An Optimal Scheduling Controller for Virtual Power Plant and Microgrid Integration Using the Binary Backtracking Search Algorithm

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***Abstract*—This paper presents a novel binary backtracking search algorithm (BBSA) for an optimal scheduling controller applied to the IEEE 14-bus test system for controlling distributed generators (DGs) in microgrids (MGs) in the form of virtual power plant (VPP) toward sustainable renewable energy sources integration. The VPP and MGs models are simulated and tested based on real parameters and loads data recorded in Perlis, Malaysia, employed on each bus of the system for 24 h. BBSA optimization algorithm provides the best binary fitness function, i.e., global minimum fitness for finding the best cell to generate the optimal schedule. The fitness function is generated based on real conditions such as solar irradiation and wind speed and preparation of battery charge/discharges, fuel states and demand of the specific hour. The obtained results show that the BBSA algorithm provides the best schedule to control DGs ON and OFF based on controller decision. Results obtained from the BBSA are compared with binary particle swarm optimization in terms of objective function and power saving to validate the developed controller. The developed BBSA optimization algorithm minimizes the power generation cost, reduces power losses, delivers reliable and high-quality power to the loads, and integrates priority-based sustainable MGs into the grid. Thus, VPP can enable efficient integration of DGs and MGs into the grid by balancing their variability.**

***Index Terms*—Binary backtracking search algorithm (BBSA), microgrid (MG), scheduling controller, virtual power plant (VPP).**

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I. Introduction

The fossil fuel depletion and carbon emission problems of the conventional power generation have a huge impact toward renewable energy sources (RES) power generation. The coordination between the RES and the existing systems is necessary as RES generation depends on weather conditions and types of fuel. The coordination and integration of RES in forms of microgrids (MGs) could be tackled by developing virtual power plant (VPP) in order to supply quality power and add value for the power system networks [1]. VPP is an energy aggregator which combines a portfolio of small RES units to form a MG that acts as a unified and capable of being visible or manageable on an individual basis [2], [3]. The MGs in VPP can increase network efficiency, reduce cost and risk, deliver energy needed and peak load, and reduce emissions [4]. However, energy management and integration into grid are the major issues of the existing MGs [5].

A number of research works have been discussed on MG controller, energy management and integration either in grid-connected mode or islanded mode. For example, in grid-connected modes, controllers are used to control and inject power to the main grid depending on the power generation, local demand, and market policies [6]–[8]. However, in this mode, master power and power quality issues are the main challenges for the controllers [9]. Intelligent controllers are used in energy management strategies to ensure the smooth transition of MG operation in both grid-connected and islanded mode and also to control the energy price of MGs [10], [11]. The neural and fuzzy-based intelligent controllers perform well; however, they need huge optimized data as well as trial-and-error procedures for setting controller parameters.

To solve the aforementioned issues, MG controllers are utilized with optimization to predict and smooth MG operation to ensure control accuracy, reliability, and minimization of cost [12]. For example, ant colony algorithm, genetic algorithm (GA), and evolutionary algorithms have been used to minimize the generation cost and emission, increase load balance and reliability [13], [14]. However, to find the best fitness value, the algorithms are facing parameter complexities and coding difficulties [15], [16]. Agent-based particle swarm optimization (PSO) and binary PSO (BPSO) have been used in MGs for

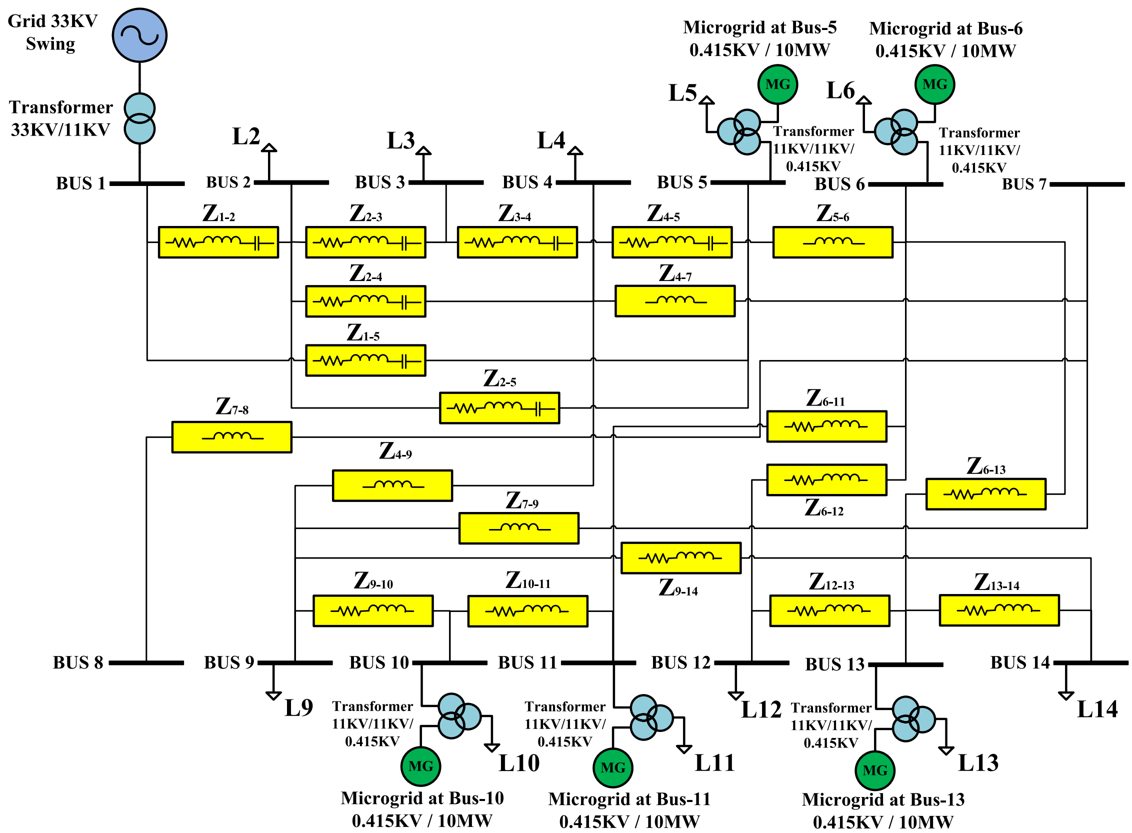

Fig. 1. VPP system includes the IEEE 14-bus test system and five MGs.

designing filter, controlling power flow, and regulating voltage and frequency to reduce cost, power losses, improve steady-state responses, solve unit commitment and multiobjective uncertainty problems [17]–[19]. However, PSO has a severe drawback which is always hang on the first local global minimum and inefficient for multiobjective models. The backtracking search algorithm (BSA) has the capability of solving multimodal problems and can avoid the local global minimum trap [20], [21]. However, BSA is hampered by the unrealistic assumptions of the distribution problems [20]. To solve the unrealistic constraint, binary BSA (BBSA) is to be developed in this research to search for the optimal schedule.

Scheduling ON and OFF of the DGs are the essential process for MG operation [22]. Accordingly, symbiotic organisms search and dolphin echolocation optimization algorithms are used for MGs scheduling [23]. In [24], optimal schedules of distributed generations are utilized to the super short-term load forecasting. However, in conventional and initial schedule, optimization methods did not use to tackle scheduling operation.

In this study, a novel BBSA optimization algorithm is utilized to search the best optimal schedule for VPP and MGs integration to main grid for 24 h. The optimization process is done in 100 iterations to run the VPP system to search for the best schedule in order to get the target objective. The concepts of VPP and MGs integration would scale up the implementation of DGs into the main grid as well as allow more profitable access of electricity markets.

II. MG and VPP System Modeling

VPP is a multitechnology unit connected with smart devices, and advanced communication and information technology systems. A VPP is essentially an aggregated parcel of energy savings and energy efficiency of DG [25]. IEEE 14-bus system is implemented in MATLAB/Simulink using real loads in each bus and actual distribution line impedances. Five MGs are proposed to be included in this system to feed the loads each specific bus. The modeling is also included the development of the MG system involving five renewable and nonrenewable sources.

A. IEEE 14-Bus System

The IEEE 14-bus system is a distribution system which contains sources and loads at per unit value as shown in Fig. 1. In this research, the system is converted into actual values to feed the actual power in the controller. In the original system, there were two main generators at Buses 1 and 8; however, the system is modified and fixed with one generator at Bus 1 which is considered to be the national grid. The national grid is connected to Bus 1 to supply 200 MW of power to the whole system through the main substation transformer rated 33 kV/11 kV, 50 Hz. Each bus bar is connected to one or more bus to increase the reliability of the system including the impedance of R, X_L, and X_C and the maximum peak load of active and reactive power of the IEEE 14-bus as shown in Table I.

TABLE I
DISTRIBUTION IMPEDANCE AND PEAK LOADS FOR THE IEEE 14-BUS SYSTEM

Bus	R (Ω)	X_L (Ω)	X_C (Ω)	Bus	P (MW)	Q (MVAR)
1–2	0.0234498	0.0715957	0.063880	1	No load	No load
1–5	0.0653763	0.2698784	0.071632	2	15.29507	10.27344
2–3	0.0568579	0.2395437	0.052998	3	68.03108	18.244215
2–4	0.0703131	0.2133472	0.045254	4	35.13784	–0.683445
2–5	0.0689095	0.2103948	0.041140	5	5.4860295	1.51510208
3–4	0.0810821	0.2069463	0.041866	6	7.8513428	5.99371266
4–5	0.0161535	0.0509531	0.015488	7	No load	No load
4–7	0	0.2530352	0	8	No load	No load
4–9	0	0.1331121	0	9	20.8230156	13.47983
5–6	0	0.3049442	0	10	6.31940556	4.6505054
6–11	0.1149258	0.2406690	0	11	2.47821826	1.475337
6–12	0.1487211	0.3095301	0	12	4.38893102	1.44703688
6–13	0.0800415	0.1576267	0	13	9.61070106	4.854701
7–8	0	0.2131415	0	14	10.6709611	4.33310932
7–9	0	0.1331121	0			
9–10	0.0384901	0.1022450	0			
9–14	0.1538031	0.3271598	0			
10–11	0.0992805	0.2324047	0			
12–13	0.2673132	0.2418548	0			
13–14	0.2068253	0.4211042	0			

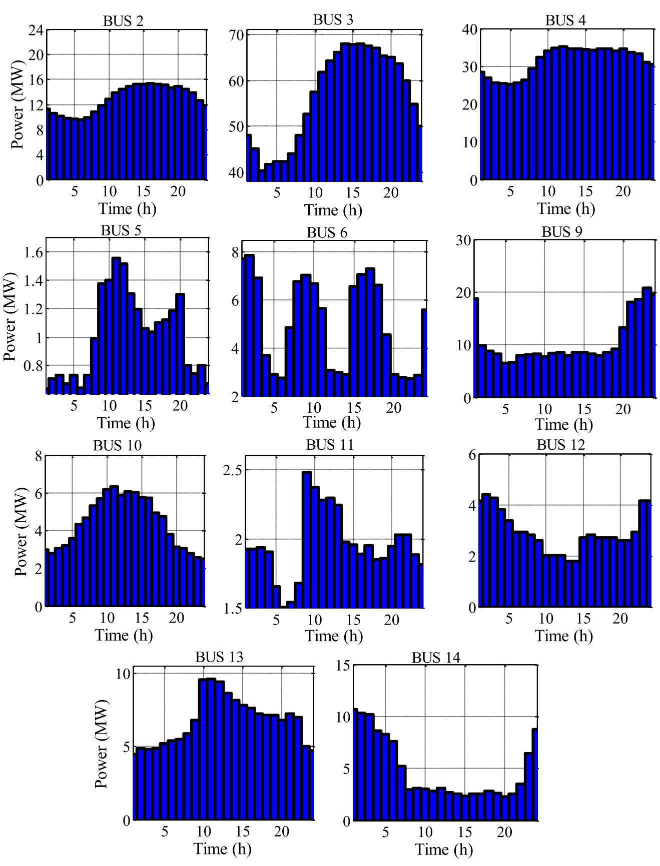

Fig. 2. Load curve for each load bus in the IEEE 14-bus test system.

The system contains nine loads located at bus 2, bus 3, bus 4, bus 5, bus 6, bus 9 bus 10, bus 11, bus 12, bus 13, and bus 14, respectively. Every bus bar represents a feeder to a specific loading area demand. Each load in the system relays on a scaled load curve based on practical industrial and official load demand recorded in February 2016 in Perlis, Malaysia. Fig. 2 shows the hourly average load curve for each load bus in IEEE 14-bus test system.

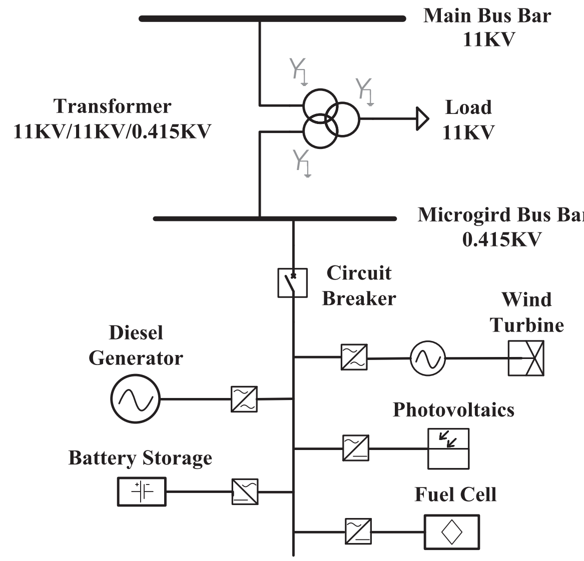

Fig. 3. Single-line diagram of the developed MG system.

B. Development of the MG System

According to the IEEE Standard 1547.4 [26], the operation and reliability of a distribution system can be improved by splitting it into multiple MGs. Therefore, five MGs are proposed and installed in the system at bus 5, bus 6, bus 10, bus 11, and bus 13, respectively, to enhance the system reliability, power quality and to reduce the transmission line losses as shown in Fig. 1. Each MG location is selected based on the loads on that bus which is less than 10 MW. This is because MG has the ability to sustain the reliable power if in case of emergency or outage in the main gird or individual buses. Each of these MGs comprised five microsources such as photovoltaic (PV), wind turbine (WT), fuel cell (FC), diesel generator, and battery storage as shown in Fig. 3.

Each MG supplies 10 MW with 415 V and 50 Hz to the chosen bus for a size consideration which has the capacity to cover that bus load in case of island mode. All five MGs have the same size, number of sources, and sizes of each resource. In the MG, all the sources are connected to ac bus in which some sources use dc-to-ac inverter such as PV, FC, and battery storage while others use ac-to-ac converter such as WT and diesel generator, respectively. Each source that participate in the system is based on optimized binary scheduled controller decision upon considering weather conditions, loading, battery status, fuel and kW·h price, respectively. Table II shows the types of sources, its capacity, and fuel for the MG of the VPP.

The management and control of the RES such as PV and WT depends on the existence of the solar irradiance and wind speed, respectively. In this work, Tenaga Nasional Berhad Research provides the real data of solar irradiance and wind speed which were recorded for a year. An hourly average has been used in the controller as shown in Fig. 4(a) and (b), respectively.

TABLE II
MG SOURCE TYPES, CAPACITY AND FUEL

Source Type	Capacity	Fuel
Diesel generator	4 MW	Diesel
PV	2 MW	Solar irradiance
WT	2 MW	Wind speed
SOFC	1 MW	H_2
Storage system	1 MW	Charging

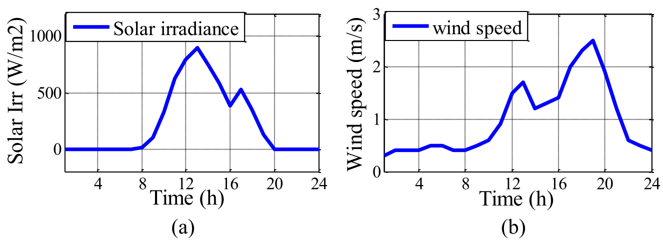

Fig. 4. (a) Real wind speed reading. (b) Real solar irradiance reading.

Furthermore, the solid oxide fuel cell (SOFC) uses a solid oxide electrolyte to conduct negative oxygen ions from the cathode to the anode at high temperatures between 500 and 1000 °C. SOFC depends on ohmic and concentration of polarizations at the lower operating temperature. Thus, the cell voltage of the SOFC is calculated as follows:

$$E_{\mathrm{SOFC}} = \frac{E_{\max} - i_{\max} * \eta_f * r_1}{\frac{r_1}{r_2} * (1 - \eta_f) + 1} \tag{1}$$

where $E_{\max}$ is the maximum voltage given by the Nernst equation, $i_{\max}$ is the maximum current, η_f is fuel utilization factor, and r_1 and r_2 are the ionic specific resistances of the electrolyte.

III. OPTIMAL SCHEDULING CONTROLLER

The VPP has a supervisory controller to schedule ON and OFF of the MGs based on DG conditions. The main task of the scheduling controller is to allow suitable source in the VPP sharing its power in an economically optimal dispatch to maintain the fulfillment of the load demands [27]. Since weather conditions are unstable due to variation of solar irradiation, wind speed, and temperature circumstance, an optimized online algorithm is very important to be used to define the energy availability and power dispatch signals to the loads. The proposed novel online BBSA algorithm plays a vital role in finding the best schedule for the VPP operation to minimize the operational cost, while delivering reliable and high-quality power to the loads.

A. Problem Formulation

To minimize the cost of the existing power network using small-distributed generations allocated in MGs areas is a problem. To solve the aforementioned issue, an intelligent scheduling controller is very attractive due its ability to control number of resources in the form of VPP. However, the conventional scheduling controller has difficulties in MG operation to ensure control accuracy, reliability, and minimization of cost. An optimization algorithm is the best way to develop such scheduling controller without any human expectations. BBSA algorithm is one of the good optimization methods similar with other evolutionary optimization algorithm such as GA and PSO [20]. Optimization algorithms are basically used to get best results available in the search space. A good optimization algorithm is one which does not get struck in the local minimum and gets the most optimized values. BBSA is a dual-population algorithm that has a random mutation strategy to find only one individual direction for each individual target. Moreover, BBSA has a simple structure which is easy to implement and does not depend much on the initial values in maximizing or minimizing the objective function in comparison to other revolutionary optimizations. The basic components of the optimization are input vectors, objective function formulation, and constraints. Each component is developed and clarified to obtain the optimal schedule.

1) Input Vector: BBSA optimization is designed by defriending the input vectors. These input vectors are schedule matrix cell, maximum number of iteration, size of the population, number of problem dimension number of hours, and number of status, respectively.

2) Objective Function Formulation: An objective function is the main parts of the optimization model either to be maximized or minimized. In this algorithm, BBSA is designed to be a global minimizer. Thus, the functions of BBSA are explained into four stages such as initialization, selection, mutation, and selecting minimum fitness with global minimum for finding the best cell. The detail stages are explained in Section IV.

3) Constraints: A set of constraints are considered to control the objective function in order to find minimum value targeted by the end of last iteration. In BBSA, a set of conditions such as the status of grid power, solar irradiance, wind speed, energy price, and battery status are considered. The value of the matrix of the objective function is minimized while satisfying the constraints by the manipulation of the historical matrix and selecting minimum fitness after each try of the objective functions.

IV. BINARY BSA SCHEDULE ALGORITHM

BSA optimization based an evolutionary computation is developed to solve the numerical problems by producing a random trial population, new crossovers, and mutation operators [20], [21]. BSA dominates the search value for the best populations and the space borders to find the very sturdy exploration and exploitation capabilities. However, finding the best schedule for the system with trial and error is a difficult task. The proposed BBSA is the modification of BSA which adds some considerations to the algorithm and converts it to binary to make the required schedule for controlling each DG in each MG in the VPP system. The BBSA converts a decimal number of BSA into a binary number by the sigmoid function in each search in order to get the best binary schedule which is either 1 or 0 state. BBSA optimization algorithm provides the best binary fitness function, i.e., global minimum fitness for finding the best cell to generate the optimal schedule. The target of the BBSA is to reduce the excessive power from the grid, contribute in the efficient distribution system, and uses the sustainable resources to be cost effective. The BBSA algorithm has several stages of initialization including conditions in which 20 population size are selected (each population is a cell i.e., schedule). The schedule concludes a matrix with 24 rows and 25 columns in which the initial condition makes random and binary cells.

A. Initialization

Initialization begins with creating a random decimal matrix, binary matrix population size and dimension. In initialization, some conditions, i.e., weather conditions and battery statuses are included to find the fitness value. Accordingly, the fitness functions of decimal population matrix and binary population matrix are calculated as follows:

$$X_{(h,s)} = rand. \begin{bmatrix} X_{(1,1)} & \cdots & X_{(1,s)} \\ \vdots & \ddots & \vdots \\ X_{(h,1)} & \cdots & X_{(h,s)} \end{bmatrix} \tag{2}$$

$$XB_{\ (h,s)} = rand. \begin{bmatrix} XB_{(1,1)} & \cdots & XB_{(1,s)} \\ \vdots & \ddots & \vdots \\ XB_{(h,1)} & \cdots & XB_{(h,s)} \end{bmatrix} \tag{3}$$

where X is a random decimal population matrix, ***XB*** is a random population binary matrix, $h = 1, 2, 3, \ldots, 24$, the number of hour and $s = 1, 2, 3 \ldots, 25$, the status of DG switch.

B. Creating Initialization Cells

Once initial random decimal and binary matrixes are created, the total of these matrixes need to be set in the form of cells in the group as in (4) and (5). The size is as population size which is $\{X_1, X_{\ 2}, \ \ldots, \ X_{20}\}$

$$XT_{(1,k)} = \left\{ \begin{bmatrix} X_{(1,1)} & \cdots & X_{(1,s)} \\ \vdots & \ddots & \vdots \\ X_{(h,1)} & \cdots & X_{(h,s)} \end{bmatrix}_{(1,1)} \cdots \begin{bmatrix} X_{(1,1)} & \cdots & X_{(1,s)} \\ \vdots & \ddots & \vdots \\ X_{(h,1)} & \cdots & X_{(h,s)} \end{bmatrix}_{(1,k)} \right\} \tag{4}$$

$$XTB_{(1,k)} = \left\{ \begin{bmatrix} XB_{(1,1)} & \cdots & XB_{(1,s)} \\ \vdots & \ddots & \vdots \\ XB_{(h,1)} & \cdots & XB_{(h,s)} \end{bmatrix}_{(1,1)} \cdots \begin{bmatrix} XB_{(1,1)} & \cdots & XB_{(1,s)} \\ \vdots & \ddots & \vdots \\ XB_{(h,1)} & \cdots & XB_{(h,s)} \end{bmatrix}_{(1,k)} \right\} \tag{5}$$

where XT is the total of all X cells, XTB is the total of all XB cells, and *k* is population size counter and $k = 1, 2, 3 \ldots, 20$.

C. Creating a Historical Cells

Creating a historical cell is the same as initial of X and XB repeating the same process of a historical random decimal matrix and historical binary matrix represented by $oldX$ and $oldXB$ to determine the historical population and calculating the search direction as follows:

$$oldX_{(h,s)} = rand. \begin{bmatrix} oldX_{(1,1)} & \cdots & oldX_{(1,s)} \\ \vdots & \ddots & \vdots \\ oldX_{(h,1)} & \cdots & oldX_{(h,s)} \end{bmatrix} \tag{6}$$

$$oldXB_{(h,s)} = rand. \begin{bmatrix} oldBX_{(1,1)} & \cdots & oldX_{(1,s)} \\ \vdots & \ddots & \vdots \\ oldBX_{(h,1)} & \cdots & oldX_{(h,s)} \end{bmatrix} \tag{7}$$

where XB is the historical decimal matrix, and $oldXB$ is the historical binary matrix.

Again once initial historical random decimal and binary matrixes are created, the total of these matrixes needs to be set in the form of cells in the group as in (8) and (9). The size is as population size which is $\{oldX_1, oldX_{\ 2}, \ \ldots, \ oldX_{20}\}$

$$oldXT_{(1,k)} = \left\{ \begin{bmatrix} oldX_{(1,1)} & \cdots & oldX_{(1,s)} \\ \vdots & \ddots & \vdots \\ oldX_{(h,1)} & \cdots & oldX_{(h,s)} \end{bmatrix}_{(1,1)} \cdots \begin{bmatrix} oldX_{(1,1)} & \cdots & oldX_{(1,s)} \\ \vdots & \ddots & \vdots \\ oldX_{(h,1)} & \cdots & oldX_{(h,s)} \end{bmatrix}_{(1,k)} \right\} \tag{8}$$

$$oldXTB_{(1,k)} = \left\{ \begin{bmatrix} oldXB_{(1,1)} & \cdots & oldXB_{(1,s)} \\ \vdots & \ddots & \vdots \\ oldXB_{(h,1)} & \cdots & oldXB_{(h,s)} \end{bmatrix}_{(1,1)} \cdots \begin{bmatrix} oldXB_{(1,1)} & \cdots & oldXB_{(1,s)} \\ \vdots & \ddots & \vdots \\ oldXB_{(h,1)} & \cdots & oldXB_{(h,s)} \end{bmatrix}_{(1,k)} \right\} \tag{9}$$

where $oldXT$ is the total of all historical $oldX$ cells, $oldXTB$ is the total of all $oldXB$ cells, and *k* is population size counter and $k = 1, 2, 3 \ldots, 20$.

Computing fitness functions for each population (Fit_a) and history population (Fit_b), the best of them is chosen by a compression as follows:

$$\text{if} \quad Fit_a < Fit_b \ \text{then} \quad oldXT = XT. \tag{10}$$

D. Mutation

This process is used to create a new population that designates the initial and historical population represented by the mutant value of trial population as follows:

$$T_{\{i\}} = XT + 3 * randn\,(oldXT - \ XT) \tag{11}$$

where T is the trial population, XT is total cells for the trial population, and $oldXT$ is the total cells for historical of trial population.

E. Converting to Binary

Converting the decimal cells to binary cells (0 or 1) using sigmoid function is expressed as follows:

$$sigmoid\left(T_{\{i\}}\right) = \frac{1}{1+e^{-T_{\{i\}}}} \tag{12}$$

$$\text{If} \quad sigmoid > rand \quad \text{then } TB_{\{i\}} = 1$$
$$\text{else } TB_{\{i\}} = 0. \tag{13}$$

Then, the simulation runs with the current cell to provide the system with binary matrix in which 0 means the specific DG is OFF and 1 means the specific DG is ON. In each run, the fitness function which is minimum cost is calculated as follows:

$$MC = \left(\frac{3}{2} IV * p.f * RM/\mathrm{MW}\cdot\mathrm{h}\right) \tag{14}$$

where MC is the minimum cost, I is total current, V is voltage, $p.f$ is the power factor, and $RM/\mathrm{MW}\cdot\mathrm{h}$ is energy price per hour.

The minimum cost is equalized with the total fitness function and then compared with the trial function to find the minimum total cells at every loop

$$FitT_{(i)} = MC \tag{15}$$

$$\text{If } FitT_{(i)} < Fit_{a\,(i)} \text{ then } Fit_{a\,(i)} = FitT_{(i)} \tag{16}$$

$$XTB_{\{i\}} = TTB_{\{i\}} \tag{17}$$

$$XTD_{\{i\}} = T_{\{i\}} \tag{18}$$

where $FitT$ is the fitness function, Fit_a is a trail fitness function, ***XTB*** is the total historical binary matrix, and ***TTB*** is the total binary cells.

F. Best Cells

In this stage, an important comparison is done between the population and trial population to obtain the best population $TB_{\{X_{\text{best}}\}}$ as well as the fitness value, Fit_a as in (19) and (20). Thus, the output of the proposed BBSA optimization provides an optimal schedule to control the VPP and MG integration toward sustainable energy management. The proposed controller is represented in pseudocode which shows that how the developed BBSA algorithm searches for the optimal schedule by the optimization scheduling controller as shown in Fig. 5. The developed controller can search for the best schedule and can control hundreds of renewable and nonrenewable resources with the conditions and limitation set in the algorithm conditions, for example (weather, storage, price, and grid status conditions)

$$globalminimum = \min\left(Fit_a\right) \tag{19}$$

$$globalminimizer = XTB_{\{X\text{best}\}} \tag{20}$$

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Pseudo-Code of the proposed BBSA based optimal scheduling controller
Input: X (Schedule matrix), I (maximum number of iteration), N (The size of the
population), D (Number of problem dimension) h (No. of hours), s (No. of status),
G (grid power status), R( solar irradiance ), W(wind speed), E (Energy price),
B(Battery status).
Output: globalminimum, globalminimizer, MC (fitness function).
// INITIALIZATION
Determine population XB_(h,s) initializes a new position of agents in the search
space, randomly.
    for k from 1 to N do
                                X_(h,s) = rand(h, s)
        for i from 1 to h do
            for j from 1 to s do
                if X_(i,j) > 0.5 then XB_(i,j) =1 else =0 end XB_(i,j)
            end; end; end
    Set Conditions: Set weather , storage, price and grid status conditions in the
population XB_(i,j)
      X_(k,1) = {X}
      XTB_(k,1) = {XB}
      Run Simulink (XB)
      Fit_a (i) = MC
// CREATING A HISTORICAL CELLS
Determine historical population oldXB_(h,s) initializes the position of agents in the
search space, randomly.
for k from 1 to N do
        oldX_(h,s) = rand (h,s)
    for i from 1 to h do
        for j from 1 to s do
            if oldX_(i,j) > 0.5 then oldXB_(i,j) =1 else oldXB_(i,j) =0 end
        end; end; end
// SELECTING THE BEST CELL
    Set conditions: Set weather , storage, price and grid status conditions in the
population old XB_(i,j)
      Xold_(k,1) = {oldX}
      oldXTB_(k,1) = { oldXB }
for iteration from 1 to I do
            if rand < rand then  oldXT = XT  end
            z=randperm(N)
            mixing Xold inside its cells values
    for q from 1 to N do
            oldXT {q} = oldXT {z(q)}
    end
    // MUTATION
   Recombination mutation using trial population (T)
    for i from 1 to N do
            T{i} = XT{i} + 3.randn.(oldXT{i} - XT{i});
    end
            determine fitnessT
    for n from 1 to N do
        for m from 1 to h do
            for j from 1 to s do
                    sig = 1/(1 + exp(-T{n}(m, j)));
                if sig>rand then TB_{i}(m,j) = 1 else TB_{i}(m,j) = 0 end
            end; end; end
    Set conditions: Set weather , storage, price and grid status conditions in the
population TB_{i}(m,j)
    Run Simulink (TB_{i}(m,j))
            Fit_T (i) = MC
    for n from 1 to N do
            if fitnessT(i) < fitnessa(i)
            then  fitnessa(i) = fitnessT(i)
                  XTB{i} = TTB{i}
                  XTD{i} = T{i}  end
    end
   Equalizing minimum fitness with global minimum for finding the best cell.
   globalminimum = min(fit_a)
   globalminimizer = XTB_{Xbest}
end
output is the optimal schedule for the EMS is the XTB_{Xbest}
```

Fig. 5. Pseudocode of the proposed BBSA for optimal schedule.

TABLE III
DGs Numbering and DG and Source Types

MG	DG numbers	DG	Source type
MG1	DG1–DG5	DG1, DG6, DG11, DG16, DG21	Diesel Gen
MG2	DG6–DG10	DG2, DG7, DG12, DG17, DG22	PV
MG3	DG11–DG15	DG3, DG8, DG13, DG18, DG23	WT
MG4	DG16–DG20	DG4, DG9, DG14, DG19, DG24	SOFC
MG5	DG21–DG25	DG5, DG10, DG15, DG20, G25	Battery

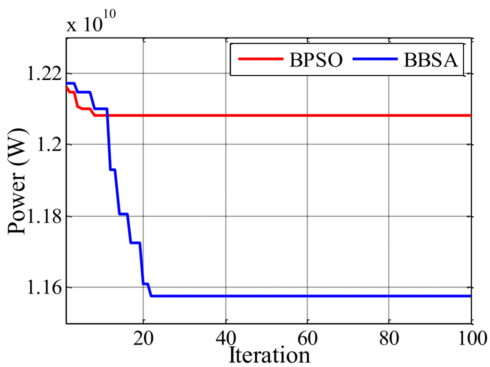

Fig. 6. BBSA and BPSO optimization of 100 iterations for the best objective function.

where $\min(Fit_a)$ is the minimum fitness function, and $XTB_{\{X\,\text{best}\}}$ is the best location of the best cell which is the targeted optimal solution.

V. Results and Discussion

This section includes MG setup, scheduling controller performance, and the cost-effective evaluation of the proposed algorithm. The main highlights of the obtained results are the best schedule, fare comparison of without and with optimization, and a cost-effective evaluation to show how the proposed BBSA-based scheduling controller of the VPP and MG reduce the consumption and increase the profit using only sustainable resources on demand.

A. MG Setup

The VPP includes five MGs and each MG includes five DGs. Table III shows the MG, each MG involved with DGs, numbers, and source types of DG. This VPP system runs for one day with change in real load data on hourly basis. In each change, the developed BBSA for the scheduling controller tries to cover the load with sustainable available energy from the MGs and the DGs throughout the system.

B. Optimal Scheduling Controller Performances

The BBSA optimal scheduling controller of the VPP is run hundred iterations to achieve the best schedule to reduce the total power by connecting available sustainable MGs or DG as shown in Fig. 6. It is seen that the proposed BBSA reduces the amount of power to 11 577 MW compared to BPSO which could reduce the main power to 12 083 MW. In this case, BBSA

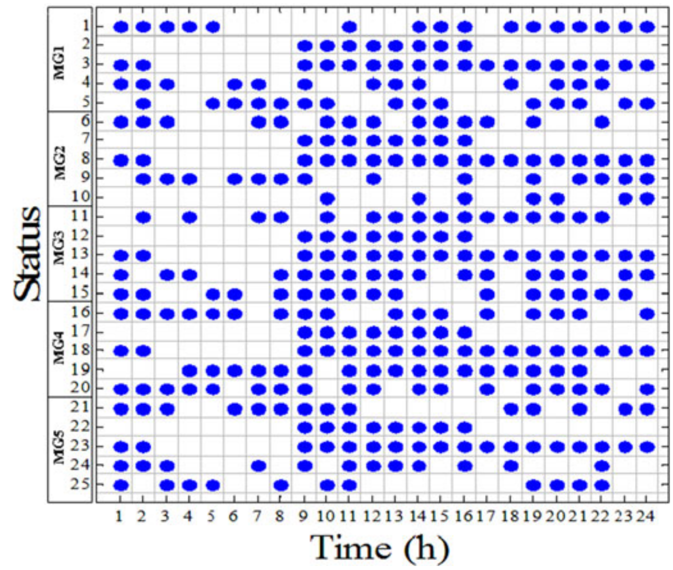

Fig. 7. Best schedule obtained from BBSA optimization.

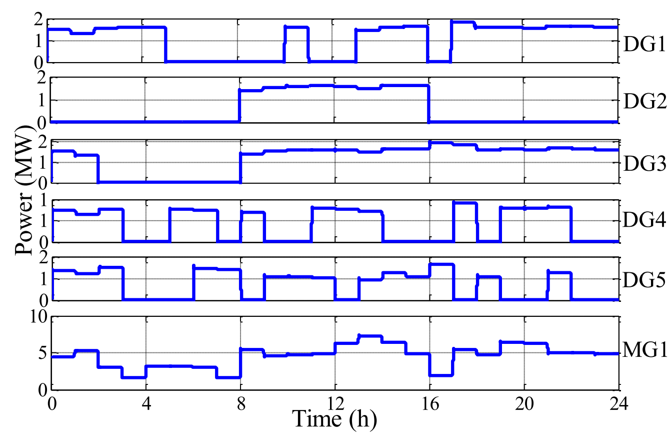

Fig. 8. DGs and MG power for MG1 at bus 5 in case of BBSA.

outperforms the BPSO performance in reducing amount of power. Both of these optimizations reduce the power to unexpected limits. However, in compared to the initial optimization which is almost impossible with normal trial-and-error process.

The BBSA optimization algorithm generates binary schedule of 0 for OFF state and 1 for ON state of the specified DG on the specific hour in the schedule. The obtained best schedule is achieved after 4000 tries of initiations and iterations stages to settle the optimal energy management. Fig. 7 shows the ON and OFF states of the DGs in the MG for 24 h which is considered as the best schedule obtained by the BBSA algorithm. Each spot in Fig. 6 represents ON state while the empty space represents the OFF state. Thus, the energy management of 25 DGs, i.e., VPP clearly represents turning DGs ON and OFF with a consideration of weather conditions, battery charge/discharges, fuel states and demand of the specific hour.

The best schedule is obtained by the BBSA which shows that the behavior of each MG and each source is unique which in turn tested in IEEE 14-bus system with MGs. Fig. 8–12 show the power for MG1–MG5 act at bus 5, bus 6, bus 10, bus 11, and

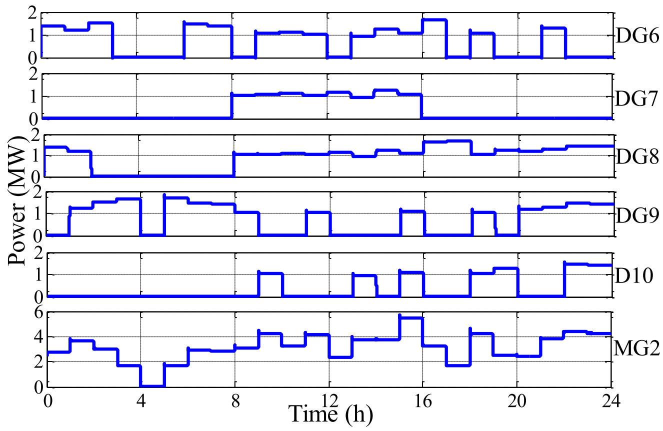

Fig. 9. DGs and MG power for MG2 at bus 6 using BBSA.

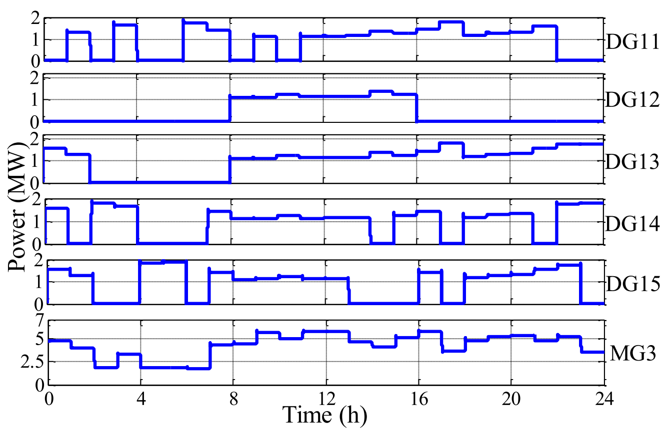

Fig. 10. DGs and MG power for MG3 at bus 10 using BBSA.

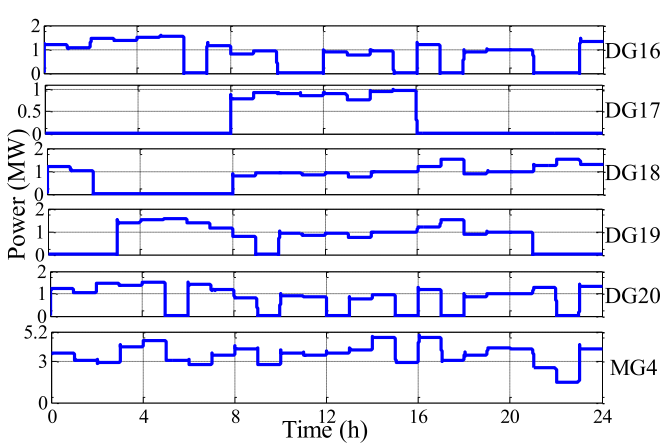

Fig. 11. DGs and MG power for MG4 at bus 11 in case of BBSA.

bus 13, respectively. Each figure includes six signals in which the first five signals are the power from DGs and the last is the total power for the MG.

The power in the system either decreases or increases is based on the controller decision which rely on the developed optimal schedule. However, the scheduling controller is responded based

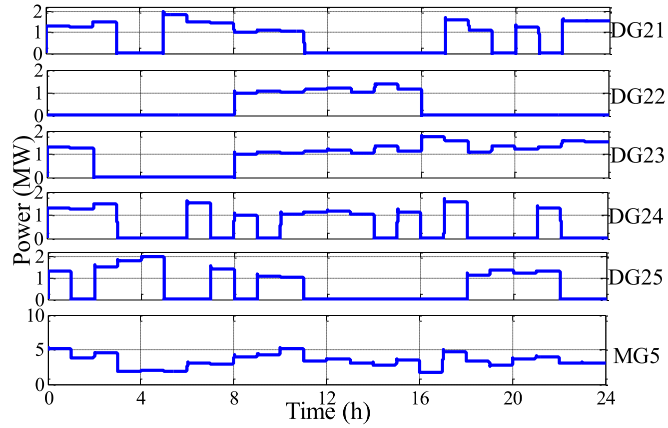

Fig. 12. DGs and MG power for MG5 at bus 13 in case of BBSA.

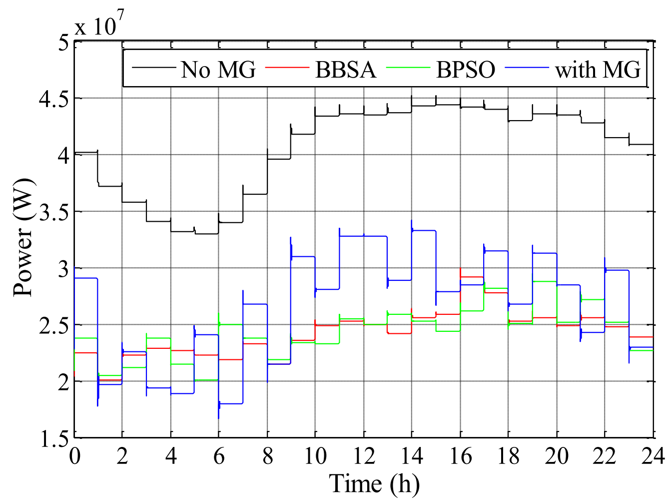

Fig. 13. Main grid power at bus 1 compared with, without MGs and with BBSA and BPSO algorithms.

on the available resources and the market price. When the markets are very low, the DG units go to OFF and the specific bus consumer imports power from national grid besides the priorities of the sustainable sources. Power demand of each MG in the corresponding bus shares with the main power is controlled by the controller of VPP.

Fig. 13 shows the comparison on main grid power at bus 1 in different cases without MGs, with MGs, and when applying the BBSA algorithm. When MGs are intrduced to the system, the power save is more which is normal by adding more DGs to the system. That addition shows a great response when the optimized schdule takes place which saves more power as shown in Fig. 16. Thus, the power saved from the grid reduces the losses in the line and increases the reliablity to the system.

Fig. 14 shows the power at bus 6 considering with and without MGs, BBSA and BPSO algorithms. It is seen that in case of without MG, the power flows according to the load curve as shown in Fig. 2. However, with optimized schedule controller, huge power is saved and BBSA outperforms the other controllers. Thus, the power saved from the grid reduces the losses

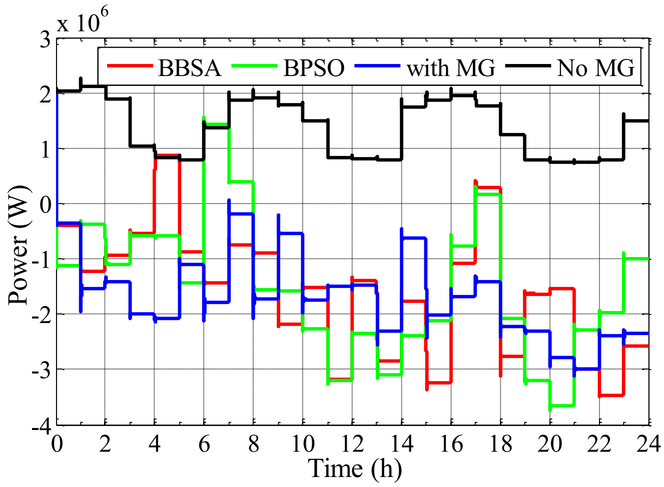

Fig. 14. Power of bus 6 compared with, without MGs and with BBSA and BPSO algorithms.

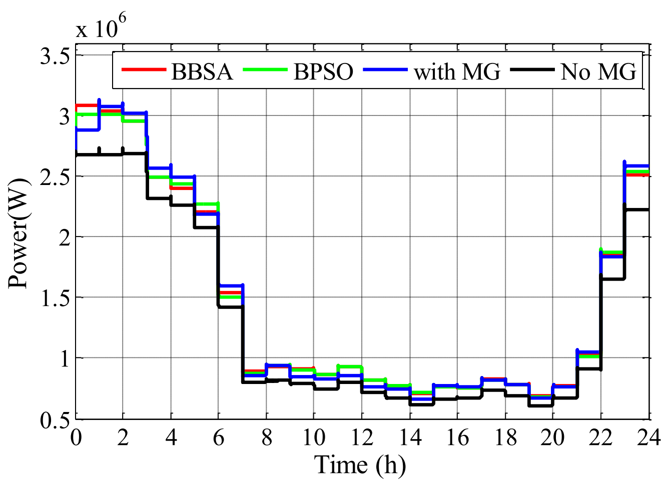

Fig. 15. Power of bus 14 compared with, without MGs and with BBSA and BPSO algorithms.

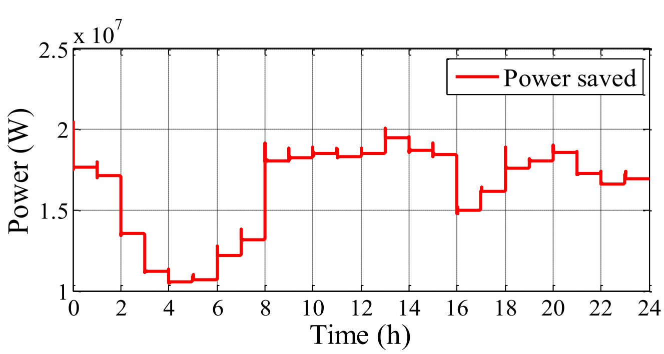

Fig. 16. Power saved for 24 h when applying the optimal schudule.

in the line and increases the reliability to the power system. Similarly, Fig. 15 shows the power at bus 14 considering with and without MGs, BBSA and BPSO algorithms. As the bus 14 is not connected with MG, it is seen that the power signal for all cases are smaller and track the load curve line as in Fig. 2 for bus 14.

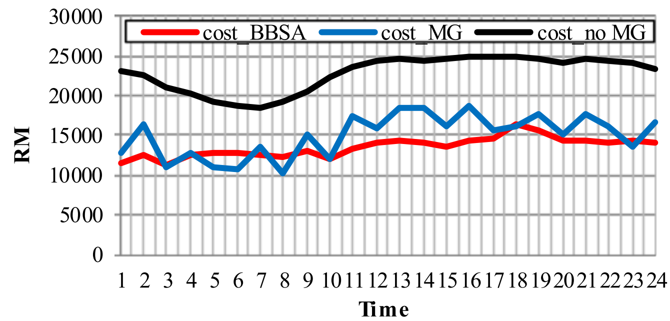

Fig. 17. Energy cost in Malaysian Ringgit from the main in case of with MGs, without MGs, and when using the BBSA.

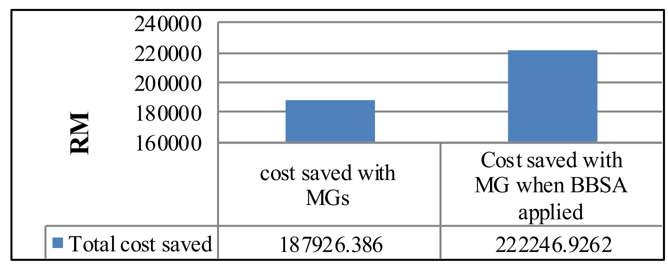

Fig. 18. Total cost saved for 24 h in case of using MGs and in case of applying the BBSA algorithm on the MGs.

C. VPP Cost-Effective Evaluation

The BBSA searches an optimal solution providing a digital signal to each source in the network to minimize cost and prevent building new plant by optimizing the available existing sources in the distribution network. Energy consumption is calculated for the energy E in megawatt-hours $(\mathrm{MW}\cdot\mathrm{h})$ per day and the electricity cost is also calculated per day in Ringgit as follows [28]:

$$E_{(\mathrm{MW\cdot h/day})} = \frac{P_{(\mathrm{W})} \times t_{(\mathrm{h/day})}}{1\,000\,000_{(\mathrm{W/MW})}} \tag{21}$$

$$Cost_{\,(\mathrm{RM/day})} = \frac{E_{(\mathrm{MW\cdot h/day})} \times Cost_{(\mathrm{cent/MW\cdot h})}}{100_{(\mathrm{cent/RM})}} \tag{22}$$

where E is energy per day, P is the actual power, t is the time, and Cost is energy cost per day.

The Malaysian Tariff rates for domestic consumer are varying from 21.8 to 57.10 cent/kW·h depending on the consumption [29]. However, 43.7 cent/kW·h is the average of this energy pricing. Fig. 17 shows the energy cost for one day from the main power connected with MGs, without MGs, and MG with optimal scheduling controller using BBSA. Fig. 18 shows the total cost saved for 24 h in case of using MGs and applying the BBSA algorithm in the MGs.

VI. Conclusion

A novel BBSA optimized scheduling controller is proposed in IEEE 14-bus system which includes MGs to form VPP toward RES integrations. The obtained results show that the BBSA optimized controller can generate a priority-based optimal schedule for MG integration in 24 h. A detail comparison on energy saving and cost reduction is investigated between VPP connected with MGs, without MGs, and MG with optimal scheduling controllers. The optimal scheduling controller addresses the shortcomings of the existing controller and investigates means of integrating MGs in a VPP. The main contribution of the proposed optimal scheduling controller is to control and coordinate the power flows in each MG to reduce the generation cost and power losses, save the power, and increase the reliability. Thus, BBSA is suitable for distribution system problems associated with growth in electricity consumption, cost of new generation, and recovering the utility risk.

References

[1] U. P. Onyewuchi, A. Shafieezadeh, M. M. Begovic, and R. DesRoches, "A probabilistic framework for prioritizing wood pole inspections given pole geospatial data," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 973–979, Mar. 2015.

[2] K. Heussen, S. Koch, A. Ulbig, and G. Andersson, "Unified system-level modeling of intermittent renewable energy sources and energy storage for power system operation," *IEEE Syst. J.*, vol. 6, no. 1, pp. 140–151, Mar. 2012.

[3] T. S. Ustun and R. H. Khan, "Multiterminal hybrid protection of microgrids over wireless communications network," *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2493–2500, Sep. 2015.

[4] P. Moutis, P. S. Georgilakis, and N. D. Hatziargyriou, "Voltage regulation support along a distribution line by a virtual power plant based on a center of mass load modeling," *IEEE Trans. Smart Grid*, vol. PP, no. 99, pp. 1–1, Nov. 2016, doi: 10.1109/TSG.2016.2624633.

[5] I. K. Song, W. W. Jung, J. Y. Kim, S. Y. Yun, J. H. Choi, and S. J. Ahn, "Operation schemes of smart distribution networks with distributed energy resources for loss reduction and service restoration," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 367–374, Mar. 2013.

[6] S. Buso and T. Caldognetto, "Rapid prototyping of digital controllers for microgrid inverters," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 3, no. 2, pp. 440–450, Jun. 2015.

[7] C. Wang, Y. Liu, X. Li, L. Guo, L. Qiao, and H. Lu, "Energy management system for stand-alone diesel-wind-biomass microgrid with energy storage system," *Energy*, vol. 97, no. 15, pp. 90–104, Feb. 2016.

[8] M. Jain, S. Gupta, D. Masand, G. Agnihotri, and S. Jain, "Real-time implementation of islanded microgrid for remote areas," *J. Control Sci. Eng.*, vol. 2016, 2016, Art. no. 5710950.

[9] Z. Zhang, W. Chen, and Z. Zhang, "A new seamless transfer control strategy of the microgrid," *Sci. World J.*, vol. 2014, 2014, Art. no. 391945.

[10] W. Shi, X. Xie, C. C. Chu, and R. Gadh, "Distributed optimal energy management in microgrids," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1137–1146, May 2015.

[11] C.-S. Karavas, G. Kyriakarakos, K. G. Arvanitis, and G. Papadakis, "A multi-agent decentralized energy management system based on distributed intelligence for the design and control of autonomous polygeneration microgrids," *Energy Convers. Manage.*, vol. 103, pp. 166–179, Oct. 2015.

[12] Y. K. Wu, C. Y. Lee, L. C. Liu, and S. H. Tsai, "Study of reconfiguration for the distribution system with distributed generators," *IEEE Trans. Power Del.*, vol. 25, no. 3, pp. 1678–1685, Jul. 2010.

[13] J. A. Ali, M. A. Hannan, A. Mohamed, and M. G. M. Abdolrasol, "Fuzzy logic speed controller optimization approach for induction motor drive using backtracking search algorithm," *Measurement*, vol. 78, pp. 49–62, Jan. 2016.

[14] E. I. Vrettos and S. A. Papathanassiou, "Operating policy and optimal sizing of a high penetration RES-BESS system for small isolated grids," *IEEE Trans. Energy Convers.*, vol. 26, no. 3, pp. 744–756, Sep. 2011.

[15] S. Conti, R. Nicolosi, S. A. Rizzo, and H. H. Zeineldin, "Optimal dispatching of distributed generators and storage systems for MV islanded microgrids," *IEEE Trans. Power Del.*, vol. 27, no. 3, pp. 1243–1251, Jul. 2012.

[16] M. Hemmati, N. Amjady, and M. Ehsan, "System modeling and optimization for islanded micro-grid using multi-cross learning-based chaotic differential evolution algorithm," *Int. J. Elect. Power Energy Syst.*, vol. 56, pp. 349–360, Mar. 2014.

[17] M. Marzband, E. Yousefnejad, A. Sumper, and J. L. Domínguez-García, "Real time experimental implementation of optimum energy management system in standalone microgrid by using multi-layer ant colony optimization," *Int. J. Elect. Power Energy Syst.*, vol. 75, pp. 265–274, Feb. 2016.

[18] M. A. Hassan and M. A. Abido, "Optimal design of microgrids in autonomous and grid-connected modes using particle swarm optimization," *IEEE Trans. Power Electron.*, vol. 26, no. 3, pp. 755–769, Mar. 2011.

[19] Y. W. Jeong, J. B. Park, S. H. Jang, and K. Y. Lee, "A new quantum-inspired binary PSO: Application to unit commitment problems for power systems," *IEEE Trans. Power Syst.*, vol. 25, no. 3, pp. 1486–1495, Aug. 2010.

[20] P. Civicioglu, "Backtracking search optimization algorithm for numerical optimization problems," *Appl. Math. Comput.*, vol. 219, pp. 8121–8144, 2013.

[21] M. G. M. Abdolrasol, M. A. Hannan, A. Mohamed, U. A. U. Amiruldin, I. Z. Abidin, and M. N. Uddin, "An optimal scheduling controller for virtual power plant and microgrid integration using binary backtracking search algorithm," in *Proc. 2017 IEEE Ind. Appl. Soc. Annu. Meeting*, Cincinnati, OH, USA, Oct. 1–5, 2017, pp. 1–8, doi: 10.1109/IAS.2017.8101737.

[22] V. Mohan, J. G. Singh, W. Ongsakul, and M. P. R. Suresh, "Performance enhancement of online energy scheduling in a radial utility distribution microgrid," *Int. J. Elect. Power Energy Syst.*, vol. 79, pp. 98–107, Jul. 2016.

[23] F. Najibi and T. Niknam, "Stochastic scheduling of renewable micro-grids considering photovoltaic source uncertainties," *Energy Convers. Manage.*, vol. 98, no. 1, pp. 484–499, Jul. 2015.

[24] Z. Wang, K. Yang, and X. Wang, "Privacy-preserving energy scheduling in microgrid systems," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1810–1820, Dec. 2013.

[25] L. Zhu, Z. Yan, W.-J. Lee, X. Yang, Y. Fu, and W. Cao, "Direct load control in microgrids to enhance the performance of integrated resources planning," *IEEE Trans. Ind. Appl.*, vol. 51, no. 5, pp. 3553–3560, Sep./Oct. 2015.

[26] *IEEE Guide for Design, Operation, Integration of Distributed Resource Island Systems with Electric Power Systems*, IEEE Standard 1547.4, 2011, pp. 1–54.

[27] C. E. Murillo-Sánchez, R. D. Zimmerman, C. L. Anderson, and R. J. Thomas, "Secure planning and operations of systems with stochastic sources, energy storage, and active demand," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2220–2229, Dec. 2013.

[28] C. Chen, S. Duan, T. Cai, B. Liu, and G. Hu, "Smart energy management system for optimal microgrid economic operation," *IET Renewable Power Gener.*, vol. 5, no. 3, pp. 258–267, 2011.

[29] *Pricing & Tariffs*, Tenaga Nasional Berhad, Kuala Lumpur, Malaysia. 2017. [Online]. Available: https://www.tnb.com.my/residential/pricing-tariffs

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