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Optimal Placement and Sizing of Energy Storage System in Distribution Network with Photovoltaic Based Distributed Generation Using Improved Firefly Algorithms

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***Abstract*—**The installation of photovoltaic based distributed generation (PVDG) in active distribution system can lead to voltage fluctuation due to the intermittent and unpredictable PVDG output power. This paper presented a method in mitigating the voltage rise by optimally locating and sizing the battery energy storage system (BESS) in PVDG integrated distribution network. The improved firefly algorithm is used to perform optimal placement and sizing. Three objective functions are presented considering the voltage deviation and BESS off-time with state of charge as the constraint. The performance of the proposed method is compared with another optimization method such as the original firefly algorithm and gravitational search algorithm. Simulation results show that the proposed optimum BESS location and size improve the voltage stability.

***Keywords*—**BESS, PVDG, firefly algorithm, voltage fluctuation.

I. Introduction

RECENTLY, the development of renewable energy based distributed generation (RE-DG) such as PVDG in active distribution system has become more popular since it provides a power system with higher flexibility, improves the power quality of the system, and decreases the environmental impact. Nevertheless, the generation of the PVDG is affected greatly by the inconstant source (sunlight), which caused the production of inconstant and intermittent output power. This can lead to undesired voltage fluctuation in the system when the DGs are connected to the network and cause both utilities and end users to suffer economically. For this reason, different methods have been suggested using load control [1], series reactor [2] and dump load [3] in order to alleviate the voltage fluctuation problem. Besides, BESS has been suggested to be effective in mitigating the voltage fluctuation problem as well [3], [4]. However, the installation of BESS at every bus in the network imposes high installation cost to the utilities. Thus, the optimal integration of BESS in the grid becomes important with the intention to get the maximum efficiency in maintaining the stability of the grid as well as saving the cost. Meanwhile, limited studies have been done for integrating BESS into PVDG integrated grid [5]-[7]. In the literature, some mathematical approaches have been applied in obtaining optimal BESS size or placement [4], [8]-[10]. Meanwhile, heuristic optimization techniques can be one of the good options for optimal integration of BESS in the PVDG integrated network since it is easier to compute and it converges faster if compared to the mathematical optimization technique. One of the first work was proposed by Chaiyatham and Ngamroo [11] in obtaining the optimal location and size of the BESS in the radial distribution network using artificial bee colony algorithm. Besides, Zhong et al. [7] suggested a multi-objective optima model for sizing and placement of BESS using particle swarm optimization (PSO). Apart from this, Nick et al. [6] proposed to locate and size the ESS using GA. Even though the meta-heuristic optimization based methods are usually easier and faster than the conventional mathematical optimization methods in getting the desired output, they are always slow in convergence due to their random searches, and the search agents can be trapped in local optimal point easily [12]. Therefore, the new improved versions of original firefly algorithm (FA) [13], namely enhanced opposition-based firefly algorithm (EOFA) and quantum inspired binary firefly algorithm (QBFA), which are proved to be perform better than original FA [14], [15] are employed in this paper in order to obtain the optimal placement and sizing of BESS in radial distributed network with the purpose of mitigating the voltage rise problem.

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II. Formulation of Optimization Problem

In this paper, the PVDG is modeled as current source, while the BESS is modeled as current source or sink. The BESS acts as current sink when there is excess output power from PVDG, while it acts as current source when more power is needed to maintain the voltage profile of the system. The BESS operates when the PVDG is active, and it discharges when the PVDG is inactive at night.

For the first part of the work, QBFA is employed to obtain the optimum locations for BESS in the PVDG integrated power system. The location of BESS in each optimization process is decided by using a BESS placement (BP) vector where the relation between the BP vector and the BESS location can be described as shown in (1). In this paper, the BP at bus 1 (slack bus) is not allowed.

$$BP(n) = \begin{cases} 1, & \text{if BESS is placed at bus } n \\ 0, & \text{if BESS is not placed at bus } n \end{cases} \quad \forall n, BP(1) \neq 1 \tag{1}$$

The BESS plays an important role in maintaining the voltage stability and reducing the voltage fluctuation, and the placement of BESS will determine the efficiency of BESS. Therefore, for this purpose the first objective function f_1 is designed in order to minimize the voltage deviation of the PVDG buses such that the solution set (searching agent) is the possible locations to place the BESS.

The power system with BESS placed at the optimum location should give the minimum value of voltage deviation.

For the second part of the work, EOFA is used in order to obtain the optimum sizes for BESS in the PVDG integrated power system.

Two optimization processes are proposed to obtain the optimal BESS size. Firstly, EOFA is used to get the optimal average hourly BESS active output power for the PVDG integrated system. The purpose of the optimization is to maintain the voltage deviation of the PVDG buses within the range of 0.95 p.u. to 1.05 p.u.

In this paper, the state of charge (SOC) of the BESS for each hour is considered and it is calculated as [16]:

$$SOC = 100\left(1 - \frac{\int I_{bs} dt}{Q}\right) \tag{2}$$

where I_{bs} is the BESS current, t is the time in hour, and Q is the BESS capacity in ampere x hour (Ah). The BESS will be turned off until it discharges or charges when the SOC reaches either its maximum limit or minimum limit.

By taking the SOC into the consideration, the optimal BESS size is determined again using EOFA. The third objective function, f_3 is used to minimize the BESS inactive hours (off-time) since the more the numbers of BESS inactive hours due to the SOC constraint, the worse the BESS performs.

III. Improved FA

The FA was developed by Yang [17] based on the flashing characteristic of fireflies. The FA is demonstrated based on three assumptions where firstly, it is assumed that all fireflies are of the same sex and consequently the attraction between each firefly is independent. Secondly, the attraction between the fireflies changes proportionally to their brightness. The less bright one will always attracted by the brighter one and in case of same brightness among all fireflies, the fireflies will move randomly. Thirdly, the brightness of a firefly is decided by the objective function.

There are two main components consisted in FA namely, variation of light intensity and the formulation of attractiveness. Since the attraction of a firefly is proportional to its light intensity as discovered by the nearby fireflies, the attractiveness function, $\beta(r)$ is defined as followed [17]:

$$\beta(r) = \beta_o e^{-\gamma r^m}, \qquad (m \geq 1) \tag{3}$$

where β_o is the attractiveness for r=0, γ is the light absorption coefficient while r is the Cartesian distance between two fireflies as defined:

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k}\right)^2} \tag{4}$$

where i and j represents two fireflies at x_i and x_j, $x_{i,k}$ is the k-th component of the spatial coordinate x_i of i-th firefly. On the other hand, the movement of the firefly i which is attracted by the brighter firefly j is defined as shown [17]:

$$x_i = x_i + \beta_o e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + alpha\left(rand - \frac{1}{2}\right) \tag{5}$$

where the second term is due to the attraction and the third term is due to the randomization. In the third term, the randomization parameter *alpha* is used while *rand* is a random number generator uniformly distributed between zero and one. Meanwhile, *alpha* is a decreasing function with a decreasing factor, *delta* as shown:

$$alpha(t+1) = alpha(t) \times delta, \qquad 0 < delta < 1 \tag{6}$$

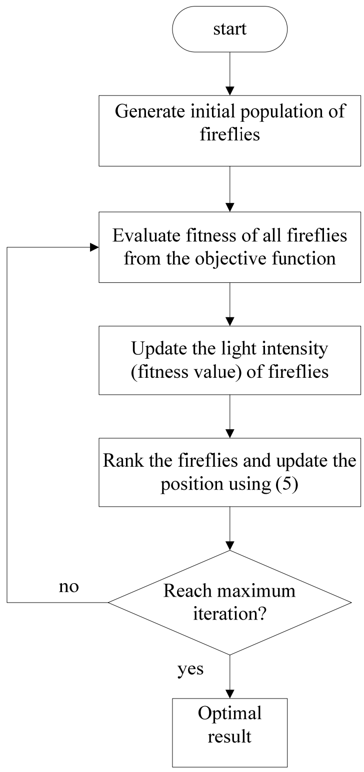


Fig. 1 Flowchart for FA

The flowchart for FA is illustrated in Fig. 1. The FA outperformed other optimization algorithms such as PSO and genetic algorithm (GA) with higher efficiency and successful rate [13]. However, the performance of FA becomes less satisfied with the increment of the dimension of search space [18]. As a result, improved FA such as QBFA and EOFA are introduced to further enhance the performance of FA.

A. Quantum Inspired Binary Firefly Algorithm (QBFA)

The QBFA which based on the principle of quantum mechanics is proposed by [14]. It is a discrete version of FA which provides binary output of either '1' or '0'. The first quantum-inspired computing theory is introduced by [19]. The smallest unit of in quantum computing is known as quantum bit (Q-bit) which can be in the state of '1' or '0' or in a linear superposition of the two as [20]:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{7}$$

where α and β are complex numbers that specify the probability amplitudes of the corresponding states. $|\alpha|^2$ and $|\beta|^2$ indicate the probability that a Q-bit can be found in a '0' or a '1' state, respectively. Therefore, the states can be normalized to unity as [20]:

$$|\alpha|^2 + |\beta|^2 = 1 \tag{8}$$

The state of a Q-bit is updated through a quantum gate and can be represented as a unitary operator U. In this paper, a rotation gate as shown in (9) which has been used in different heuristic search algorithms is applied. Two techniques known as the coordinate rotation gate and the dynamic rotation angle approach are incorporated in suggested rotation gate in order to update Q-bits and to determine the magnitude of the rotation angle. The rotation angle can be formulated as shown in (10) [14]:

$$U(\Delta\theta_i) = \begin{bmatrix} \cos(\Delta\theta_i) & -\sin(\Delta\theta_i) \\ \sin(\Delta\theta_i) & \cos(\Delta\theta_i) \end{bmatrix} \tag{9}$$

$$\Delta\theta_i = \theta \times \left(x_i + \beta_o e^{-\gamma r_{ij}^2} \left(x_j - x_i \right) + alpha\left(rand - \frac{1}{2} \right) \right) \tag{10}$$

where $\Delta\theta_i$, i = 1, 2, 3…, n, is the rotation angle of each Q-bit toward either '0' or '1' state depending on its sign and θ is the rotation angle magnitude that decreases monotonously from θ_{max} to θ_{min} along the iteration. Meanwhile, the Q-bit individual string can be updated based on the rotation angle and the rotation gate as shown in (11) and lastly, the position of the firefly is updated using the probability of $|\beta|^2$ as shown in (12) [20].

$$\begin{bmatrix} \alpha_i(t+1) \\ \beta_i(t+1) \end{bmatrix} = U(\Delta\theta_i) \times \begin{bmatrix} \alpha_i(t) \\ \beta_i(t) \end{bmatrix} \tag{11}$$

$$x_i = \begin{cases} 1, & if\ \left|\beta_i(t+1)\right|^2 > rn \\ 0, & otherwise \end{cases} \tag{12}$$

B. Enhanced Opposition-Based Firefly Algorithm (EOFA)

The EOFA is an improved version of FA with the integration of opposition-based learning and inertia weight function [18]. In this method, opposition-based theorem is used in the initialization process and the firefly location updating process. Let D(x_1, x_2..., x_m) be a set of points with dimension m in the search space where $x_i \in [a_i, b_i]$ and x_1, x_2..., $x_m \in$ R. Then the points for opposition set D_o (x_{o1}, x_{o2}..., x_{om}) can be defined as:

$$x_{oi} = a_i + b_i - x_i\ , \quad i = 1, 2, \ldots, m \tag{13}$$

Following the definition for opposite number, the opposition based optimization can be established as described in the following statement. Let the candidate solution for an optimization problem, D(x_1, x_2...., x_m) be the set of points having dimension of m in the search space.. As stated by opposition theorem, D_o (x_{o1}, x_{o2}..., x_{om}) will be the opposition set for D(x_1, x_2..., x_m). Let f(x) be the function utilized to evaluate the performance of candidate solution, thus if f(D) is greater than or equal to f(D_o), then set of points in D can be replaced by D_o or else D is maintained. Besides, inertia weight function as shown in (14) is used as well to avoid the problem in escaping from local optimum point and pre mature convergence [21].

$$\omega(t) = \omega_{\max} - \left(\omega_{\max} - \omega_{\min}\right) * \left(t / Maxgen\right) \tag{14}$$

where ω(t) is the inertia weight at t, ω_{max} and ω_{min} are the initial and final values of the inertia weight respectively through the iteration process, t is the current iteration while *Maxgen* is the maximum number of iteration as defined in the initialization process of FA. The movement of the firefly in updating its position after the integration of inertia weight function is shown as follows:

$$x_i(t) = \omega(t) x_i(t) + \beta_o e^{-\gamma r_{ij}^2} \left(x_j(t) - x_i(t) \right) + alpha\left(rand - \frac{1}{2} \right) \tag{15}$$

In EOFA, each firefly updates the light intensity (fitness value) using (15) after the evaluation of the fitness from the objective function. Then the fireflies will rank and update their positions. A jumping rate, *Jr* of 1 is used to decide if the opposite population is generated or not according to (16). The opposite population will be generated when the generated random number is smaller than *Jr*. Then the n fittest individuals will be selected from current D and D_o as the next population or else, the next population will be the same as the current population, D. The optimization procedure repeats until the maximum number of iteration is achieved.

$$generation\ of\ opposite\ population = \begin{cases} yes, & if\ Jr > rand() \\ no, & otherwise \end{cases} \quad (16)$$

IV. Implementation of QBFA and EOFA in Mitigating Voltage Rise Problem

The implementation steps of QBFA and EOFA in BP and sizing are discussed in this section. The procedures in implementing the proposed BP method in PVDG integrated power system using QBFA are summarized as follows:

a. Model the power system with PVDG installed at selected buses.
b. Run the power flow for each hour under study.
c. Observe the voltage profile at PVDG bus.
d. Determine the number of hours, h_n that violates the voltage limit of 1.05 p.u. and 0.95 p.u.
e. For hour h, generate the initial population of firefly search agents.
f. Run the power flow and evaluate the fitness function, f_1 by using data obtained from the power flow.
g. Update the fireflies' position.
h. Repeat step (f) to (g) until the stopping criteria is achieved. In this paper, the maximum iteration number is considered as stopping criteria.
i. Store the best solution (best BESS location) for the particular hour h.
j. Repeat step (e) to (i) for next hour $h+1$ until the last hr h_n.

After the solutions for all hours are obtained, the proposed procedures in obtaining the optimal BP are repeated again for m number of times. The optimal location that repeats for the most number of times among all hours h_n is regarded as the optimal BESS location for the system. After the optimal location for BESS is determined, the optimal sizing of BESS can be done by using EOFA. On the other hand, the procedures in implementing the proposed BESS sizing method in PVDG integrated power system using EOFA are summarized as:

a. Model and simulate the power system with PVDG installed at selected bus.
b. Observe the voltage profile at PVDG buses.
c. Determine the number of hours, h_m for the voltage profile that go beyond the limit of 1.05 p.u. and 0.95 p.u.
d. Identify the location of BESS using the optimal placement method described above.
e. Generate the opposition-based initial population of firefly search agents which represent the solution set for BESS hourly output power.
f. Run the power flow and evaluate the fitness from the objective function, f_2 by using the data obtained from the power flow.
g. Rank and update the fireflies' position according to opposition-based method.
h. Repeat step (f)-(g) until the stopping criteria (maximum iteration number) is achieved.
i. Store the best solution (optimal BESS output power) for the particular hour h.
j. Repeat step (e)-(i) for next hour $h+1$ until the last hour h_m.
k. After the BESS hourly output power values are obtained, determine the optimal capacity for BESS using EOFA again by considering the limit for SOC.
l. Generate the opposition-based initial population of firefly search agents which represent the solution set for BESS capacity.
m. Evaluate the fitness of the fireflies according to the objective function, f_3.
n. Rank and update the fireflies' position according to opposition-based method.
o. Repeat step (m)-(n) until the stopping criteria (maximum iteration number) is achieved.

After the optimal capacity of BESS is obtained, the BESS off-time is identified, and the power flow is run again by considering the BESS off-time. The voltage profile at PVDG buses is then observed and compared with the voltage profile before the BESS is installed.

V. Results and Discussion

The 69-radial-bus system as shown in Fig. 2 is used in this paper where the system data can be obtained from [22]. Two PVDG with the capacity of 3.21 MWp each are installed at Bus 21 and Bus 61, respectively. In this work, the PVDG output power for every hour starting 9 am until 6 pm was collected for the duration of three months where the values are obtained from a smaller scale grid connected PVDG system placed at the Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia. According to the PVDG bus voltages at a particular hour, if either one of the PVDG bus voltage goes beyond the acceptable limit within 1.05 p.u. and 0.95 p.u. as suggested by IEEE Std. 1547, the BESS will be activated. The amount of BESS power for that particular hour either to discharge or to charge power from the system will be determined by the optimization process. Meanwhile, the upper and lower limits for the SOC of the BESS are set to be 100% and 20% respectively. When the BESS reaches either upper or lower limit, the BESS is turned off temporarily. All system modeling and simulations in this study are done using MATLAB software and forward backward sweep distribution load flow program [23], [24]. Furthermore, BESS optimized with FA and GSA is included in this paper to validate the effectiveness of EOFA in BESS sizing. Also, BFA and QBGSA are used in obtaining the optimal BESS location so as to validate the effectiveness of QBFA in BP. The parameter setting such as population size, the number of maximum iteration, and some parameters from the optimization algorithms are decided through trial and error procedure, and experimentation depends on the size of the system, the complexity of the objective functions, performance of the optimization algorithms, and also the time taken for the optimization process to be completed. For the BP, the maximum iteration number and the population size, n in all algorithms is set to be 50 and 20 respectively for QBFA, BFA, and QBGSA. Meanwhile, for the optimization process in obtaining the hourly optimal BESS output power, the maximum iteration number and the population size for all three algorithms are set to be 50 and 10 respectively, while the parameters are assigned to be 100 and 50 respectively for all three algorithms, namely EOFA, GSA, and FA, for the optimization process in attaining the optimal BESS capacity.

A. BESS Placement and Sizing for Power System with Two PVDG

In this case study, single BESS is to be placed in the power system with two PVDG installed at Bus 21 and Bus 61 respectively. The optimal locations of the BESS are obtained using the discrete binary version of optimization algorithms. Bus 13 is chosen as the optimal location to place the BESS where it is located between the two PVDG buses. It can be observed that the BESS is required to be placed as close as possible to the PVDG bus in order to get the best performance in controlling the voltage fluctuation. Besides, Fig. 3 illustrates the performance of the algorithms in terms of convergence rates. The number of iteration taken to converge is analyzed using a box plot with 20 repetitions of data. It can be concluded that QBFA has better performance than the other algorithms since the first and the third quartile of the QBFA data lean toward the minimum solution with a narrow inter-quartile range.

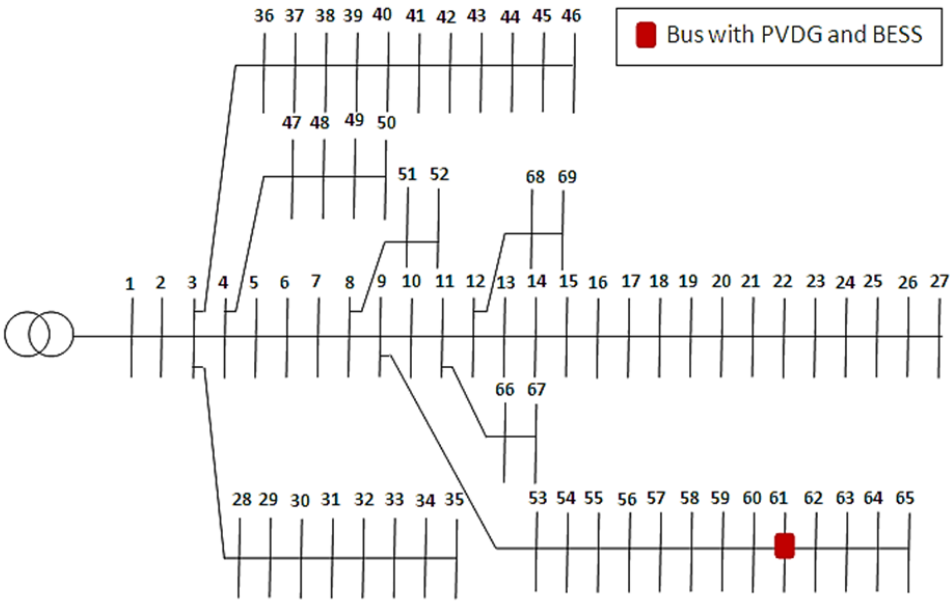


Fig. 2 Single-line diagram of the 69-bus distribution system with a single PVDG at bus 61

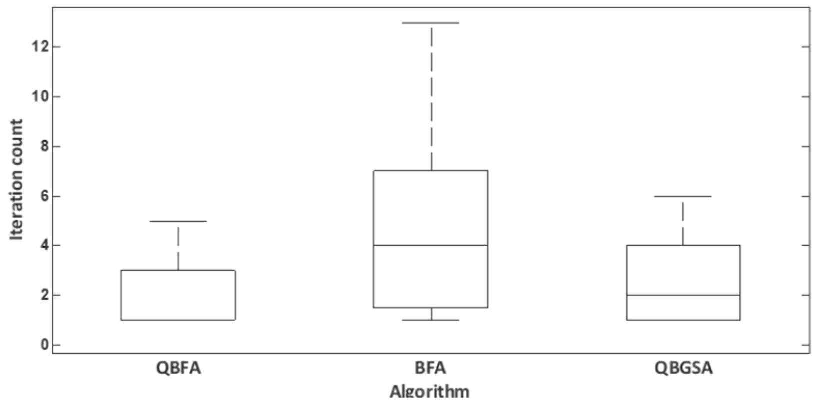
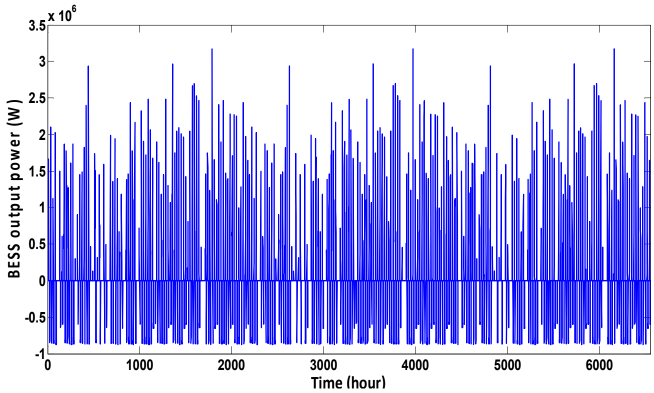
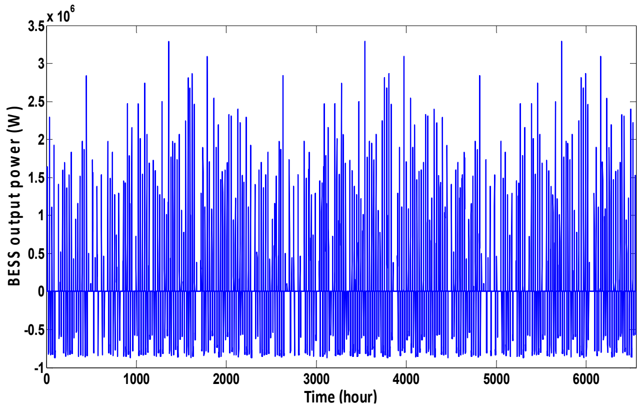


Fig. 3 Convergence rates of QBFA, BFA, and QBGSA in obtaining optimal BESS locations in power system with two PVDG and single BESS for h=10

The performances of EOFA, FA, and GSA in getting the optimal BESS sizes for single BESS located at Bus 13 are analyzed as follows. Fig. 4 presents the hourly BESS charging or discharging powers at BESS buses in the 69-bus system considering the SOC of optimal BESS size obtained from all three algorithms. Fig. 5 illustrates the SOC for EOFA, FA, and GSA. In the figure, each red marker (*) denoted the particular hour where the BESS was turned off. By taking the SOC constraint into account, the BESS was turned off for a total of 2566 hours, 2464 hours, and 2440 hours for EOFA, FA, and GSA respectively while the optimal BESS size obtained were 6.32 MWh, 6.30 MWh, and 6.28MWh, respectively. From the result, it can be noticed that the BESS off-time increases when the BESS is located far from the PVDG buses. This is due to the greater output power required to control the voltage rise problem at PVDG buses. Besides, the optimal BESS capacity and the BESS off-time obtained by using EOFA give the greatest values among all algorithms. It seems like EOFA does not perform well in this case. However, the BESS capacity and the BESS off-time are not the only factors to determine the performance. The performance should be further analyzed by observing the voltage profiles before and after the BESS is installed.



(a)



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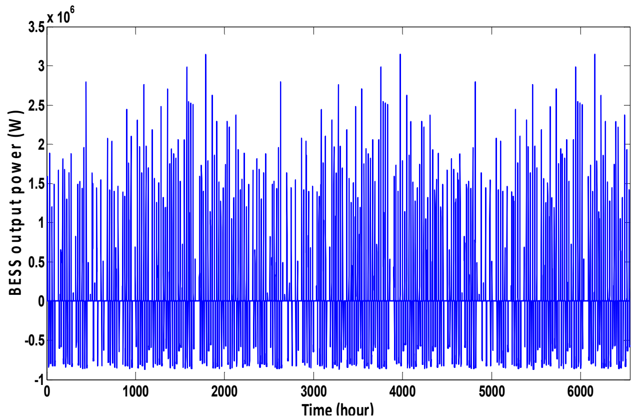
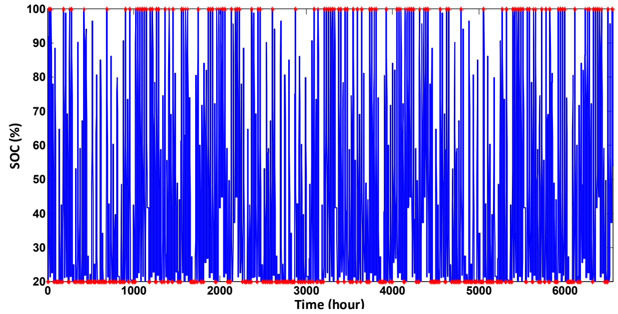
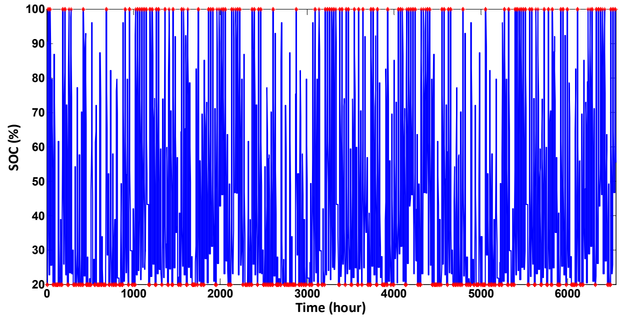


(c)

Fig. 4 Hourly BESS output power for optimal BESS size obtained with (a) EOFA, (b) FA and (c) GSA for two PVDG installed power system with single BESS



(a)



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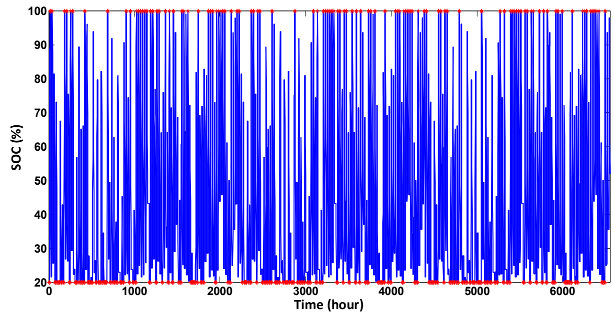


(c)

Fig. 5 SOC for optimal BESS size obtained with (a) EOFA, (b) FA and (c) GSA for two PVDG installed power system with single BESS

At the same time, Fig. 6 shows the comparison of the voltage profile at the PVDG buses (Bus 21 and Bus 61) with and without BESS for 6552 hours. Each red marker (*) in the figure indicates the voltage value for a particular hour that exceeds 1.05 p.u. It can be observed that at Bus 21, most of the voltage values fall between the range for EOFA optimized BESS size with a total of 239 hours out of 6552 hours (3.65%) for the voltage values exceed 1.05 p.u... Meanwhile, the total number of hours for the voltage values exceeding 1.05 p.u. for FA and GSA optimized BESS size is 533 hours (8.13%) and 504 hours (7.69%), respectively. It is obvious that EOFA has the best performance in mitigating voltage rise problem at this bus. Apart from that, the voltage profiles at Bus 61 show that for EOFA, the voltage values exceed 1.05 p.u. for a total of 176 hours out of 6552 hours (2.69%), while for FA and GSA, the total number of hours for the voltage values exceeding 1.05 p.u. is 173 hours (2.64%) and 179 hours (2.73%), respectively. The performance of FA is slightly better than the

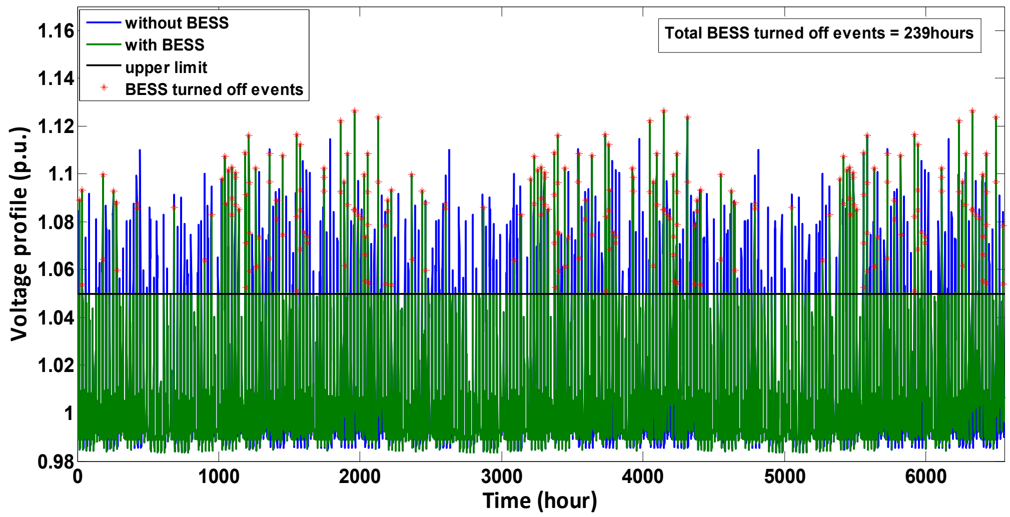
EOFA. However, by evaluating the overall performance at both buses, still EOFA shows the best overall performance comparatively to FA and GSA. Table I shows the summary and comparative results obtained from EOFA, FA, and GSA.

VI. Conclusion

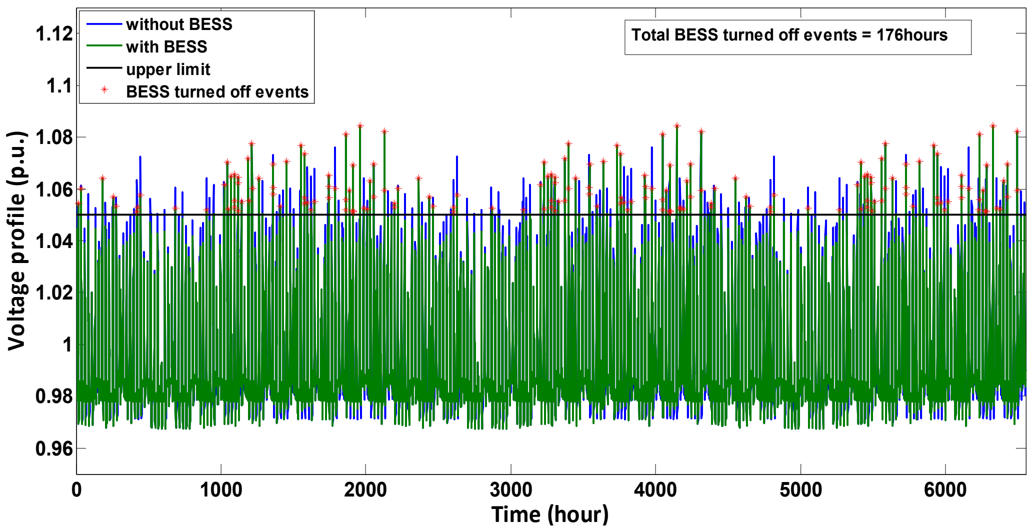
In this paper, the optimum placement and sizing of BESS in a PVDG integrated distribution system has been done in order to enhance the voltage profile of the power system. Two optimization algorithms, QBFA and EOFA, have been applied in obtaining the optimal BESS location and capacity respectively. A case study for power system with one BESS and two PVDG was studied. Generally, the BESS optimal location shows that the BESS should be placed near to PVDG buses for the best performance in improving the voltage fluctuation. On the other hand, the BESS optimal sizing was achieved where SOC was considered as the constraint. This method was tested on 69-radial-bus system, and the results were compared with QBGSA and GSA. As a conclusion, QBFA and EOFA can perform better than BFA, QBGSA, FA, and GSA in obtaining the optimal BESS location and capacity.

TABLE I
Comparison of Performance for GSA, FA and EOFA in Battery Sizing for Two PVDG Installed Power System with Single BESS

Opt. alg.	PV size (MWp)		Max load (MW)	Min load (MW)	BESS cap. (MWh)	BESS off-time (hr)	Total number of hours the voltage exceeding 1.05p.u.			
							With BESS (hr)		Without BESS (hr)	
	Bus 21	Bus 61					Bus 21	Bus 61	Bus 21	Bus 61
GSA	3.21	3.21	1.52	0.61	6.28	2440	504	179	987	327
FA	3.21	3.21	1.52	0.61	6.30	2464	533	173	987	327
EOFA	3.21	3.21	1.52	0.61	6.32	2566	239	176	987	327



(a)



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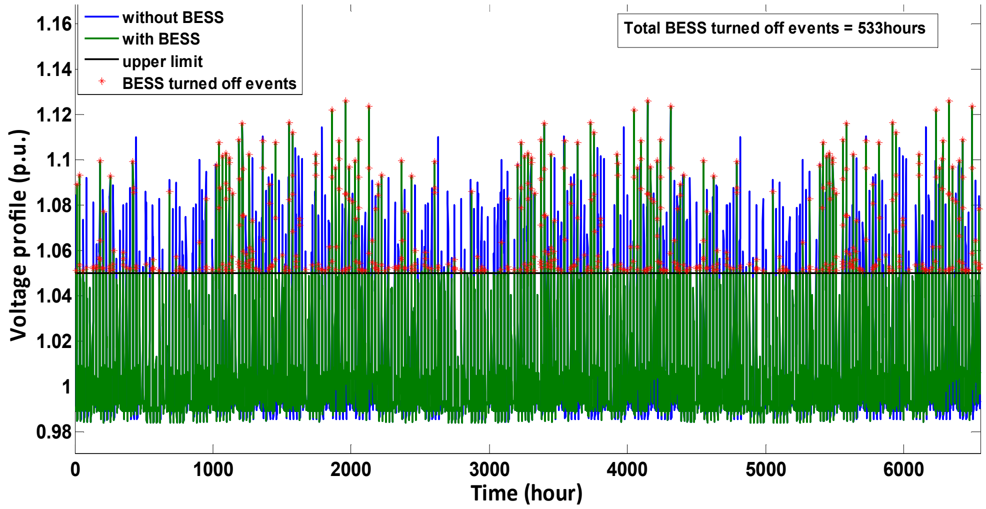
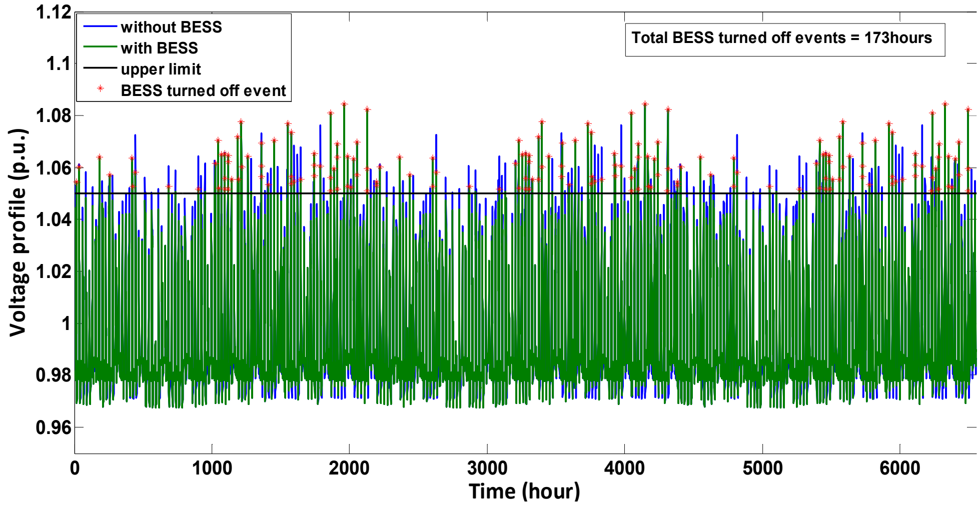
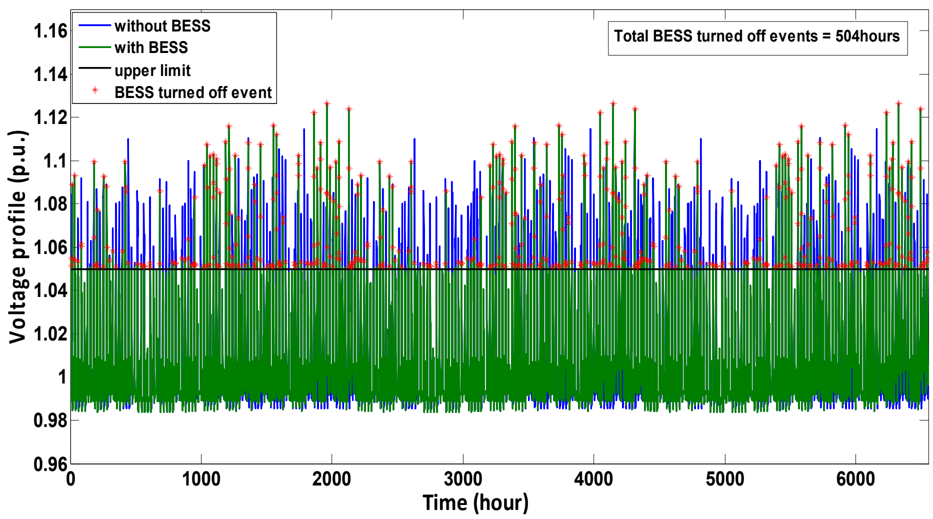

without BESS
with BESS
upper limit
BESS turned off events
Total BESS turned off events = 533hours
Voltage profile (p.u.)
Time (hour)
1.16
1.14
1.12
1.1
1.08
1.06
1.04
1.02
1
0.98
0
1000
2000
3000
4000
5000
6000

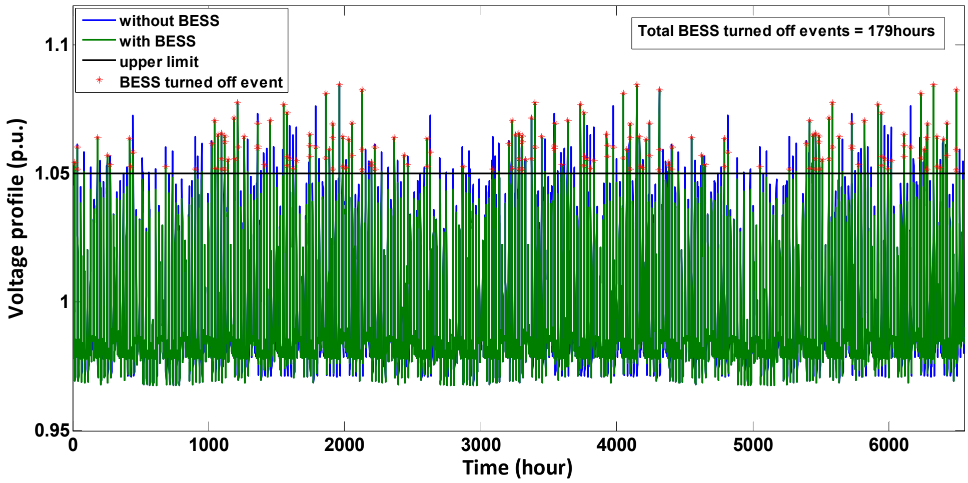
(c)


without BESS
with BESS
upper limit
BESS turned off event
Total BESS turned off events = 173hours
Voltage profile (p.u.)
Time (hour)
1.12
1.1
1.08
1.06
1.04
1.02
1
0.98
0.96
0
1000
2000
3000
4000
5000
6000

(d)


without BESS
with BESS
upper limit
BESS turned off event
Total BESS turned off events = 504hours
Voltage profile (p.u.)
Time (hour)
1.16
1.14
1.12
1.1
1.08
1.06
1.04
1.02
1
0.98
0.96
0
1000
2000
3000
4000
5000
6000

(e)



(f)

Fig. 6 Comparison of voltage profile with and without optimal BESS size obtained with: EOFA with PVDG placed at (a) Bus 21 and (b) Bus 61, FA with PVDG placed at (c) Bus 21 and (d) Bus 61, GSA with PVDG placed at (e) Bus 21 and (f) Bus 61 for two PVDG installed power system with single BESS

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