considered.

work, the stochastic methods are considered and required huge assessment, which can be carried out by several random simulations to achieve the optimal operating point in the MGs. Furthermore, an intelligent controller, for example, the neural network and fuzzy-based controller, is also introduced for scheduling the energy management of MGs for two operating modes in [18,19]. However, these techniques require an enormous amount of data and procedure that is based on trial and error for setting up the parameters.

The optimal scheduling of the MG system is a complex constraint nonlinear optimization problem and regarded as the main tool for a reliable and economical operation of the system. Haddadian and Noroozian [20] developed an approach of the DR program for the MG system that is solved on the basis of the nondominated genetic algorithm technique. However, the limitation of the work is ignorance of the uncertainty issues. Xu et al. [21] proposed an approach of EMS of interconnected biogas–solar and wind renewables with the MG system but neglected the network constraints. Various optimization techniques, such as dynamic programming [22], stochastic dynamic programming [23], linear programming [24,25], mixed-integer programming [24,25], and mixed-integer linear programming [26,27], have been proposed to solve this nonlinear optimization problem. However, the drawbacks of these traditional programming optimization methods include falling into local optimum, slow convergence rate, and inability to deal with nonlinear optimization problems. Furthermore, an intelligent optimization method with an ability to search for an optimum point from different initial points has been widely recently utilized in the MG systems to improve the performance while minimizing the overall costs and cutting down the energy consumption. In [28], an economic dispatch scheme is developed for the MG system on the basis of particle swarm optimization (PSO) to minimize the operating cost of the MG system. In [3], an EMS scheme that considers the degradation cost of the energy storage system based on a chance-constrained programming in MGs is presented. However, the drawbacks of the techniques are the complexity of techniques and parameter sensitivity. Furthermore, the operating cost of MGs is neglected.

A multi-agent decentralized EMS-based distributed intelligence also manifests the capability for optimal carbon–energy combined flow in a large scale power system [29]. However, the limitations of these techniques are the high investment costs and the huge amount of data required. Population algorithms, such as PSO [30–33], differential evolution [34,35], gravitational search algorithm (GSA) [36,37], backtracking search algorithm (BSA) [38], and harmony search algorithm [39], have been used to solve optimal scheduling problems for MGs. Nevertheless, the shortcomings of these techniques are a huge set of parameter setting, high tendency to fall into local optimum, and parameter sensitivity. Besides, the performance of these algorithms is still in the testing or validation phase to yield the best outcome in terms of convergence, robustness, and capability in finding an optimal solution. Table 1 shows the comparative study of recent methodologies with related literature. In these approaches, substantial work is still needed to consider the reduction of operating cost, reliability improvement, optimum battery storage system performance, and emission reduction. The EMS system is implemented on the basis of centralized and decentralized supervisory control [35,37–40]. Many objectives deserve to be explored in detail, such as battery storage system performance, effect of DGen in the MG system, and reliability and sustainability of the operating system [3]. A few authors also used uncertainty quantification methods, such as point estimate method and scenario generation and reduction method, to examine the effect of MG uncertainties and provide a sustainable EMS.

To solve the research gap summarized in Table 1, this study proposed a new metaheuristic optimization technique called the lightning search algorithm (LSA) to address the EMS of MGs system and reduce the total operating costs. Fast convergence speed, reduced error margin, and superior characteristics are the advantages of implementing a LSA algorithm in this study. The efficiency and reliability of this technique are demonstrated and evaluated by using 24 benchmark functions with different characteristics in [44]. The LSA technique based on the natural phenomenon of lightning to search for an optimal solution by using fast particles known as projectiles. The LSA algorithm was implemented to find the optimal scheduling of the power management of MGs in the IEEE 14-bus test system considering real load varying conditions for 24 h

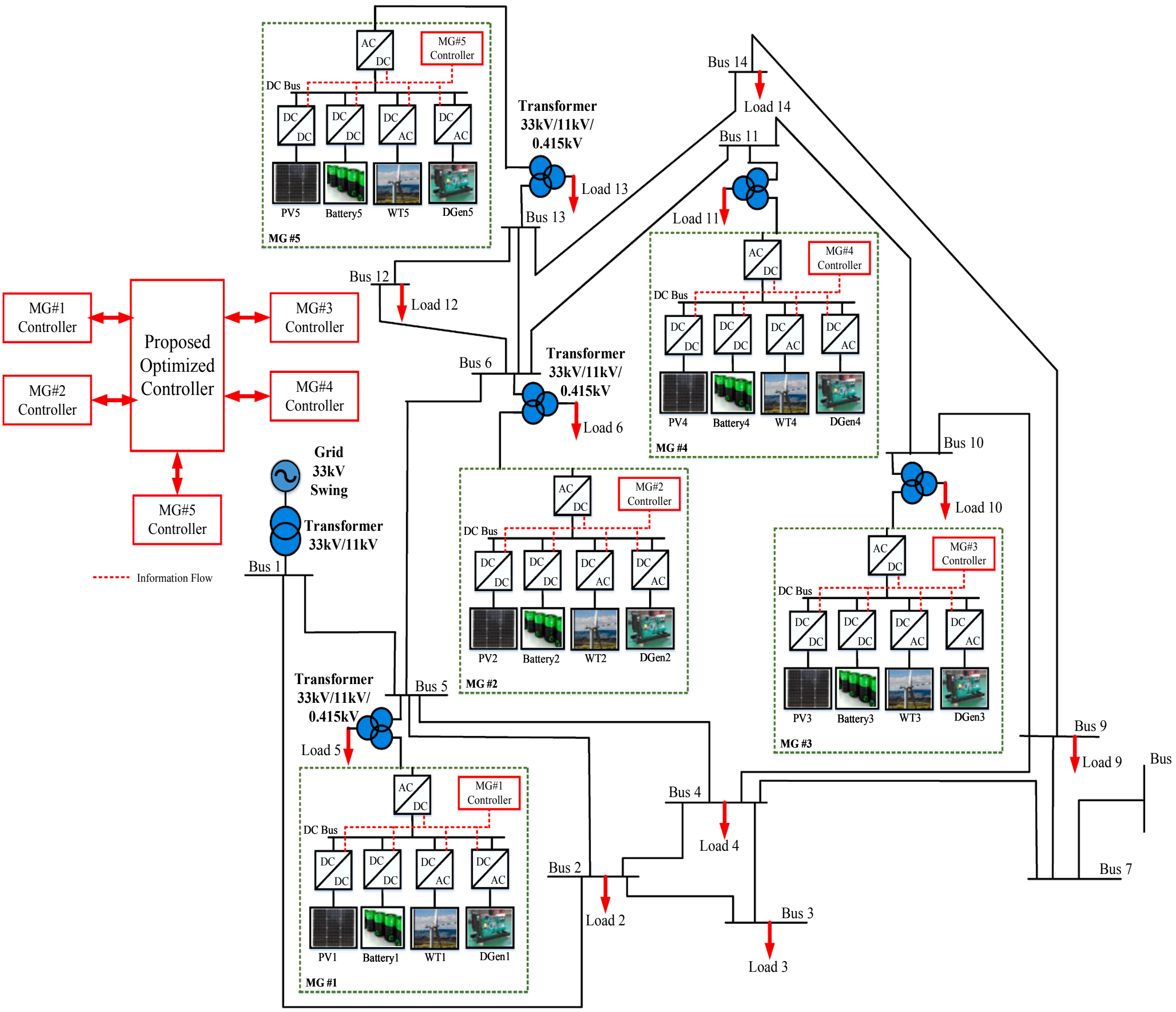


Fig. 1. Modified IEEE 14-bus test system with an integrated MG system.

of operation. Five MGs are proposed in this system to feed the loads at each specific bus with every MG containing four RES units. Furthermore, the comparison of the formulated total operating costs with different optimization algorithms is also discussed in detail in this work. The following key points demonstrate the main objective of this work:

- Propose an optimized controller for the MGs system based on the LSA optimization technique considering DER in the MGs and battery storage system
- Develop an optimized controller to solve a complicated optimization problem while minimizing the total operating cost of the MGs system in the IEEE 14-bus test system for providing a sustainable power supply
- An LSA-based optimized controller is used for EMS of MGs to minimize the expenses of electricity generation and energy purchase from the utility grid and decrease the carbon dioxide (CO_2) emission.
- Verify the performance of the proposed optimized controller with different types of optimization techniques under real load varying conditions.

The remainder of this paper is structured as follows: Section 2 formulates the mathematical model of the system and presents the optimization problems; Section 3 demonstrates the proposed LSA optimization technique with the implementation method to solve the problems; Section 4 presents the simulation results and comparison with the proposed algorithm; Section 5 provides the concluding remarks.

2. System description

2.1. Power flow scheduling energy management of the MG system

This study focuses on the use of LSA-based algorithm optimization to optimize the renewable energy system's performance in the IEEE 14-bus test system that contains five MGs. The MG systems are comprised of a PV system, WT system, battery storage system, and DGen unit. The proposed LSA-based optimization algorithm is expected to provide the following solutions to the MGS system:

- A scheduling power management for all elements in the MGs while reducing the electricity generation cost and expense for energy purchase from the grid
- A control strategy to optimize the trade-off between the system's performance and the operating cost

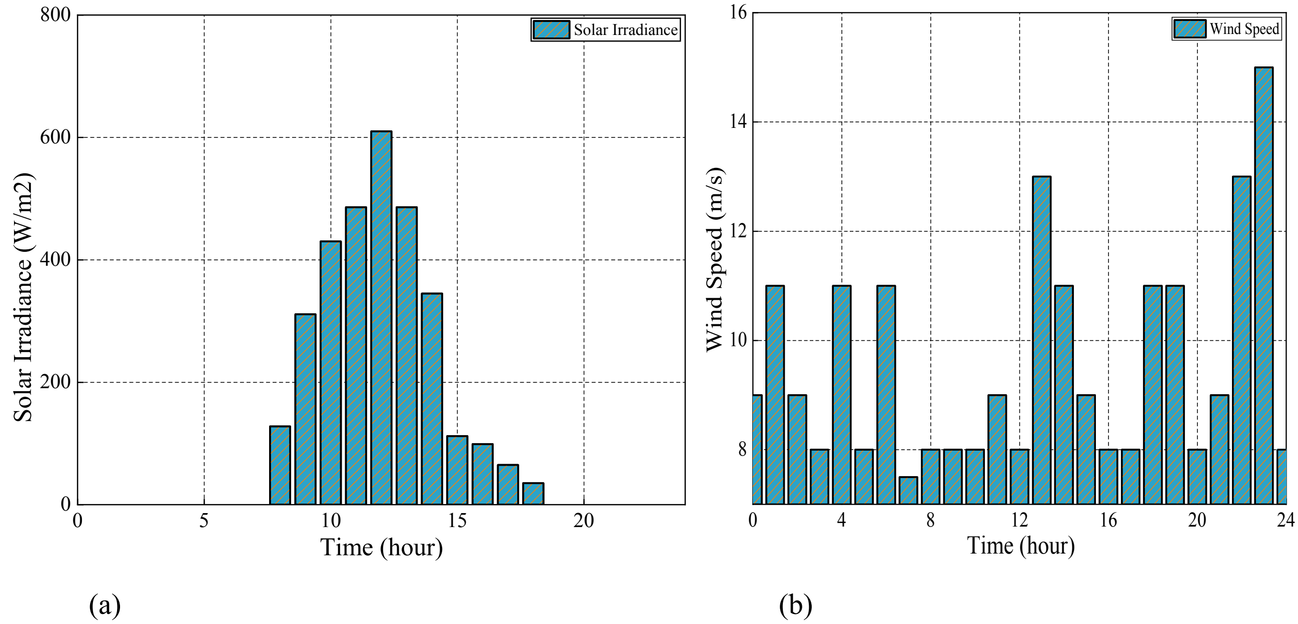


Fig. 2. Real hourly forecast curve: (a) average solar irradiance and (b) average wind speed.

- Optimization of the MG system's operation considering the varying loads and intermittency of the RES, and
- Optimal usage of each component in the MGs.

2.2. System architecture

The overview of the MG system implementation in the IEEE 14-bus distribution system with the proposed optimized controller-based scheduling EMS is shown in Fig. 1. Each MG contains a PV system, WT system, battery storage system, and DGen. The two main generators in the original system are located at buses 1 and 8. However, the system is modified to have only one generator at Bus 1 to control the grid. The main grid is connected to Bus 1 with 200 MW power supplied to the whole system through the main substation transformer of 33 kV/11 kV at 50 Hz system. The actual power value is considered in this study for the IEEE 14-bus standard networking system for control purposes. According to the IEEE 1547 standard system, the stability and reliability of a system can be enhanced by implementing multiple MGs in the system compared with a single MG [45,46]. Hence, the five MGs installed in buses 5, 6, 10, 11, and 13 in this work (Fig. 1) are expected to improve the system's reliability and power quality and reduce transmission losses. The proposed optimized controller acts a as central controller to provide the necessary decision to each of DER in the MG system. The developed optimized controller will analyze the availability of each DER unit in the system and optimally and economically provide supply to the loads. Each MG supplies 10 MW power output in which loads located are less than 10 MW to sustain the reliability power of the busses if outage supply happened on the main grid. The distribution system network, including the MG system, is simulated using Matlab/SimPower System for a 24 h scenario.

2.3. Modeling of the MG system

The interconnection of the DER units in the MG system on the IEEE 14-bus is described in Fig. 1. The total output power of each MG is 10 MW operated at 415 V at 50 Hz of frequency. The MGs are connected to the distribution bus via star three winding transformers. Each DER that participated on the bus is based on a decision provided by the proposed optimized controller. The optimized controller-based LSA optimization generated the decision for power scheduling energy management to the DER to allow power dispatch. The optimized parameters in this study are weather data, battery status, load curve capacity, fuel usage, and per unit price. The solar irradiance and wind speed are conducted on the basis of the real hourly forecast average provided by Tenaga Nasional Berhad Research (TNBR), Malaysia (Fig. 2). Table 2 shows the characteristic of RES in the MG system.

Table 2
Characteristic of renewable generation in the MG system.

Description	Specifications
PV system	
Type	Monocrystalline
Efficiency (%)	10
Area (m^2)	5000
Rated power (MW)	4
Battery storage system	
Nominal voltage (V)	415
Efficiency (%)	96
Rated power (MW)	1
Battery capacity (Ah)	96,000
WT	
Nominal power output (MW)	4
Nominal wind speed (m/s)	15
Minimum operating wind (m/s)	5
DGen	
Nominal power output (MW)	1
Nominal voltage (kV)	11

3. System modeling

The penetration of the system with five MGs into the IEEE 14-bus test system is formed. The MGs contain independent units, such as PV system, WT system, battery storage system, DGen unit, and loads. The detailed modeling of the system components is further discussed in this section.

3.1. Photovoltaic (PV) system

This renewable energy involving energy conversion from sunlight into electricity is considered to be the most common and easiest way of energy production because of its small size and lower cost compared with the WT system. The output power of the PV system is associated with solar irradiance, which can be obtained as follows [3,47,48].

$$f_{ird}(ird) = \frac{1}{ird.\sqrt{2\pi\sigma_{ird}^2}} exp\left[\frac{-(In(ird) - \lambda_{ird})^2}{2\sigma_{ird}^2}\right] ird \geq 0, \tag{1}$$

$$P_{PV} = \begin{cases} P_{PV,rated}\cdot\left(\frac{ird^2}{ird_{std}.ird_{cer}}\right), ird < ird_{cer} \\ P_{PV,rated}\cdot\left(\frac{ird}{ird_{std}}\right), ird > ird_{cer} \end{cases} \tag{2}$$

3.2. Wind turbine (WT) system

A WT system is one of the promising technologies in the electrical system that generates electrical power according to the linear relationship with the wind speed. The WT captures the kinetic energy of the wind and transform it into electrical energy. Moreover, the WT produces power when the wind speed is between the cut-in condition and the nominal value. However, the WT will disconnect from the grid if the wind speed exceeds the maximum value and connects back once the wind speed returns to its nominal value. The potential WT model is as follows:

$$P_{WT} = \begin{cases} 0(v < v_{cut-in}), (v > v_{cut-out} \\ \left(\frac{v - v_{cut-in}}{v_{nom} - v_{cut-in}}\right)^3 .P_{max}(v_{cut-in} \leq v < v_{nom}) \\ P_{nom}(v_{nom} \leq v \leq v_{cut-out}) \end{cases} \tag{3}$$

where P_{WT} is the WT output power (W), P_{max} is the maximum power of WT (W), v is the wind speed (m/s), v_{nom} is the nominal wind speed (m/s), and v_{cut-in} is the cut in wind speed (m/s), $v_{cut-out}$ is the cut out wind speed and P_{nom} is nominal power (W) [49,50].

3.3. Battery storage system

The battery storage system is used for storing surplus power to support the system voltage and frequency and deliver the power to the load in case the RES system experiences power supply shortage [47]. Furthermore, the battery storage system can smoothen the fluctuation of the PV and WT systems when the load changes. When the power generated by RES in the MG system is higher than the load demands, the excess power can be stored in the battery storage system for future use. The simple dynamics of the battery storage system is modeled as follows [48,49,50]:

$$SOC_{bat}^{(t)} = 100\left[1 + \left(\frac{1}{Q_{bat}}.\int_0^t i_{bat}(t)dt\right)\right] \tag{4}$$

$$B_{AH} = \frac{1}{3600}\int_0^t i_{bat}(t)dt \tag{5}$$

where SOC_{bat}^t is the battery state of charge (SOC); Q_{bat} is the maximum battery capacity (Ah); i_{bat} is the battery current, which is positive for discharge and negative for charge; and B_{AH} is the battery ampere hour. The energy stored in the battery storage system depends on the previous battery SOC, output power of the RES system, and total loads of the system at time t. The energy of the battery storage system can be obtained as follows:

$$E_{bat}^{(t)} = E_{bat}^{(t-1)} + \left(\frac{E_{RES}^{(t)} - E_{laod}^{(t)}}{\eta_{DC/AC}}\right)\eta_{charge} \text{ if the battery is charged} \tag{6}$$

$$E_{bat}^{(t)} = E_{bat}^{(t-1)} + \left(\frac{E_{laod}^{(t)} - E_{RES}^{(t)}}{\eta_{DC/AC}}\right)\Big/\eta_{discharge} \text{ if the battery is discharged} \tag{7}$$

where η_{charge} and $\eta_{discharge}$ are the battery charging and discharging efficiencies, respectively. The $E_{RES}^{(t)}$ is the amount of total energy produced by the RES, and $E_{laod}^{(t)}$ is the total required energy in the MG system. The battery initial SOC is 80% for this system, and the charging efficiency is 90%.

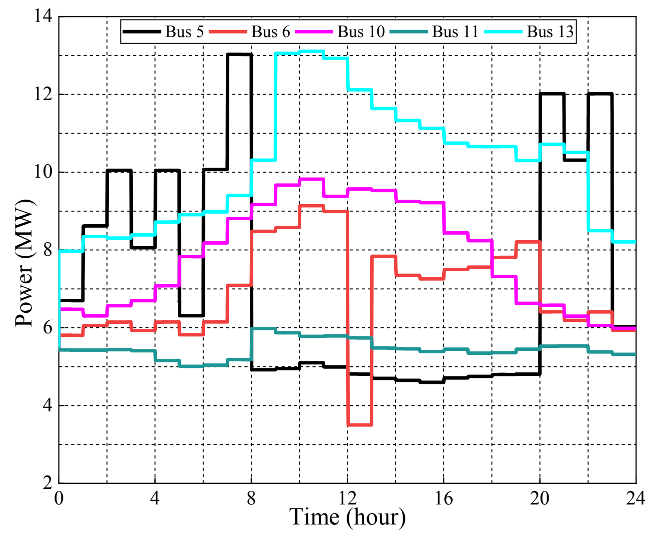


Fig. 3. Hourly average load curve for each MG bus.

3.4. DGen

The DGen provide balance on the MG system to the load demands whenever the generation from PV and WT is inadequate, and the stored energy in the battery storage system is not compensating. The model comprises a diesel engine, governor, excitation system, and synchronous machine, which provides diesel engine mechanical power. The model of DGen can be expressed as follows [53]:

$$F(t) = a_1.P_{DGen}^{(t)} + a_2.P_r \tag{8}$$

where $F(t)$ is fuel consumption (L/hour), P_r is the rated capacity of DGen, and $P_{DGen}^{(t)}$ is the generated output power of DGen at time t. The a_1 and a_2 represent the coefficients of the fuel consumption curve, which are 0.246 and 0.08415, respectively.

3.5. Loads

The dynamic load demand induced by the stochastic behavior of the electricity consumers is one of the factors that cause uncertainty in the power system. In this study, the IEEE 14-bus system has nine loads, which are located in buses 2, 3, 4, 6, and 9 to 14, respectively. Every bus system represents a specific feeder with load area demands. The loads are modeled according to the daily consumption profile of Perlis, Malaysia, which was recorded in February 2016. The hourly average load curve for each system with five MGs in the IEEE 14-bus test system is shown in Fig. 3.

4. Power scheduling energy management strategy (EMS)

The optimal power scheduling energy management problem for MGs considering load uncertainties is a nonlinear optimization problem. This mode aims to optimize the power dispatch of each DER unit and minimize the total operating cost by satisfying all the system constraints. Given that the irradiance and the wind speed are intermittent nature output, the fast online algorithm is a crucial element for the EMS of MGs to define the energy capacity and the optimized power dispatch to the loads. In the MG system, the total power produced by DER, the stored energy in a battery storage system, and exchanged power by the grid are used to supply system loads. The amounts of load power consumed in buses 5, 6, 10, 11, and 13 are supplied by RES. When the output power of these types of RES is more than the load demand, the surplus power is used to charge the battery storage system. In this state, if the surplus power still exists, the excess power is sold to the grid. When the load demands are more than the power provided by RES, the stored energy in the battery storage system will be exported to the loads and supported by the power delivery by DGen to balance the load demands. If the total generated power in the MG system cannot satisfy the load demands, then the required power is purchased from the grids.

4.1. Problem formulation

The MG contains various DER units and a battery storage system. The objective problem and constraint function of the optimization model for an optimal power scheduling energy management in the MG system are formulated in this section. This model aims to minimize the energy production cost of DGen and the costs of exchanging power with grids and MG during a 24 h period. The objective function of the problem can be written as Eq. (9) as follows:

$$minf = \sum_{t=1}^{T}\left\{\sum_{i=1}^{N_g} B_{Gi}\left(P_{Gi}^{(t)}\right) + C_{grid}^{(t)}\right\} + \sum_{t=1}^{T}\sum_{k=1}^{n}\{(\gamma_{1j}+\gamma_{2j})B_{kj}.F_k(P_{k,t})\} \quad (9)$$

The first term of the objective function in Eq. (9) is to provide optimal power of the DER unit and minimum total operating cost of the MG system. The second term of the objective function defined in Eq. (9) is to minimize the environmental cost to control the CO_2 emission of power generation pollution for the DGen unit in the MG system, where n is the number of DGen unit, and k is the index of the DGen unit. Variables γ_{1j} and γ_{2j} are the penalty costs and environmental values of pollutant j, respectively. B_{kj} represents the emission of pollutant j from the DGen power k per unit of power generation, and $P_{k,t}$ is the power generated by DGen power k at time t.

The DGen is considered a dispatchable resource for power generation. The fuel cost function of the DGen unit in economic dispatching can be expressed as Eq. (10) [54]:

$$F_k(P_{k,t}) = a_kP_{k,t}^2 + b_kP_{k,t} + c_k, \quad (10)$$

where a_k,b_k, and c_k are the unit coefficients of the fuel cost function.

4.2. Cost-effective evaluation

The LSA-based optimization algorithm provides an optimal solution to power management and minimizes the operating cost in the distribution network. The energy consumption is calculated for the energy (E) in megawatt hours (MWh) per day. The energy cost ($C_{grid}^{(t)}$) is formulated per day in Ringgit Malaysia as in Eqs. (11) and (12) [51].

$$E_{(MWh/day)} = \frac{P_{(W)}.t_{(h/day)}}{1000000_{(W/MW)}}, \quad (11)$$

$$C_{grid}^{(t)}(RM/day) = \frac{E_{(MWh/day)}.C_{grid}^{(t)}(cent/MWh)}{100_{(cent/RM)}}, \quad (12)$$

where E is the energy per day, P is the active power, and t is the time.

4.3. Problem constraints

The total power generated by the DER unit, the stored energy in the battery storage system, and the exchange energy with the grid should satisfy the load demands. Therefore, the objective function formulated above is subjected to the following constraints, which include the output power of the DER unit, the stored energy in the battery storage system, and the power balance in the MG system.

4.3.1. System load balance

This constraint states that the summation of load demand ($P_L^{(t)}$) must be equal to the summation of the DER power ($P_{Gi}^{(t)}$) and main grid power ($P_{grid}^{(t)}$) at hour t and DGen power ($P_{DGen}^{(t)}$) at time t. Thus, the mathematical expression of such constraints can be written as follows:

$$\sum_{l=1}^{N_L} P_L^{(t)} - \sum_{i=1}^{N_g} P_{Gi}^{(t)} - P_{Grid}^{(t)} - \sum\nolimits_{k=1}^{N_{DGen}} P_{DGen}^{(t)} = 0, \quad (13)$$

where P_L^t is the load demand power at time t, and N_L is the number of total load demands.

4.3.2. Real power generation capacity

A DER has a generation capacity and should produce power according to its capacity to efficiently generate the output power in the MG system and ensure that the DER limits are not exceeded. The following constraints can be formulated as Eq. (14):

$$\left.\begin{array}{r} P_{Gi,min}^{(t)} \le P_{Gi}^{(t)} \le P_{Gi,max}^{(t)} \\ P_{Grid,min}^{(t)} \le P_{Grid}^{(t)} \le P_{Grid,max}^{(t)} \\ P_{DGen,min}^{(t)} \le P_{DGen}^{(t)} \le P_{DGen,max}^{(t)} \end{array}\right\} \quad (14)$$

4.3.3. Battery storage system constraints

At all times, the stored energy in the battery storage system is limited by the maximum and minimum acceptable storage capacities to avoid deep discharging and overcharging, which can be formulated as Eq. (15):

$$E_{bat,min}^{(t)} \le E_{bat}^{(t)} \le E_{bat,max}^{(t)}, \quad (15)$$

where $E_{bat,min}^t$ and $E_{bat,max}^t$ are the minimum and maximum limits of energy stored in the battery storage system, respectively. Eq. (16) should be satisfied in each time interval according to a restriction that may exist on the charge and discharge rates of the battery storage system.

$$SOC_{bat,min}^{(t)} \le SOC_{bat}^{(t)} \le SOC_{bat,max}^{(t)}, \quad (16)$$

$$E_{bat}^t = E_{bat}^{(t-1)} + P_{charging}.(\Delta t).\eta_{charge} - \frac{P_{discharging}}{\eta_{discharge}}.(\Delta t), \quad (17)$$

where $E_{bat}^{(t-1)}$ andE_{bat}^t are the amounts of energy storage inside the battery at a time ($t-1$) and (t), respectively. The $P_{charging}$ and $P_{discharging}$ are the rates of charge and discharge at a definite period of time Δt. The η_{charge} and $\eta_{discharge}$ are the battery efficiencies during charging and discharging, respectively.

5. LSA

An advanced metaheuristic optimization called LSA was first invented by Shareef et al. in 2015 to solve the constraint problem [41]. The technique was inspired by the natural phenomenon of lightning and the mechanism of step leader propagation by using the concept of fast particle known as projectiles [52]. The three-step process involved in the LSA optimization implementation includes transition, space, and lead projectiles. The projectiles similar to "swarm" or "particles" that are used in other optimization methods, such as the PSO technique. The transition projectiles represent the random generate solutions, the space projectiles regarded as the search space of the solution population, and lead projectiles, which are the optimum solution with the best fitness values. The optimum solution with the best fitness can be determined by implementing these three steps in the system. Recent research proves the robustness of the LSA-based optimization technique with fast convergence speed, good fitness curves, and rapid settling time in various applications. Reference [53] presented the LSA-based optimization to

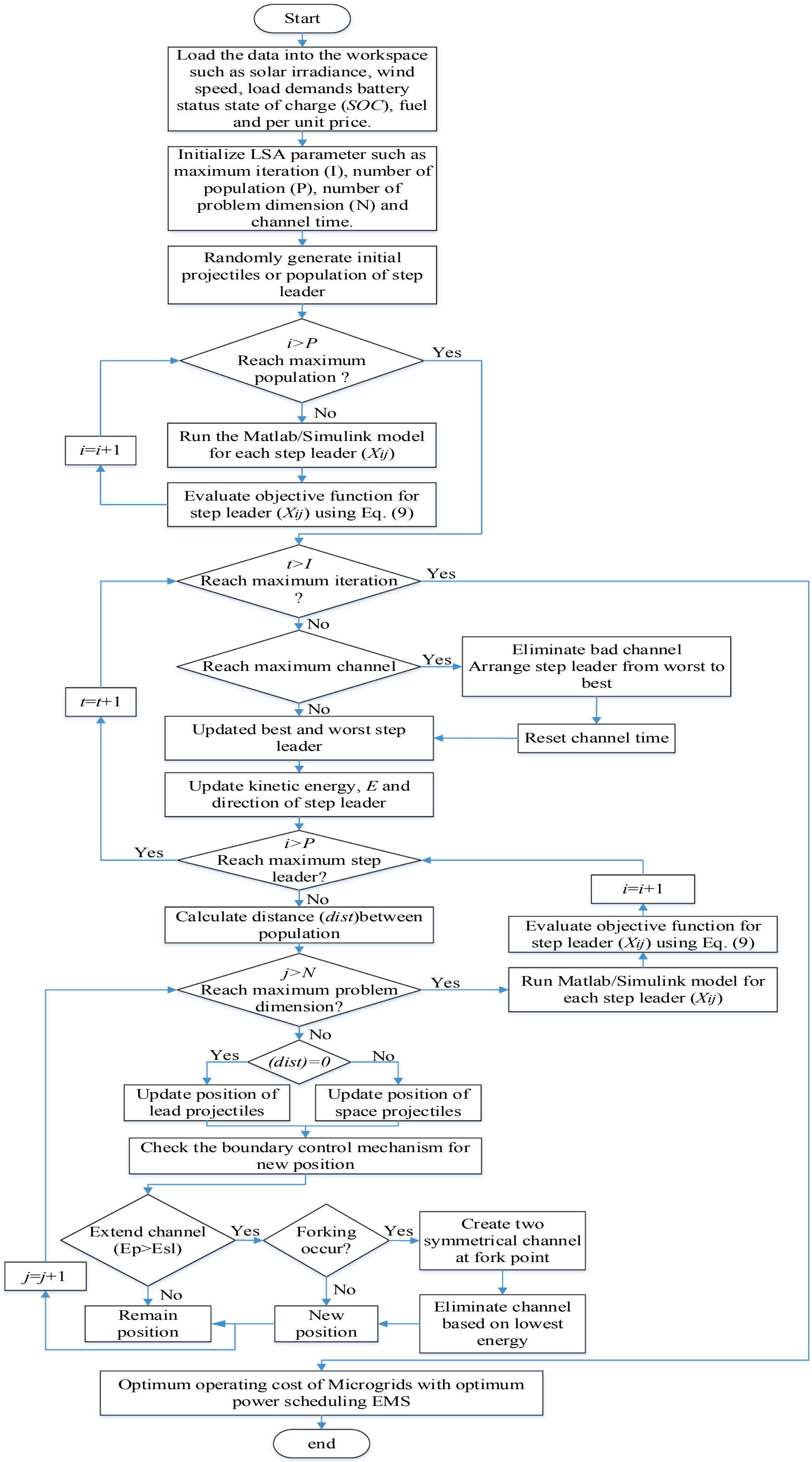


Fig. 4. Flowchart of the proposed LSA-based optimization.

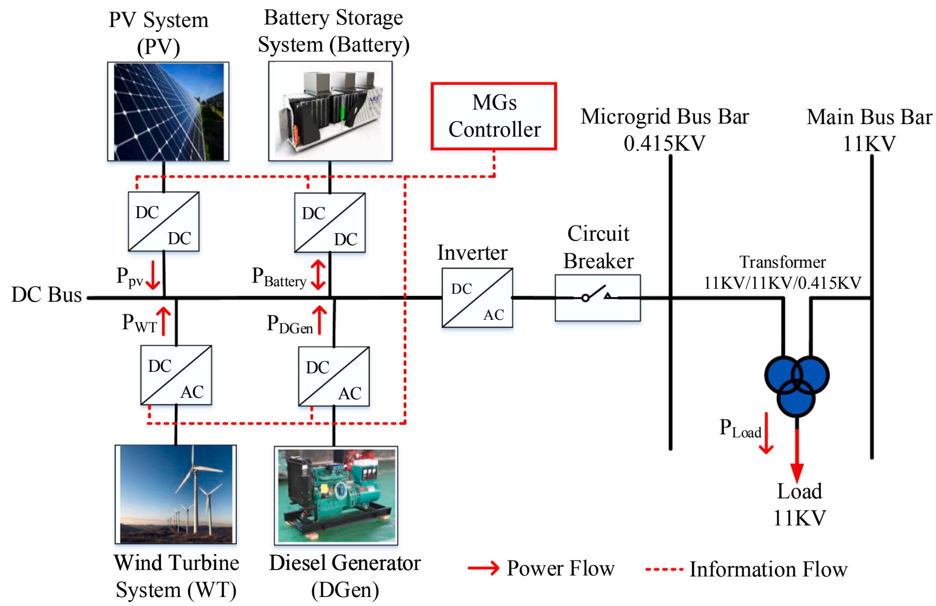


Fig. 5. Single line diagram of interconnected renewable sources in each MG system.

optimize the economic dispatch in a power system by minimizing the total generation cost and power losses. The performance of LSA has achieved better results than other optimization techniques. The optimal value of the weighting factor in the wind power model is also presented in [54]. The algorithm obtained the lowest fitness value and is more accurate compared with PSO optimization. Hannan et al. [55] and Ali et al. [52] used an improved version of LSA optimization called quantum LSA (QLSA) to optimize the parameters of a fuzzy logic controller for monitoring the speed response of the induction motor drivers. The result shows the robustness of the techniques compared with other optimization techniques with real-time experimental validation. This result proved that the LSA optimization-based technique is robust and efficient and has a fast convergence speed in finding an optimal solution for optimization problems. The detailed explanation on the characteristic of the technique is presented in [56,57,60].

5.1. LSA-based optimization implementation

Several steps were considered in the implementation of LSA-based optimization. The aim is to achieve the best solution by solving the objective problems and constraints through an iterative procedure [57]. Several parameters, namely, weather data, battery status, load curve capacity, fuel, and per-unit price, are considered in the optimization implementation. The proposed approached was implemented by using MATLAB script (Version 2020) 3.00 GHZ PC with 16 GB RAM. The flowchart of the LSA-based optimization is shown in Fig. 4. The procedure of the LSA implementation are summarized as follows:

Step 1: Load the data, such as solar irradiance, wind speed, load demands battery status state of charge ($SOC_{bat}^{(t)}$), fuel, and per unit price, into the workspace.

Step 2: Assign and evaluate the optimization problem constraints, which are the limits of the variables.

Step 3: Initialize the LSA parameters, such as the maximum number of iteration (I), the number of population (P), the number of problem dimension (N), and the channel time. Initialize the upper bound (UB) and lower bound (LB). Variable I is chosen as 100, P is 50, N is 18, and the maximum channel time considered is 10.

Step 4: Randomly generate the initial projectile or population of the step leader. Create the population of the projectiles on the basis of the Eqs. (18) and (19).

$$Dpoint_{i,j} = rand(P,1)*(UB(j) - LB(i) + LB(j)) \tag{18}$$

where $i = 1,2,3\cdots.,P$, and $j = 1,2,3\cdots,N$.

The initial value of the projectiles in the population vectors is as follows:

$$Dpoint_{i,j} = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,j} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,j} \\ \vdots & \vdots & \ddots & \vdots \\ X_{i,1} & X_{i,2} & \cdots & X_{i,j} \end{bmatrix} \tag{19}$$

Step 5: Reset or initiate a channel time. The maximum channel time used is 10. Chanel time is reset by eliminating a bad channel. Update a best channel from the worst channel.

$$Dpoint_{i,j} = 10^{10}*(ones(1,j)) \tag{20}$$

Step 6: Evaluate the objective function of every step leader, and estimate the best or worst step leader.

Step 7: Update kinetic energy (E), and re-evaluate the objective function.

$$E = 2.05 - 2*\exp(-5*\frac{100 - (t+0)}{100}) \tag{21}$$

Step 8: Eject the space and lead projectiles.

Step 9: Update the position and direction of the space and lead projectiles for each variable. Re-evaluate the objective function to find a better direction.

$$Dpoint_{i,j} = Dpoint\_test_j + direct(j)*0.005*(UB(j) - LB(j)) \tag{22}$$

Step 10: Evaluate the forking procedure with the revised channel time, and eliminate the lowest E.

Step 11: Stopping criterion: if the number of iterations exceed the maximum number of iterations, then stop optimization; otherwise, repeat steps 5 to 10.

6. Results and discussion

The result demonstrated the MG system performance with different load curves of the profile consumption recorded in February 2016 in Perlis, Malaysia. The optimized controller performance and cost-effective evaluation of the proposed algorithm are also discussed in this section. The main highlight of the obtained result is to provide the

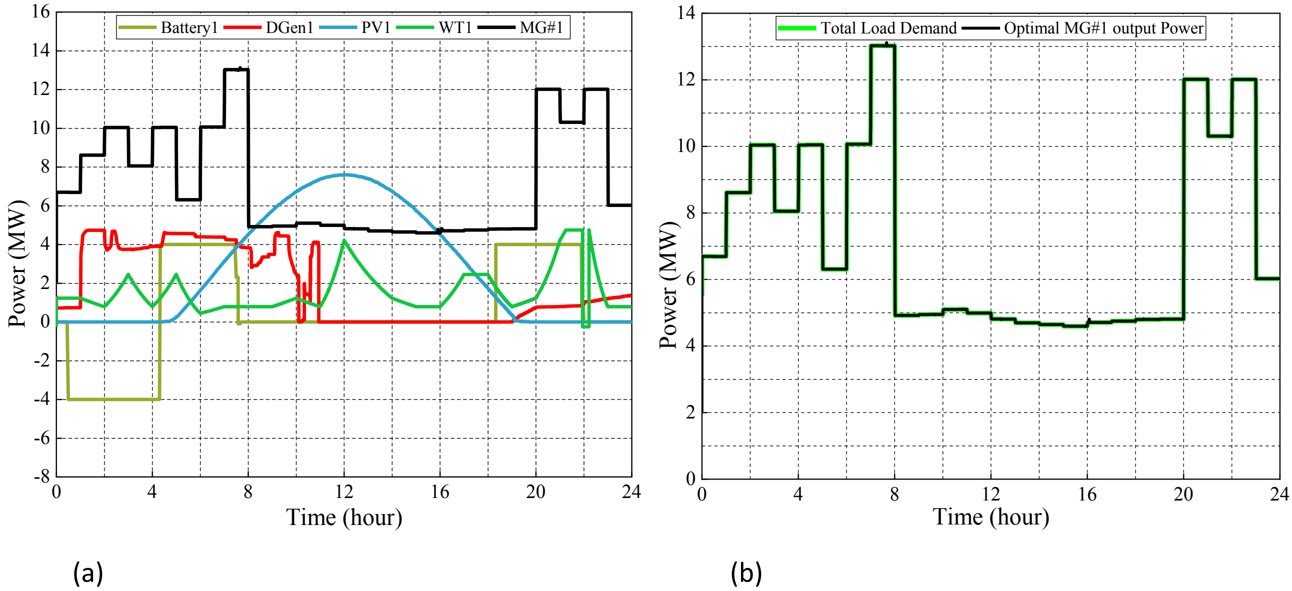


Fig. 6. Performance of an optimal power of MG #1 at bus 5 based on the proposed optimized controller: (a) daily output scheduling of the DER power and (b) power balance of the total load demand with optimal MG #1 output power.

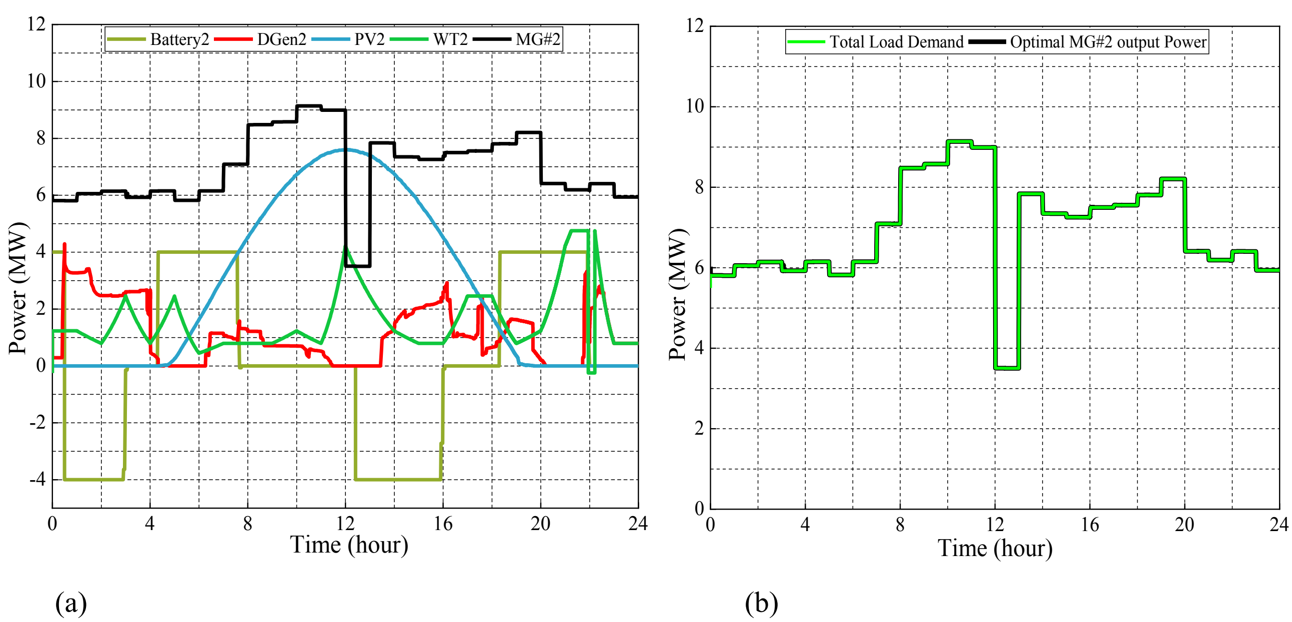


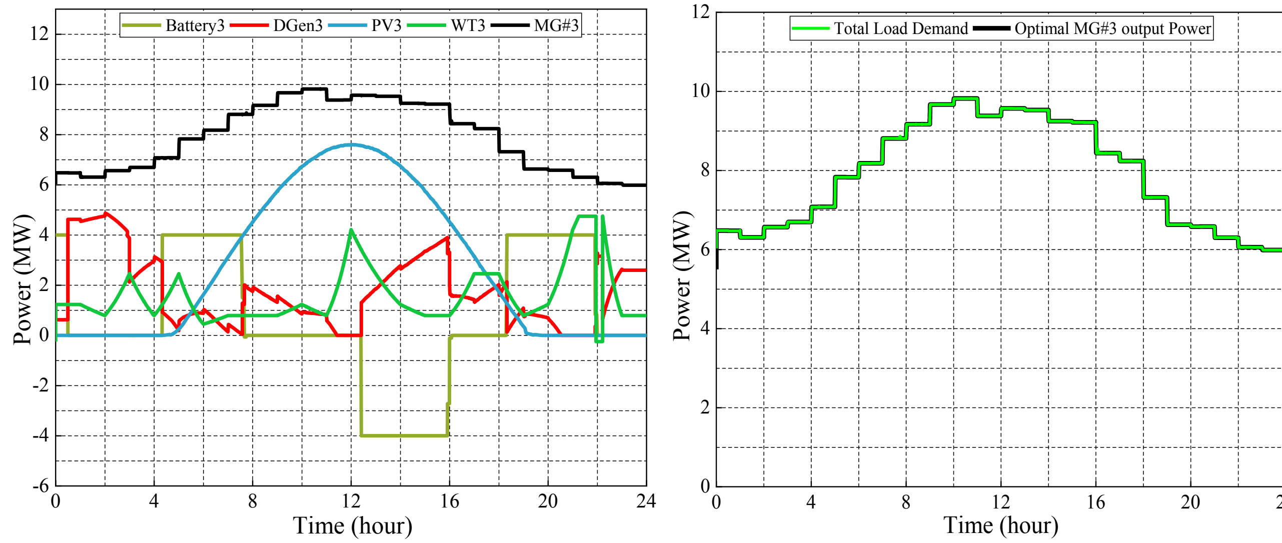
Fig. 7. Performance of an optimal power of MG #2 at bus 6 based on the proposed optimized controller: (a) daily output scheduling of the DER power and (b) power balance of total load demand with optimal MG #2 output power.

best optimum power scheduling of the MG system located at the IEEE 14-bus test system to provide a robust optimization technique and obtain an energy-saving cost on the basis of the sustainable resources on demand. The system was demonstrated by using Matlab/Simulink SimScape Power system environment with 3.00 GHz PC and 16 GB of RAM. Modification on the IEEE 14-bus test system is performed by adding a system with five MGs on the feeders. Each MG system was located at the specific feeder based on the load consumption on that bus, which is less than 10 MW output power, to provide a sustainable supply in case of outage on the grid side. Each MG comprises four renewable sources, such as PV system, WT system, battery storage system, and DGen unit system (Fig. 5).

Each renewable source provides an AC power to the loads through a direct current (DC) bus voltage, which will convert into the alternating current (AC) sinusoidal output voltage and produce an AC active power to the load, thereby resulting in similar frequency with the main bus bar of the system. The simulation was carried out for a 24 h time by using a phasor mode to provide a fast simulation time. Each MG system provides a 415 V with 10 MW output power to supply the loads' demands, which are based on the real hourly average loads curve. Several scenarios, such as load uncertainties and resource fluctuations were simulated to evaluate the performance of controller architecture.

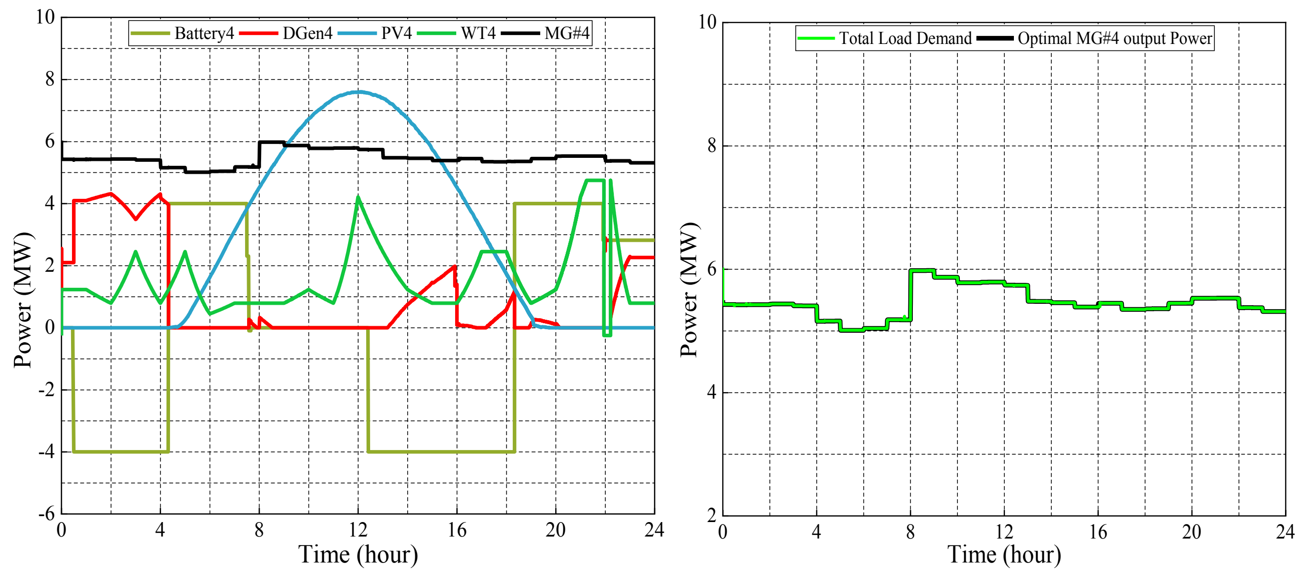
6.1. Load uncertainties and resources fluctuation

In this scenario, the IEEE 14-bus test system ran based on the load profiles and renewable resource input parameter, as shown in Figs. 2 and 3, respectively. This scenario was simulated to determine and analyze



(a) (b)

Fig. 8. Performance of an optimal power of MG #3 at bus 10 based on the proposed optimized controller: (a) daily output scheduling of the DER power and (b) power balance of the total load demand with optimal MG #3 output power.



(a) (b)

Fig. 9. Performance of an optimal power of MG #4 at bus 11 based on the proposed optimized controller: (a) daily output scheduling of the DER power and (b) power balance of the total load demand with optimal MG #4 output power.

the system performance during a normal operation when no disturbance occurred. Such a phenomenon also proved that the MG system can supply the power output to the IEEE 14-bus system with different load curve profiles. The optimum power scheduling output of each system with five MGs during a normal operation throughout the day is shown in Figs. 6–10.

The Figs. 6–10 show the optimal power management for MG #1 to MG #5 act on buses 5, 6, 10, 11, and 13, respectively. Each figure includes two subfigures. The first figure shows an optimum output power scheduling of MGs, which based on the decision of the optimized controller. The second figure shows the power balance between the total load demands and the total generated power by the MG system on the respective bus. The developed optimized controller was simulated randomly on the IEEE 14-bus test system and control the fives of MG at same time. It optimized the DER unit and start to balance the generation based on the demands, respectively. The power deviation in the system is based on the optimized controller decision, which was relied on the developed optimal power scheduling. The proposed developed optimized controller responded based on the available resources and market prices. Given that the market prices are low, the DGen unit will not operate, and the specific bus consumer imports power from the main grid. First, the IEEE 14-bus test system was simulated and randomly run, and the system was optimized based on the developed optimized controller to manage the output power of the MG system based on the loads demands. The power output from the PV and WT units are based on the environment and weather conditions, which can store the surplus

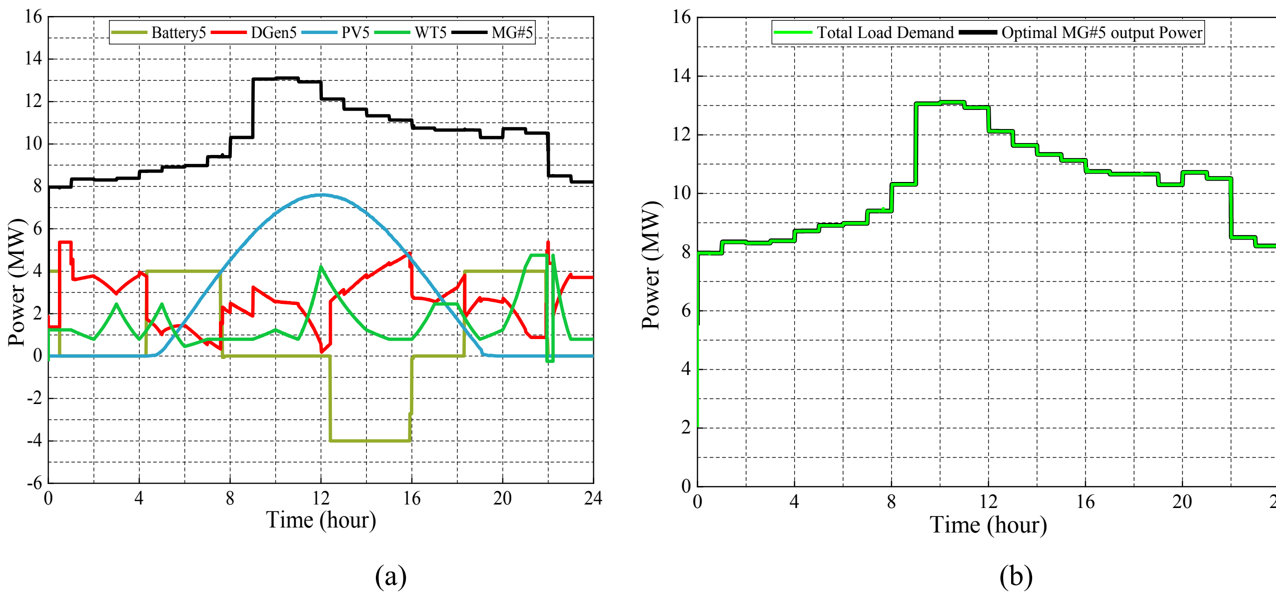


Fig. 10. Performance of an optimal power of MG #5 at bus 13 based on the proposed optimized controller: (a) daily output scheduling of the DER power and (b) power balance of the total load demand with optimal MG #5 output power.

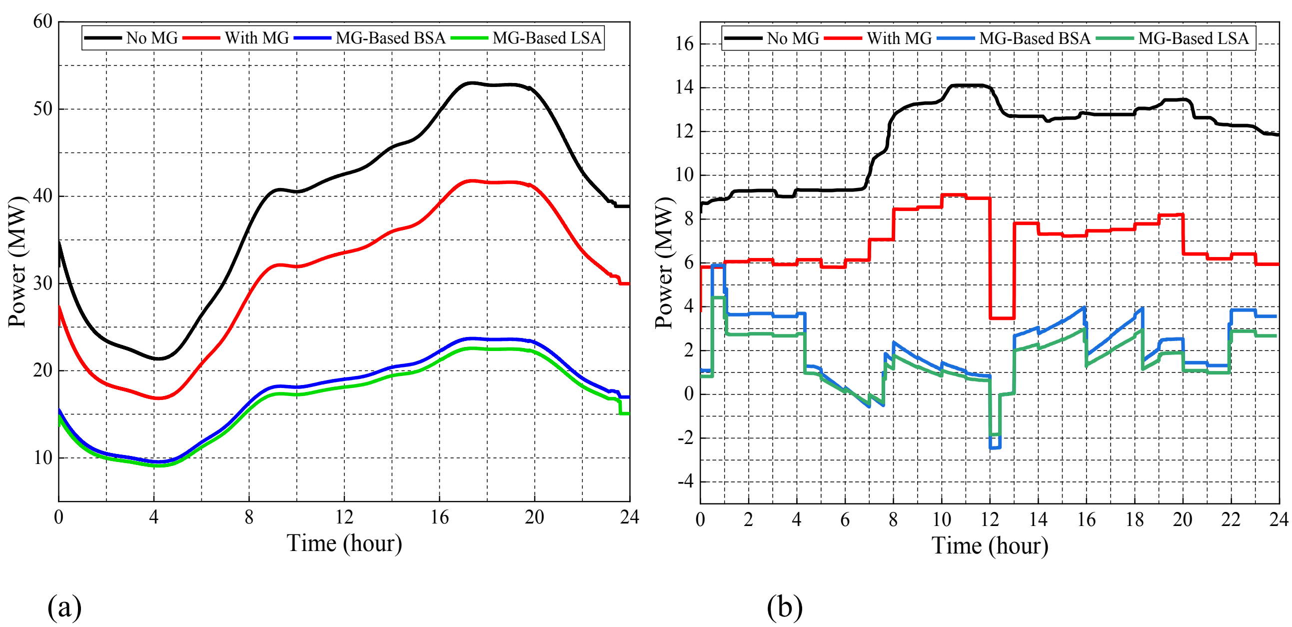


Fig.11. Performance comparison of the output power with the proposed optimized controller based on the condition of no MG system, with MG system, with MG-BSA, and with MG-LSA optimization: a) total output power of the main grid at bus 1; b) total output power consumed at bus 6.

power to the battery storage system during operation. Utilization of the battery storage system into the MG system leads to significant savings in fuel consumption. The system can act as energy back up to the MGs whenever the PV and WT unit output power cannot satisfy the loads. This phenomenon leads to proper usage of the output power of MGs on the IEEE 14-bus test system and reduces the fuel consumption of the DGen units.

Fig. 11 (a) shows the comparison of total main grid power at bus 1 on the system. The result was obtained based on the condition of without MG system, with MG system, with MG-based BSA optimization, and with MG-based LSA optimization. The obtained result shows that the total power generation at main grid power bus 1 during a 24 h operation is 971.65 MW with no MG. However, total power generation is 364.3 MW with MG-based LSA optimization. Accordingly, the amount of total power saving is 607.4 MW. The output power consumed at main grid bus 1 is reduced and saved when the condition of the MG system is applied compared with the condition without MG system. The proposed optimized controller provides a great response when it is introduced, resulting in less usage of the output power at main bus 1. Fig. 11 (b) presents the total power of bus 6 based on the condition without MG system, with MG system, with MG-based BSA optimization, and with MG-based LSA optimization. The power output obtained is based on the load demand at bus 6 (Fig. 3). The result indicated that in the condition without MG system, the amount of power consumed in bus 6 is fully equal to the load demands, which may lead to high operating costs from the utility grids. This phenomenon occurs because the loads take a large amount of power from the main grid to fulfil the demands. Such as situation will lead to the high cost of power consumption to the consumers.

Table 3
Optimal power scheduling management considering the operating cost objectives.

Hour	PV (MW)					Battery (MW)					WT (MW)					DGen (MW)				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
1	0	0	0	0	0	−4	−4	0	0	0	1.312	1.232	1.135	1.140	1.185	0.873	8.571	4.585	4.145	3.62
2	0	0	0	0	0	−4	−4	0	−4	0	1.294	0.791	1.183	0.791	0.922	4.862	9.261	4.692	4.317	3.71
3	0	0	0	0	0	−4	−0.145	−2.329	−4	0	2.521	2.455	2.040	2.455	2.102	3.966	7.327	2.331	3.491	3.14
4	0	0	0	0	0	−4	0	0	−4	0	0.982	0.790	1.043	0.791	1.042	4.016	5.133	3.017	4.307	3.83
5	1.252	0.245	0.353	0.246	0.353	3.996	4	4	4	4	2.523	2.454	1.910	2.170	2.171	4.322	−0.551	0.718	0	1.20
6	1.855	1.622	1.766	1.623	1.920	4	4	4	4	4	0.233	0.447	0.478	0.447	0.510	4.319	−0.2507	0.967	0	1.28
7	2.126	3.113	3.259	3.402	3.402	−0.122	4	4	4	4	0.855	0.790	0.791	0.791	0.791	4.198	−1.754	0.371	0	0.60
8	3.984	4.512	4.646	4.766	4.766	0	0	0	−1.542	0	0.873	0.791	0.791	0.791	0.791	3.981	1.784	1.865	0.021	2.37
9	4.921	5.740	5.862	5.862	5.972	0	0	0	0	0	0.873	0.791	0.830	0.831	0.871	3.551	1.946	1.488	0	3.11
10	5.862	6.730	6.789	6.789	6.879	0	0	−1.571	−1.542	0	1.121	1.232	1.183	1.183	1.135	4.196	0.615	0.923	0	2.54
11	6.262	7.377	7.401	7.406	7.455	0	0	−1.571	−1.571	0	0.872	0.791	0.998	0.997	1.232	0	0.969	0.487	0	2.12
12	7.635	7.585	7.592	7.592	7.592	0	0	−3.201	−1.571	0	4.118	4.214	3.815	3.815	3.815	0	−2.809	0	0	0.35
13	7.230	7.396	7.296	7.296	7.296	0	−4	−4	−4	−4	2.924	2.455	2.171	2.170	2.171	0	−2.350	2.031	0.006	3.08
14	6.852	6.746	6.489	6.533	6.563	0	−4	−4	−4	−4	1.533	1.232	1.088	1.111	1.135	0	3.857	2.835	0.910	3.81
15	5.937	5.748	5.517	5.420	5.517	0	−4	−4	−4	−4	1.318	0.791	0.791	0.791	0.791	0	4.806	3.454	1.591	4.41
16	5.128	4.524	4.399	4.399	4.261	0	−0.108	−0.004	−0.004	0	0.8729	0.791	0.912	0.912	1.043	0	4.660	1.565	0.071	2.80
17	3.825	3.143	3.006	2.853	2.854	0	0	0	−0.286	0	2.132	2.455	2.455	2.454	2.455	0	1.898	1.388	0.020	2.67
18	1.987	1.736	1.454	1.454	1.454	4.112	0	0	0	0	2.213	2.455	2.036	2.036	2.036	0	3.364	1.913	0.933	3.58
19	0.131	0.359	0.067	0.067	0.067	4	4	4	4	4	1.323	0.791	0.871	0.871	0.870	0	2.656	0.845	0.255	2.68
20	0	0	0	0	0	4	4	4	4	4	1.286	1.231	1.662	1.437	1.663	0.873	2.975	0.458	0.045	2.53
21	0	0	0	0	0	4	4	4	4	4	3.511	4.214	4.749	4.639	4.639	0.873	−1.804	0	0	0.94
22	0	0	0	0	0	0.116	0	0	0	0	4.831	−0.249	−0.249	−0.249	−0.25	1.262	5.601	3.153	2.813	4.37
23	0	0	0	0	0	0	0	0	0	0	1.286	0.791	0.791	0.791	0.791	1.305	5.613	2.598	2.263	3.71
24	0	0	0	0	0	0	0	0	0	0	0.861	0.791	0.790	0.791	0.791	1.322	5.143	2.598	2.263	3.71

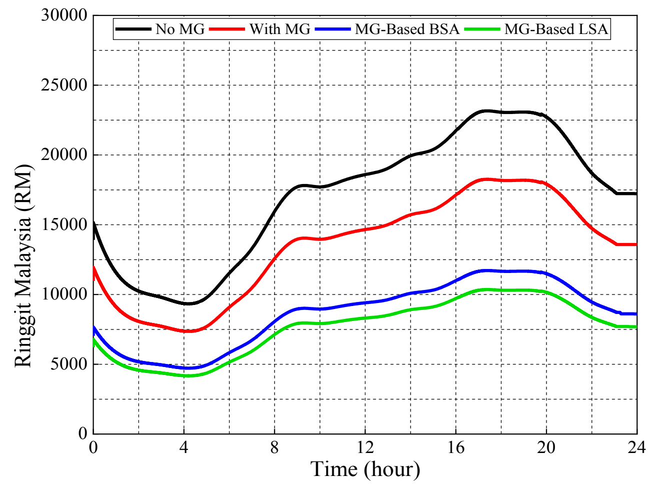


Fig. 12. Comparison of the total cost of the total output power at main bus 1 consumed in 24 h based on the proposed optimized controller.

However, in conditions with the proposed approaches of MG-based LSA optimization, the total output power consumed in bus 6 is less and saved more, and the proposed optimized controller outperforms the other controllers. Thus, the power saved from the grids reduces the losses in the line and increases the reliability of the power system. Moreover, the implementation of LSA optimization algorithm into the optimized controller can manage and optimize the output power of RES towards an optimum level of power consumption on bus 6 based on load demands which can reduce the cost of power consumed from the main grid.

The numerical results obtained from simulations by simultaneously considering the operating cost of the MG system at each bus in the IEEE 14-bus test system by using the LSA-based optimization technique are presented in Table 3. The simulations results illustrate that most loads at each bus are supplied by the WT and DGen in the first hour of the day. Accordingly, the DER units increase their generation according to the priority requirements of minimum costs due to the load peak offered. Furthermore, the battery charging in the MGs occurred in the early hours of the day, such as battery1 and battery2. The battery will discharge its power during the shortage of supply from PV and WT. The surplus power from PV and WT during the 13–16 h is used to charge the battery storage system. If the shortage occurred, especially at 21–24 h, then the extra power is taken from the DGen units to support the load demands. This operation controlled and optimized the generation on the basis of the optimized controller approach implemented in the system. The LSA-based optimization technique provides decisions to the controller of the MGs to optimally dispatch and manage the output power with an economically superior operation.

The comparison of the total cost generated at main bus 1 power with different conditions in the IEEE 14-bus test system during a 24 h operation is presented in Fig. 12. The result indicated that the condition without MG system in the system has shown a higher amount of cost for the utility grid to support the load demands compared with the other conditions. The MG-based LSA optimization technique achieves the best cost and reduces a huge amount, thereby saving substantial energy from the utility grid system to support load demands. This result verifies that the proposed optimized controller can minimize the expenses in generating electricity and purchasing energy from the grid. The MG-based LSA optimization achieves RM 265432.06 amount of total cost saved compare with MG-based BSA optimization, which reaches RM 234953.71 (Fig. 13). Furthermore, the energy cost is calculated on the basis of the Malaysia Tariff rates, which varies from 21.8 cents/kWh to 57.10 cents/kWh based on the load consumptions. However, the average energy cost is chosen to be 43.7 cents/kWh. Thus, the MG-based LSA optimization has shown 62.5% of energy saved, which is higher

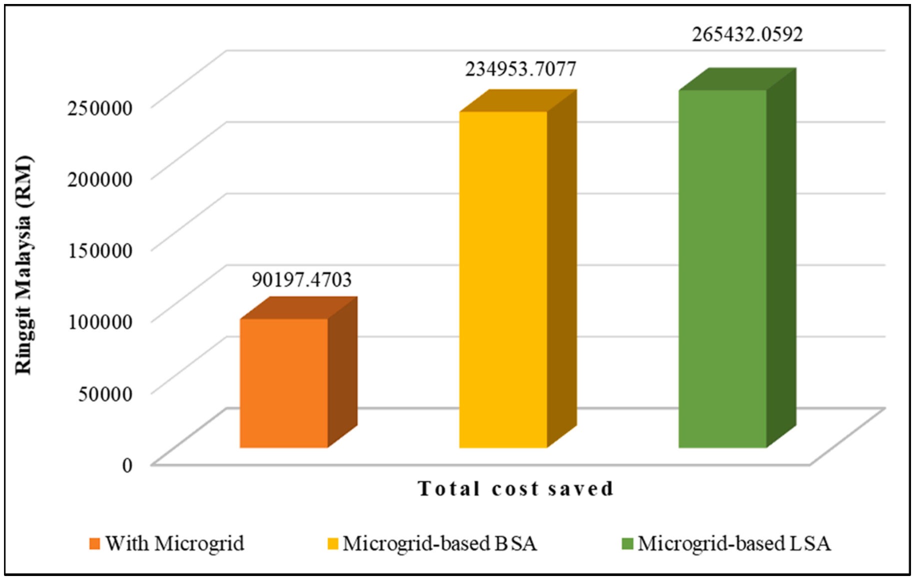


Fig. 13. Amount of total cost saved at main bus 1 from a different technique in the IEEE 14-bus test system during a 24 h operation.

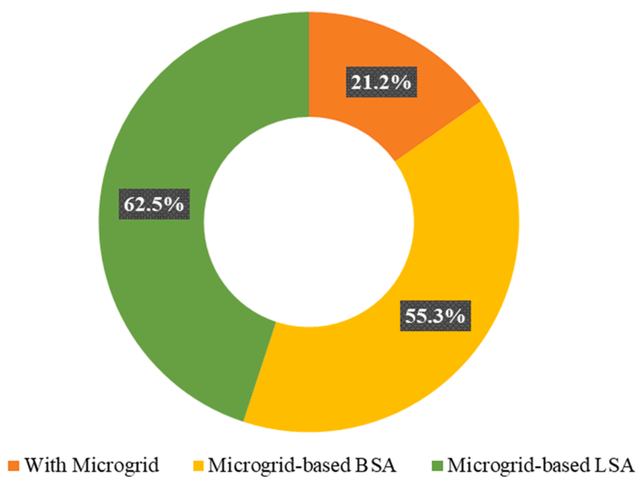


Fig. 14. Percentage of cost saved at main bus 1 from different techniques during a 24 h operation.

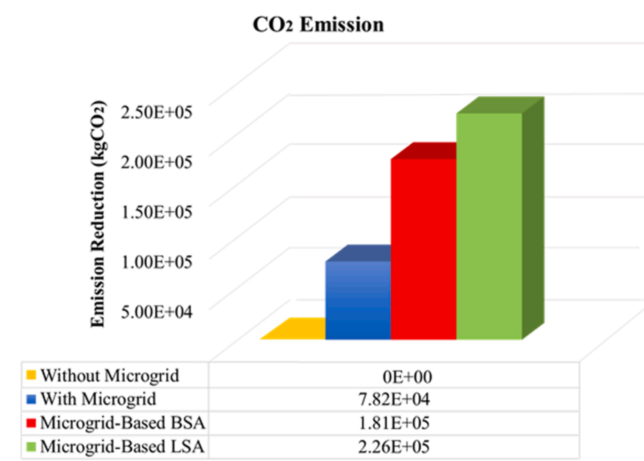


Fig. 15. Comparison of the CO_2 emission reduction of the MG system during a 24 h operation.

than those of other techniques during a 24 h operation (Fig. 14). Hence, the proposed optimized controller provides low operating cost to consumers and improves the efficiency and stability of the system in terms of power dispatch and power quality to the system.

6.2. CO_2 emission reduction

The carbon emission calculation considers various factors, such as power consumption, composite electricity, or heat factor. CO_2 emissions are estimated on the basis of the information on fuel consumption in units and heat content of fuel, which are a multiplication of MMBtu by specific emission factors (EFs) [58]. However, an emission per kWh is used with power quality data related to electricity efficiencies [59]. Recently, reference [60] stated that CO_2 released into the atmosphere is approximately 27 Gt from various sources and 10 Gt from electricity generation, which accumulates to 37% of the global emissions according to the Intergovernmental Panel on Climate Change (IPCC). Furthermore, the largest source of carbon emission is high power consumption. Hence, the carbon emission used in power consumption must be effectively measured. In this study, CO_2 emission due to power consumption is measured by multiplying the EF with the number of kilowatt hours (kWh) consumed in the IEEE 14-bus test system. According to the International Energy Agency, the composite electricity or heat factor in Malaysia is 0.74884244 $kgCO_2/kWh$. Thus, the calculation of CO_2 emission in power consumption can be calculated as in Eq. (23).

$$kWh.EF = GHG(kgCO_2), \tag{23}$$

where GHG denotes greenhouse gases, EF is the emission factor, and kWh is the amount of power consumed by the IEEE 14-bus test system. Fig. 15 shows the reduction of CO_2 emission from the different optimization technique with and without MG system. The model of IEEE 14-bus test system is simulated and run in order to validate the performance of optimized controller along with the CO_2 emission calculation as in Eq. (23). The IEEE 14-bus test system is run with CO_2 emission calculation at different conditions approach as shown in Fig. 15.

The Fig. 15 shows that each type of optimization technique implemented in the power management of MG systems promotes reduced the CO_2 emission footprints with different amounts of CO_2 emission reduction. The MG-based LSA optimization technique is proven to reduce the most amount of CO_2 emission by 0.226 $MkgCO_2$ compared with other techniques in which most of the CO_2 emission is generated from DGen. However, the IEEE 14-bus test system without MG, no reduction of CO_2 emission occurred as it does not contain any of MG system. Therefore, there will be no diesel fuel consumption are used for this case. The DGen unit were consist in the MG system together with RES by means of DER unit. Meanwhile, the reduction of CO_2 emission is much lesser in case of with only MG system. This is due to the absence of MG energy management system and its optimized controller decisions which lead to an improper control and management of the MG system as well as not optimum usage of DER units. This phenomenon is attributed to the LSA-based optimization technique that has provided an optimum power usage of the DER in the MG system by minimizing the usage of DGen in the IEEE 14-bus test system. Thus, the technique reduced the usage of fuel consumption in the DGen unit for the MG system.

7. Conclusion

The improper control and management of a MG system in a distribution network results in an inefficient and unstable power delivery to the loads and causes high operating cost to consumers, especially in a grid-connected mode. However, the DER in the MG system requires an intelligent optimized controller to organize and manage the operation optimally and efficiently. Thus, the objective of this study is achieved by developing an optimized controller for an EMS of the MG system in the IEEE 14-bus test system. This system contains five MGs under different load conditions and is modeled and simulated on the basis of real load varying conditions recorded in Perlis, Malaysia during a 24 h operation. The primary objective of the optimized controller is to minimize the total operating cost and CO_2 emission. The contributions of the study are as follows:

- An LSA-based optimized algorithm for solving optimization problems to obtain minimum operating costs, achieve optimum usage of DER, and reduce CO_2 emission
- An optimal scheduling optimized controller for the energy management of the MG system in the IEEE 14-bus test system under a day ahead real load condition
- An optimum charging and discharging controller for battery storage system based on the availability of DER units and loads' demands.

The obtained result demonstrated a cost saving of 62.5% and CO_2 emission reduction of 61.98% compared with that of MG-based BSA optimization. Thus, an optimized controller-based LSA optimization shows better performance in cost-saving, diminished power consumption, optimum usage of DER, and CO_2 emission reduction. Furthermore, the LSA-based optimization algorithm provides a fast convergence rate instead of consuming a long computational time and can obtain an optimal usage of the DER in the MG system. The effectiveness of the proposed approach outperformed other techniques with a minimum total operating cost of the DER and solved complicated constraints in the optimization problems.

CRediT authorship contribution statement

Conceptualization by MAH, Data curation by MFR, Formal analysis by MFR, Funding acquisition by MAH and PJK, Investigation by RAB, Methodology by MFR and MAH, Project administration by MAH, Resources by TMIM, Software by RAB, Supervision by MAH and PJK, Validation by ZYD, Visualization by TMIM and ZYD, Writing - original draft by MFR, Writing - review & editing by MAH, PJK, RAB, TMIM and ZYD.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This work is supported by the Ministry of Higher Education, Malaysia under the long-term research grant scheme (LRGS) program project grant no. 20190101LRGS through the Universiti Tenaga Nasional.

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