ARCHIVES OF ELECTRICAL ENGINEERING VOL. 67(3), pp. 499–513 (2018)

DOI 10.24425/123659

Short-term optimal energy management in stand-alone microgrid with battery energy storage

Navin Kumar Paliwal, Asheesh Kumar Singh, Navneet Kumar Singh

Motilal Nehru National Institute of Technology
Allahabad, India
e-mail: {nvn.paliwal/nvnt.kmr.sngh}@gmail.com, asheesh@mnnit.ac.in

(Received: 13.09.2017, revised: 07.05.2018)

Abstract: The optimal energy management (OEM) in a stand-alone microgrid (SMG) is a challenging job because of uncertain and intermittent behavior of clean energy sources (CESs) such as a photovoltaic (PV), wind turbine (WT). This paper presents the effective role of battery energy storage (BES) in optimal scheduling of generation sources to fulfill the load demand in an SMG under the intermittency of the WT and PV power. The OEM is performed by minimizing the operational cost of the SMG for the chosen moderate weather profile using an artificial bee colony algorithm (ABC) in four different cases, i.e. without the BES and with the BES having a various level of initial capacity. The results show the efficient role of the BES in keeping the reliability of the SMG with the reduction in carbon-emissions and uncertainty of the CES power. Also, prove that the ABC provides better cost values compared to particle swarm optimization (PSO) and a genetic algorithm (GA). Further, the robustness of system reliability using the BES is tested for the mean data of the considered weather profile.

Key words: artificial bee colony, battery energy storage, clean energy sources, optimal energy management, stand-alone microgrid

1. Introduction

These days, the concept of a microgrid (MG) system is increased rapidly to fulfill the electricity demand in a limited geographical area [1]. The MG system integrates the clean energy sources (CESs), namely a wind turbine (WT) and photovoltaic (PV), small dispatchable sources, i.e. a fuel cell (FC), diesel engine (DE) and a microturbine (MT), battery energy storage (BES) as well as a cluster of load demand [2]. The CES helps in cutting the carbon-emission along with serving the electricity demand. The MG can be operated in stand-alone microgrid (SMG) mode and on-grid MG mode. The optimal energy management (OEM) in the MG is a challenging job, because of uncertain and intermittent nature of the CES, and dynamic behavior of load and bid cost. The BES can perform important part in the OEM of the MG system and in reducing the intermittency/uncertainties of the CES by optimally managing their charging or discharging operations, in accordance to excess or shortage in available energy from the generation sources. Also, the BES has better ramping capabilities than small dispatchable sources. The OEM in the MG is a latest issue and quite a lot of research is being carried out in this area.

The economic dispatch in the MG, considering several mathematical objectives and their constraints through various heuristic approaches is discussed in literatures [3–16]. The MG operation is optimized for its operational cost with the help of forecasting and energy storage management modules in [3]. A WT-BES-hydro based hybrid MG is optimally scheduled to maximize the net profit under wind uncertainty through various heuristic approaches in [4]. This hybrid MG optimal operation is also handled in [5] by additionally imposing a system of penalty costs using an artificial bee colony (ABC) algorithm. The stochastic operation costs and power losses of the MG under intermittency of the CES are taken as an objective function for economic operation of the MG in [6]. In [7], the authors discuss the optimal component sizing of the MG elements for economic load scheduling. Paper [8] minimizes the active power differences in uncertain conditions through effective charge-discharge processes of the BES. The BES is optimized in [9] to fulfill the residual load, which is the difference of load and the CES power due to uncertain nature of the CES.

Two layer strategies are used for energy scheduling in the MG [10–12]. An optimal control is performed based on forecasting data profiles in the first layer and in the layer second, a robust control is applied to minimize the forecasting errors in [10]. The BES benefits of maximum exploitation of the CES is used for energy scheduling in the lower level, whereas the upper level optimizes the operational cost, using a genetic algorithm (GA) in [11]. Paper [12] presents economic operation based on predicted data in the schedule layer, and controllable units' power is dispatched as per real-time data in the dispatch layer. A multi-objective problem is formulated in [13–16] for the economic operation of the MG. The problem consisting of minimization of operational costs and pollutant emissions is solved by applying particle swarm optimization (PSO), a GA and normal boundary intersection techniques in [13, 14]. A fuzzy multi-objective problem to minimize the economic cost and power losses under uncertainty scenarios is solved through chaotic binary PSO in [15]. Paper [16] realizes economic operation for minimization of generation and BES life-loss costs through a non-dominated sorting GA.

The above literatures discussed the OEM in the MG or SMG by minimizing various costs, losses and pollutant emissions for a single or multi-objective problem using the heuristic approaches. But, these are lacking in considering the effective role of BES for fulfilling the load demand in the SMG and at the same time, taking the penalty costs imposed on the SMG and BES ageing constraint. The main contribution of this work is as follows:

a) The non-linear models of the WT, PV and BES are introduced to express a more realistic case, but at the cost of non-linearity.

b) Optimal generation scheduling of the SMG is executed to minimize the objective problem, which is a mixed integer non-linear problem (MINLP) in nature and it is a precisely formulated cost function with applicable system constraints.

c) A weather profile consisting of moderate solar and wind resources is generated for the problem simulation.

d) The problem is simulated in four cases as without and with the BES having a different level of initial energy to analyze the system reliability with handling the uncertain nature of the CES.

e) The results obtained from the ABC method of such an MINLP are compared through the PSO and GA techniques.

The remaining part of the paper is structured as: SMG elements, considered weather profile and the OEM of the SMG are modeled in Section 2 and 3, respectively. A brief of the ABC algorithm and its implementation is described in Section 4. Section 5 demonstrates the SMG system and, the results and discussions of the objective problem. Finally, the work is concluded in Section 6.

2. Modeling of SMG elements and weather profile

The SMG has uncontrollable sources as a WT and PV, controllable sources as a MT and FC, BES as an energy storage device and locally connected load demand. The mathematical model of the SMG elements is as follows:

2.1. PV modeling

The output power of a PV array is varying according to the solar radiation at a particular interval t and expressed as:

$$P_v(t) = \eta_v \cdot r(t) \cdot A, \tag{1}$$

where A represents the PV cell area in m^2/W, $r(t)$ is the solar radiation at interval t and η_v is the PV array efficiency.

2.2. WT modeling [4]

The WT power at each interval t depends on the value of wind speed. The output power is normally relatively proportional to the cube of wind speed, if speed lies in between the cut-in and nominal speed. The mathematical formulation of power generation from the WT is written as:

$$P_w(t) = \begin{cases} 0 & v_{ci} > v \geq 0 \\ P_w^{\max} \cdot (v^3 - v_{ci}^3)/(v_r^3 - v^3) & v_r > v \geq v_{ci} \\ P_w^{\max} & v_{co} > v \geq v_r \\ 0 & v \geq v_{co} \end{cases}, \tag{2}$$

where v, v_{co}, v_{ci}, and v_r are the actual, cut-out, cut-in and nominal wind speed, correspondingly and $P_w^{\max}$ is maximum power output from the WT.

2.3. BES modeling

The BES is having a set of battery blocks, which are connected in the combination of series and shunt to deliver the nominal output voltage and current to the system. The state-of-charge (SOC) of the BES is a measure that decides the BES operation at each interval as idle or charging or discharging. At each interval, the SOC value is calculated on the basis of the BES power and it is formulated for discharging and charging in (3) and (4), respectively.

$$\mathrm{SOC}\,(t) = (1-\lambda)\cdot \mathrm{SOC}\,(t-1) - P_b(t)/(E_b^{\max}\cdot \eta_{\mathrm{dch}}), \tag{3}$$

$$\mathrm{SOC}\,(t) = (1-\lambda)\cdot \mathrm{SOC}\,(t-1) - (P_b(t)\cdot \eta_{\mathrm{ch}})/E_b^{\max}, \tag{4}$$

where λ is the self-releasing energy rate, $E_b^{\max}$ and $P_b(t)$ are the maximum capacity and power at interval t of the BES (negative/positive value of the BES power for charging/discharging operation), respectively, and $\eta_{\mathrm{ch}}/\eta_{\mathrm{dch}}$ is the charge/discharge efficiency of the BES.

C-rate: The discharging/charging power in each hour is scaled by *C-rate* of the BES. The *C-rate* of 1 C is showing that the BES can completely discharge its power in one hour. Hence, *C-rate* of 1 C is called as a 1-hour discharge. Similarly, *C-rate* of 0.5 C is indicating a 2-hour discharge.

State-of-health (SOH) [10]: It is a ratio that represents the BES state comparing to the ideal state of the BES. This is computed by (5) only for the BES discharging process, where, $E_b(t)$ shows the degradation in capacity of the BES at dispatch interval t.

$$\mathrm{SOH}(t) = E_b(t)/E_b^{\max}. \tag{5}$$

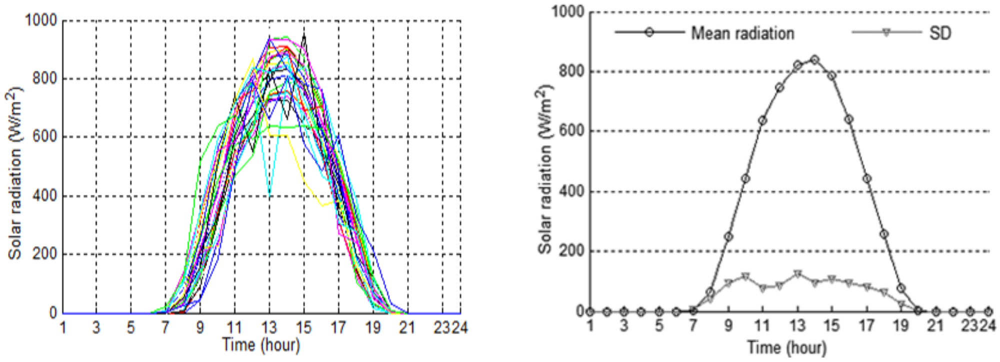
A value of 3×10^{-4} linear ageing coefficient (δ) [20] is considered for SOH evaluation. The degraded BES capacity $E_b(t)$ is found out as:

$$E_b(t) = E_b(t-1) - \delta\cdot E_b^{\max}\cdot(\mathrm{SOC}\,(t-1) - \mathrm{SOC}\,(t)), \tag{6}$$

The discharge power of the BES at that interval is again evaluated in accordance to the BES capacity obtained from (6).

2.4. Analysis of solar radiation and wind speed

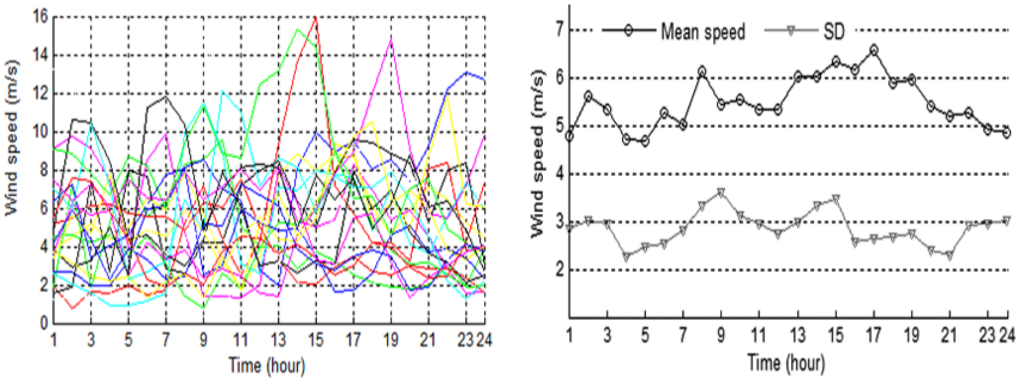
The hourly solar radiation (W/m^2) and wind speed (m/s) data [18] from January-April, 2010 are considered to generate the moderate CES power profile. A range of 450–650 W/m^2 of the average value of solar radiation between the hours 8:00–19:00 of each day is taken to create the stochastic days of a solar radiation profile as shown in Figure 1(a). In addition, the range



(a) (b)

Fig. 1. (a) Solar radiations of chosen profile and (b) mean and SD value of the profile

3.5–10 m/s (as per the cut-in and nominal speed of WT) of wind speed found more than 50% of hours in each day is chosen to generate the wind speed profile as presented in Figure 2(a). The mean and standard deviation (SD) of the solar radiation and wind speed profile are presented in Figures 1(b) and 2(b), respectively. Hence, these stochastic solar radiation and wind speed profiles are considered in determining the available CES power for problem simulation.



(a) (b)

Fig. 2. (a) Wind speeds of chosen profile and (b) mean and SD value of the profile

3. Mathematical model for OEM of SMG

3.1. Objective problem

The problem is proposed to minimize the operational cost of an SMG for optimal generation scheduling. The proposed problem consisting of various costs is described as:

$$\text{Min}\, C = \sum_{t=1}^{T} (P_w(t) \cdot B_w + P_v(t) \cdot B_v + P_b(t) \cdot B_b + P_m(t) \cdot B_m + \\ + P_f(t) \cdot B_f + P_{nu}(t) \cdot B_{nu} + P_{ns}(t) \cdot B_{ns} + C_m(t) + C_f(t)), \tag{7}$$

where B_k (k is w, v, b, m, f, nu and ns) is the bid cost of the WT, PV, BES, MT, FC, unused CES and unserved demand, respectively. $P_m(t)$, $P_f(t)$, $P_{nu}(t)$ and $P_{ns}(t)$ are the MT, FC, unused CES and unserved demand power at interval t, respectively. $C_m(t)$ and $C_f(t)$ are the startup/shutdown cost of the MT and FC, respectively, and T is the study period of problem simulation.

a) Penalty costs [5]: Two types of penalties are included in a cost objective function, one is due to not fully utilizing the available WT and PV power of each interval and other is because of not fulfilling the load demand of each interval. Hence, the imposed penalties are promoting the maximum utilization of the CES (or decreasing the uncertainty of CES) and system reliability. These are described as:

$$P_{nu}(t) = \text{available CES power} - P_v(t) - P_w(t), \tag{8}$$

$$P_{ns}(t) = P_d(t) - P_w(t) - P_v(t) - P_m(t) - P_f(t) - P_b(t), \tag{9}$$

where $P_d(t)$ is the load demand at interval t.

b) Startup/Shutdown Cost [13]: Startup/shutdown operation of the MT and FC involves certain costs, and these can be modeled as:

$$C_m(t) = (C_{um} \cdot (1 - U_m(t-1)) \cdot U_m(t)) + (C_{dm} \cdot (1 - U_m(t)) \cdot U_m(t-1)), \tag{10}$$

$$C_f(t) = (C_{uf} \cdot (1 - U_f(t-1)) \cdot U_f(t)) + (C_{df} \cdot (1 - U_f(t)) \cdot U_f(t-1)), \tag{11}$$

where C_{um}/C_{dm} and C_{uf}/C_{df} represent the startup/shutdown costs of the MT and FC, respectively, and $U_m(t)/U_f(t)$ is the off or on status of the MT/FC at interval t, equal to 0 for off and 1 for on.

3.2. SMG constraints

The constraints applicable for the considered SMG system are as follows [4, 10, 13, 15]:

a) The system balance constraint at each period t is written as:

$$P_d(t) = P_v(t) + P_w(t) + P_m(t) + P_f(t) + P_b(t). \tag{12}$$

If the load demand at any of the interval of the study period is not satisfied, then the total unserved demand is represented by the loss of load probability (LOLP) index [19], which is expressed as:

$$\text{LOLP} = \sum_{t=1}^{T} P_{ns}(t) \Big/ \sum_{t=1}^{T} P_d(t). \tag{13}$$

b) The minimum and maximum boundary value of the MT power at dispatch interval t is given as:

$$P_m^{\min} \le P_m(t) \le P_m^{\max}. \tag{14}$$

c) The minimum turn on and off time of the MT at interval t are given as:

$$T_{m,\,\text{on}}(t) \ge T_{m,\,\text{on}}^{\min}, \qquad T_{m,\,\text{off}}(t) \ge T_{m,\,\text{off}}^{\min}. \tag{15}$$

where $T_{m,\,\text{on}}(t)$ and $T_{m,\,\text{off}}(t)$ are the turn on and off time of the MT, respectively.

d) The output power of a FC is restricted by minimum and maximum value as follows:

$$P_f^{\min} \le P_f(t) \le P_f^{\max}. \tag{16}$$

e) The minimum turn on and off time of the FC at interval t are given as:

$$T_{f,\,\text{on}}(t) \ge T_{f,\,\text{on}}^{\min}, \qquad T_{f,\,\text{off}}(t) \ge T_{f,\,\text{off}}^{\min}, \tag{17}$$

where $T_{f,\,\text{on}}(t)$ and $T_{f,\,\text{off}}(t)$ are the turn on and off time of the FC, respectively.

f) The boundary values of the BES power at each interval t are considered as:

$$P_b^{\min} \le P_b(t) \le P_b^{\max}. \tag{18}$$

g) The minimum and maximum energy storing capacity of the BES is provided as:

$$E_b^{\min} \le E_b \le E_b^{\max}. \tag{19}$$

h) The SOC of the BES is limited by minimum and maximum value in each interval, given as:

$$\mathrm{SOC}^{\min} \le \mathrm{SOC}(t) \le \mathrm{SOC}^{\max}. \tag{20}$$

i) SOH value of the BES is restricted by minimum value at each period t as:

$$\mathrm{SOH}(t) \ge \mathrm{SOH}^{\min}. \tag{21}$$

4. ABC algorithm and implementation

The objective problem with its constraints for OEM is formulated in the previous section is an MINLP in nature [24]. The conventional optimization algorithms are not suitable for solving the MINLP. The heuristic approaches provide appreciable solutions for such type of non-linear problems. In this paper, three heuristic algorithms, i.e. an ABC, PSO and a GA are applied for problem simulation. The PSO was first discovered in 1995 by Kennedy and Eberhart [21], and the GA was first proposed in 1967 by Holland [22], they are established and popular algorithms. The theory of these algorithms is omitted here due to space limitation. The brief overview of the ABC technique is as follows:

4.1. ABC algorithm

The ABC algorithm was first discovered [17] by Dervis Karaboga, which is based on the nature of swarm of honey bees for locating the food sources. It has two types of bees, i.e. employed and unemployed, which shares information to locate food sources successfully. The employ group of bees exploits a food source and the unemployed group of bees searches for a food source continuously. Further, the unemployed group of bees is classified into onlookers and scout bees, the scout bees explore the food sources nearer to the nest and the onlooker bees look at the nest to set-up the communication with the bees of the employed group.

At the initialization phase, solutions (S_N) are randomly created which are likely to the food sources. The ratio of the employed bees and food sources is one to one. To evaluate the new solution of the employed bees (22) is used.

$$v_{i,j} = \begin{cases} x_{i,j} + \psi_{i,j}(x_{i,j} - x_{r1,j}) & \text{if } j = j1 \\ x_{i,j} & \text{otherwise} \end{cases}, \tag{22}$$

where $x_{i,j}$, $v_{i,j}$ and $x_{r1,j}$ are the j-th element of x_i, v_i and x_i, respectively; $\psi_{i,j}$ is randomly chosen from ε $[-1,\ 1]$; $j1$ is a random integer ε $[1,\ D]$ and D is representing the problem dimension; x_i and x_i are the various solutions in the current population; v_i is the new solution, if this solution v_i is superior than x_i, then x_i is updated by v_i, otherwise x_i is unchanged.

An onlooker bee opts the food source randomly as per the probability calculated by (23). Then, all onlooker bees have to update their better food sources by comparing the solutions evaluated using (22).

$$p_i = \mathrm{fit}_i \Big/ \sum_{j=1}^{S_N} \mathrm{fit}_j\,, \tag{23}$$

where fit_i is the fitness value of x_i computed by (24).

$$\mathrm{fit}_i = \begin{cases} \dfrac{1}{(f(x_i)+1)} & \text{if } f(x_i) \geq 0 \\ |f(x_i)| + 1 & \text{otherwise} \end{cases}. \tag{24}$$

In an ABC, a predetermined limit of the number of cycles is introduced. In the case of a food source, it is not upgraded to the limit. This food source should be discarded and the bee becomes the scout bee and again, a randomly generated solution for food sources are created by scout bees.

4.2. Implementation of ABC algorithm

```
Initialization of the food sources $x_{i,j}$, i.e. $P_m(t)$ and $P_f(t)$, $i = 1, 2, \ldots, S_N$, $j = 1, 2, \ldots, D$ and trial = 0, where the trial is representing the abandoned food sources solution $x_i$
Obtain the food sources
Iteration = 1
repeat
    /*employed bees phase*/
    for $i = 1$ to $S_N$ do
        Obtain a new food source $v_i$, using (22) and determine its quality in terms of fitness of an objective problem, using (7) and (24)
        Apply a greedy selection procedure
        If food source solution $x_i$ remains unimproved, then trial = trial + 1, otherwise trial = 0
    end for
    Determine the values of probability $p_i$ by (23) for the fitness values of food sources solutions
    /*onlooker bees phase*/
    $t = 0$, $i = 0$
    Repeat
        if rand < $p_i$ then
            Evaluate a new food source $v_{i,j}$ using (22)
            Apply a greedy selection procedure
            If food source solution $x_i$ remains unimproved, then trial = trial + 1, otherwise trial = 0
            $t = t + 1$
        Endif
    until ($t = S_N$)
    /*scout bees phase*/
    if limit < max (trial) then
        Initialize $x_i$ again with randomly generated food sources
    Endif
    Remember the best solution obtained so far
    Iteration = 1+ iteration
until (iteration = maximum iteration)
```

5. SMG system description and discussions of simulation results

Figure 3 shows the basic architecture of the considered SMG [13]. It is located in remote rural areas, where expansion of a transmission system is not feasible. It has two dispatchable sources, i.e. a MT and FC along with BES and a CES to meet the connected load demand. The parameters of the SMG elements are listed in Table 1. The bid costs and, power and time limits of the SMG elements are provided in Table 2. April 03, 2010 [18] is selected from the generated weather profile, for the hourly data of solar radiation and wind speed. Table 3 presents the hourly values of demand.

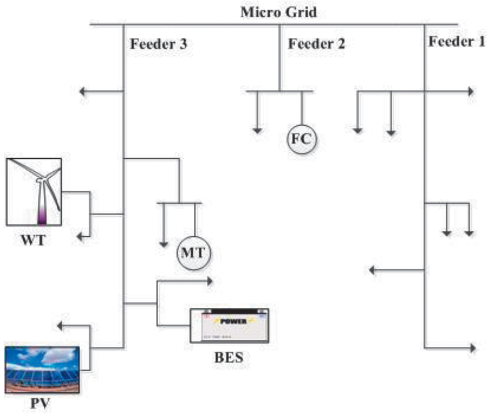


Fig. 3. SMG architecture

Table 1. Values of system parameters [4, 10]

Parameter	Value	Parameter	Value
SOC^{min}	0.1	η_{ch}/η_{dch}	0.9/1.0
SOC^{max}	0.9	*C-rate*, η_v	0.1 C, 0.14
SOH^{min}	0.5	A (m^2/W)	0.00694
E_b^{min} (kWh)	30	v_{ci}, v_{co} (m/s)	3.5, 23
E_b^{max} (kWh)	300	v_r (m/s)	11
λ	0	T (h)	24

The OEM is performed for an hourly varying load profile and a moderate WT and PV power scenario. The power output of the MT and FC are taken as decision variables. When demand is low, the BES extracts power from generation sources and releases back to load demand whenever required to fulfil the demand. The SOC of the BES at each dispatch interval defines the available/require capacity for discharge/charge operation. The objective function with its related constraints as described in Section 3 is simulated in MATLAB® for a day with one hour as the lead interval. The bid cost for penalties due to not utilized CES power (1.0 €ct/kWh) is slightly lesser than the bid cost of unserved demand (1.029 €ct/kWh) as the serving load is given on priority. A factor 0.85 tons/MWh [23] is used to address the reduction in carbon-emission in an

Table 2. Values of power and time limits, bid and other costs [13, 15]

Type	$P^{\min}$ **(kW)**	$P^{\max}$ **(kW)**	**SUC/SDC (€ct/kWh)**	$T_{\text{on}}^{\min}$ **(h)**	$T_{\text{off}}^{\min}$ **(h)**	**Bid Cost (€ct/kWh)**
WT	0	15	0	0	0	1.073
PV	0	25	0	0	0	2.584
MT	6	30	0.96	2	2	0.457
FC	3	30	1.65	2	2	0.294
BES	−30	30	0	0	0	0.38

Table 3. Hourly values of load demand [13]

Hour (h)	1	2	3	4	5	6	7	8	9	10	11	12
Load (kW)	52	50	50	51	56	63	70	75	76	80	78	74
Hour (h)	13	14	15	16	17	18	19	20	21	22	23	24
Load (kW)	72	72	76	80	85	88	90	87	78	71	65	56

MG through the exploitation of the moderate CES. The OEM of the SMG is carried out in four different cases based on the level of the BES initial energy capacity as follows:

Case-I: The OEM without BES.

Case-II: The OEM with BES.

Case-III and IV: The OEM with BES having 15% and 20% initial energy.

5.1. *Case-I*: The OEM without BES

In this, optimal energy scheduling of an SMG is performed without an energy storage device. The power of a WT and PV is given first priority to supply the demand to promote the use of a CES and reduce the carbon-emission. The remaining unfulfilled load is optimally shared by controllable sources as a MT and FC. The output power of these controllable sources is restricted by their constraints and cost associated with them. Figure 4 depicts that a FC is sharing its full capacity at all of the intervals to satisfy the demand with optimizing the objective problem, as the bid cost of the FC is lesser than the MT. Table 4 provides the various costs for all three algorithms, and an LOLP index at optimal cost. The results establish that the ABC provides the most consistent and better results with reference to all costs and other factors compared to PSO and GA. As, the variation in mean cost (1127.392 €ct) and best cost (1127.385 €ct) is very less. The unserved demand at optimal cost is depicted in Figure 8 and it shows that load is not fully met at hours 7 to 9 and 17 to 23. The value of the LOLP index is 0.0814 and cost of total unserved demand is 141.94 €ct, which indicates the amount of grid energy exchange cost to fulfill the unmet demand, if the MG is in on-grid mode. It is concluded that a larger portion of load is not satisfied in this case.

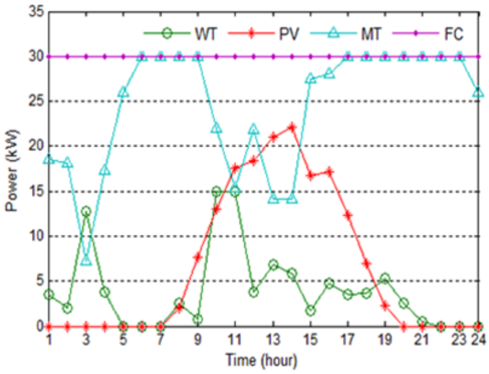


Fig. 4. Optimal generation power scheduling in SMG for *Case-I*

Table 4. Results of various costs and LOLP for all cases

	Algorithm	Best cost (€ct)	Mean cost (€ct)	Worst cost (€ct)	LOLP at best cost
Case-I	ABC	**1127.385**	1127.392	1127.402	0.0814
	PSO	1235.013	1274.616	1325.512	
	GA	1135.342	1139.053	1143.635	
Case-II	ABC	**1062.313**	1062.313	1062.314	0.0125
	PSO	1062.69	1062.979	1062.998	
	GA	1062.823	1063.085	1063.365	
Case-III	ABC	**1052.576**	1052.576	1052.577	0.0036
	PSO	1052.685	1052.968	1052.993	
	GA	1052.746	1052.871	1053.048	
Case-IV	ABC	**1047.885**	1047.896	1047.906	0
	PSO	1047.905	1048.184	1048.947	
	GA	1048.126	1048.255	1048.378	

5.2. *Case-II*: The OEM with BES

The BES with its minimum initial capacity (30 kWh) is included in optimal operation of an SMG. The optimal scheduling of generation and the BES is presented in Figure 5, which shows that both a MT and FC are operating at their rated value at all intervals to supply the load and charge the BES. The BES is charged at hours 1 to 5 and 10 to 16 to store energy for fulfilling the demand latter at shortage of power generation. At hour 22, the BES fully released energy up to its boundary limit, after that the BES is unable to fulfill the unserved demand. Therefore, some amount of load is not met in last dispatch intervals as depicted in Figure 8. Also, this figure presents that the unserved demand is effectively reduced at most of the intervals by adding the BES in the SMG compared to *Case-I*. The cost of total unsatisfied demand (21.67 €ct) is drastically reduced compared to *Case-I*. Table 4 listed the several costs for an ABC, PSO and a GA, as well as LOLP at best cost. The ABC provides better optimal cost (1062.313 €ct) than PSO

(1062.69 €ct) and the GA (1062.823 €ct). The LOLP index and the best cost are better, compared to *Case-I*.

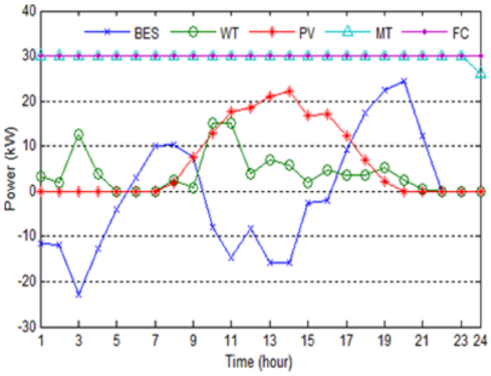


Fig. 5. Optimal generation and BES power scheduling in SMG for *Case-II*

5.3. *Case-III and IV*: The OEM with BES having 15% and 20% initial energy

The optimal load sharing by generation sources and the BES for *Case-III* and *IV* are shown in Figures 6 and 7, respectively. The BES plays an efficient role in order to meet the demand by optimal charging-discharging processes. The BES is fully discharged at hour 23 and it enhances the system reliability at last dispatch intervals in *Case-III*, comparing to *Case-II* as described in Figure 6 and Figure 8. The load demand is completely satisfied at all intervals in *Case-IV*. Figure 8 depicted that the unserved demand in *Case-III* is only at intervals 22 and 23, which is also less compared to *Case-I* and *Case-II*. It ensures that the BES with initial energy is working as a dispatchable source to satisfy the power balance constraint of the SMG to handle the uncertain nature of a CES. It is indicated by greatly reduced value of the LOLP index as presented in Table 4 for the *Case-III* and *Case-IV*. Also, the best costs for *Case-III* and *Case-IV* are better than the cost of *Case-I* and *Case-II*.

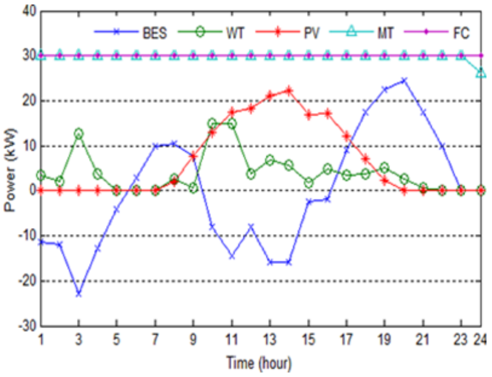


Fig. 6. Optimal generation and BES power scheduling in SMG for *Case-III*

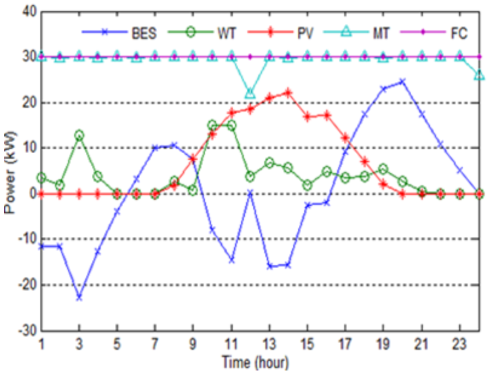


Fig. 7. Optimal generation and BES power scheduling in SMG for *Case-IV*

It is concluded that by adding the BES, system becomes reliable with much less amount of unserved power and also, reduces system operational cost. The cost due to not utilized CES power is zero in all the cases, as demand is higher than the CES power at each interval. Besides, the utilization of the CES with moderate energy in the SMG approximately reduces 0.22 tons carbon-emission in a day compared to conventional energy sources. The optimized values of SOC obtained at each interval points of dispatch period for *Case-II, Case-III* and *Case-IV* are presented in Figure 9 and it indicates that the SOC gains higher values, when load demand is at a lower level and its vice-versa. Also, the values of the SOC rise at each interval in sub-sequent cases with the increasing value of initial energy. A curve between the increase in initial energy and system operational cost is depicted in Figure 10, which describes that after 20% initial capacity, the cost does not decrease significantly, because of load is fully met at the BES with 20% initial energy of the BES. Further, the OEM is performed to analyze the robustness of the SMG for mean solar and wind data of the selected weather profile as presented in Figures 1(b) and 2(b), respectively. Figure 11 illustrates the economic load sharing by sources and the BES with 40%

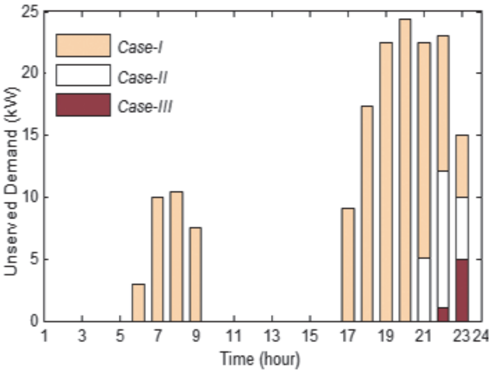


Fig. 8. The bar chart of unserved demand at best cost for *Case-I*, *II* and *III*

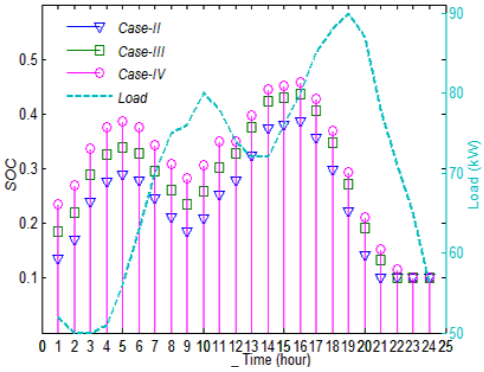


Fig. 9. The load and optimized values of the SOC for *Case-II*, *III* and *IV*

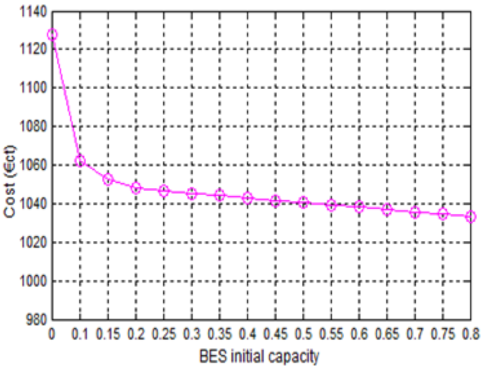


Fig. 10. Effect on cost of SMG with increasing the BES initial capacity

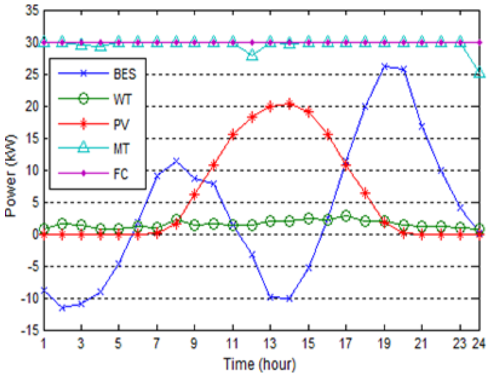


Fig. 11. Optimal energy scheduling in SMG for mean wind and solar data

initial capacity to meet the demand using ABC technique. And, the value of optimal cost for these data is 983.23 €ct.

6. Conclusions

Four operational cases based on BES having different initial energy capacity in OEM of an SMG are deliberated for the moderate solar and wind resources data in this paper. The results show that load demand is partially or fully met, when the BES with or without initial energy is included in the system compared to the system without the BES. The system operational cost is reduced with the addition of the BES in the system. The unserved demand and its cost, and LOLP are reduced drastically in the system with the BES. Hence, it is concluded that BES in an SMG plays an efficient role by optimally managing its charging or discharging or idle operations in OEM and maintaining the reliable power supply under the chosen weather profile and weather uncertainties. Also, the results for all cases present that an ABC performed better to solve the MINLP compared to PSO and GA approaches. The best, mean and worst costs results describe that the ABC always provides a solution near to the optimal values than to PSO and GA techniques. Hence, the ABC technique is more reliable and feasible. In future, OEM in the system can be performed including some controllable load demand and probabilistic uncertainty factors of weather, and reducing the nonlinearity in the system due to the startup/shutdown cost of a MT and FC using alternative formulation with a slack variable, which will help to relieve computational burden.

References

[1] Hatziargyriou N., Asano H., Iravani R., Marnay C., *Microgrids: An overview of ongoing research, development, and demonstration projects*, IEEE Power Energy Mag., vol. 5, no. 4, pp. 78–94 (2007).

[2] Driesen J., Katiraei F., *Design for distributed energy resources*, IEEE Power Energy Mag., vol. 6, pp. 30–40 (2008).

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

[4] Paliwal N.K., Singh N.K., Singh A.K., *Energy scheduling of wind-battery-hydro based hybrid micro-grid system using heuristic techniques*, IEEE 2016 Annual India Conf. (INDICON), Bangalore, India, pp. 1–6 (2016).

[5] Paliwal N.K., Singh N.K., Singh A.K., *Optimal power flow in grid connected microgrid using artificial bee colony algorithm*, IEEE 2016 Region 10 Conf. (TENCON), Singapore, pp. 671–675 (2016).

[6] Su W., Wang J., Roh J., *Stochastic energy scheduling in microgrids with intermittent renewable energy resources*, IEEE Transactions on Smart Grid., vol. 5, no. 4, pp. 1876–1883 (2014).

[7] Bogaraj T., Kanakaraj J., Kumar K.M., *Optimal sizing and cost analysis of hybrid power system for a stand-alone application in Coimbatore region: a case study*, Archives of Electrical Engineering, vol. 64, no. 1, pp. 139–155 (2015).

[8] Liu H., Wu Y., Qian C., Liu X., *The application of dynamic programming in the stand-alone microgrid optimal operation*, IEEE 2012 APPEEC, Shanghai, pp. 1–5 (2012).

[9] Komarnicki P., *Energy storage systems: power grid and energy market use cases*, Archives of Electrical Engineering, vol. 65, no. 3, pp. 495–511 (2016).

[10] Sachs J., Sawodny O., *A two-stage model predictive control strategy for economic diesel-PV-battery island microgrid operation in rural areas*, IEEE Transactions on Sustainable Energy., vol. 7, no. 3, pp. 903–913 (2016).

[11] Wu X., Wang X., Qu C., *A hierarchical framework for generation scheduling of microgrids*, IEEE Transactions on Power Delivery, vol. 29, no. 6, pp. 2448–2457 (2014).

[12] Jiang Q., Xue M., Geng G., *Energy management of microgrid in grid-connected and stand-alone modes*, IEEE Transactions on Power Systems, vol. 28, no. 3, pp. 3380–3389 (2013).

[13] Izadbakhsh M., Gandomkar M., Rezvani A., Ahmadi A., *Short-term resource scheduling of a renewable energy based microgrid*, Renewable Energy, vol. 75, pp. 598–606 (2015).

[14] Moghaddam A.A., Seifi A., Niknam T., Pahlavani M.R.A., *Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source*, Energy, vol. 36, no. 11, pp. 6490–6507 (2011).

[15] Li P., Xu D., Zhou Z., Lee W.J., Zhao B., *Stochastic optimal operation of microgrid based on chaotic binary particle swarm optimization*, IEEE Transactions on Smart Grid, vol. 7, no. 1, pp. 66–73 (2016).

[16] Zhao B., Zhang X., Chen J., Wang C., Guo L., *Operation optimization of standalone microgrids considering lifetime characteristics of battery energy storage system*, IEEE Transactions on Sustainable Energy, vol. 4, no. 4, pp. 934–943 (2013).

[17] Karaboga D., Basturk B., *A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm*, Journal of Global Optimization, vol. 39, pp. 171–459 (2007).

[18] http://www.nrel.gov/midc/nwtc_m2/, accessed June 2017.

[19] Kazem H.A., Khatib T., *A novel numerical algorithm for optimal sizing of a photovoltaic/wind/diesel generator/battery microgrid using loss of load probability index*, International Journal of Photoenergy, p. 8 (2013).

[20] Lemaire-Potteau E., Mattera F., Delaille A., Malbranche P., *Assessment of storage ageing in different types of PV systems technical and economical aspects*, 2008 Proc. 24th EU Photovoltaic Solar Energy Conf., Valencia, Spain (2008).

[21] Kennedy J., Eberhart R.C., *Particle swarm optimization*, Proc. of the 1995 IEEE International Conf. on Neural Networks, Piscataway, NJ (1995).

[22] Holland J.H., *Adaptation in Natural and Artificial Systems*, Ann Arbor, MI: University of Michigan Press (1975).

[23] *Climate Investment Funds*, 2015 Meeting of the SERP sub-committee, Washington D.C., vol. 4, no. 14, pp. 1–113 (2015).

[24] Ortega-Vazquez M., *Optimizing the spinning reserve requirements*, Univ. of Manchester, Sch. of Elect. and Electron. Eng., UK., pp. 1–219 (2006)