Hindawi
Journal of Engineering
Volume 2020, Article ID 8131952, 10 pages
https://doi.org/10.1155/2020/8131952

Research Article

Power Prioritization and Load Shedding in an Island with RESs Using ABC Algorithm

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Received 23 January 2020; Accepted 11 March 2020; Published 13 April 2020

Academic Editor: Kamran Iqbal

The main aim of a power utility company is to supply quality and uninterrupted power to customers. This becomes a growing challenge as the continued increase in population calls for proportional increase in power supply to additional loads. If not well planned, this steady increase in power demand can lead to voltage collapse and eventual power blackouts. In instances where power demand exceeds generation within islanded microgrid or due to an occurrence of a contingency, optimum load shedding should be put in place so as to enhance system security and stability of the power system. Load shedding is traditionally done based on undervoltage measurements or underfrequency measurements of a given section of the grid. However, when compared with conventional methods, metaheuristic algorithms perform better in accurate determination of optimal amount of load to be shed during a contingency or undersupply situations. In this study, an islanded microgrid with high penetration of Renewable Energy Sources (RESs) is analyzed, and then Artificial Bee Colony (ABC) algorithm is applied for optimal load shedding. The results are then compared with those of Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and GA-PSO hybrid. Both generation and overload contingencies are considered on a standard IEEE 30-bus system on a MATLAB platform. Different buses are assigned priority indices which forms the basis of the determination of which loads and what amount of load to shed at any particular time.

1. Introduction

Globally, energy demand has been steadily increasing as a result of increase in population and industrial and economic growth in various sectors [1]. Hence, in order to provide energy to this steady increase in power demand, clean RESs distributed generators (DGs) are being installed to operate either in grid connected or islanded modes. These sources are preferred because they are environmentally friendly and assist in reducing the cost of transmission line construction. However, these DGs may not adequately meet the load requirements within the island in case of a contingency that can lead to loss of mains.

In order to ensure there is continuity of supply of power to important loads and maintain the system stability, utility companies resort to optimal shedding of loads within the island based on the given criteria guided by IEEE 1547 standard [2, 3]. Optimal shedding of some loads within the island is used to minimize the difference between the connected active and reactive load and the power that the connected RESs can supply [4]. Through the load shedding action, the disturbed MG is made to settle to a new different equilibrium state. Undervoltage Load Shedding (UVLS) and Underfrequency Load Shedding (UFLS) are the criteria mainly used for load shedding [5]. Through the shedding of some loads, the perturbed system is forced to settle to a new state of equilibrium [6]. However, for any method of load shedding to be successful, the amount to be shed should be optimal, at the correct location and be done on the right time so as to prevent any possibility of voltage instability and also avoid losing the customer trust in the utility company [7, 8]. For improved accuracy in the determination of the amount of load to be shed in a given island, real-time monitoring and control of the system is preferred. However, this is a costly undertaking especially for small grids.

A number of studies have been done on UFLS as can be seen in [9–11]. In this method, frequencies are measured at a point of interest and compared with the set thresholds. If the values exceed the limits, then some loads will be shed to equalize power generation and supply. It is shown that automatic UVLS performs far much better than manual UVLS during emergencies in [12]. In [13], a Comprehensive Learning Particle Swarm Optimization (CLPSO) method in the optimal subdivision of a section of the grid when there is loss of mains is suggested. Power supply and demand are then balanced by optimally shedding some loads from each islanded subsection. In [14], optimal load shedding is achieved using Artificial Neural Network (ANN) algorithm. In [15], loads were classified into noncritical and critical loads before optimally shedding them in case generation is less than loads. However, this method takes a lot of time to complete the load shedding process as the algorithm has to go through the two classes of loads. In [5], the author used a combination of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to find an optimal amount of load to be shed in smart grids under stress. The sum of squares of the difference between the connected loads and the supplied power and ABC algorithm to arrive at the optimal amount of load to be shed during a contingency is proposed in [6]. However, in this case, the priority of important loads and buses was not considered in the study before shedding of the loads. In [16], the author evaluated an implementation of optimal UVLS in competitive electricity markets using Particle Swarm Optimization. In [17], the authors developed an optimal load shedding model using Particle Swarm Optimization in order to control voltage instability in a system. However, this approach has a long convergence time since it comprises of multiobjectives. A hybrid of GA and PSO is proposed in [18] for load shedding. However, this method leads to suboptimal load shedding since it does not consider voltage instability constraint. There is continued research being undertaken on the usage of computational intelligence algorithms such as fuzzy logic, genetic algorithms, particle swarm optimization among others. The merits and drawbacks of these methods are briefly discussed in [9].

There is need for additional studies that involves high penetration of RESs with the aim of minimizing the total amount of load to be shed during a contingency. There is also need to improve the voltage profile of the system and improve the security of the power system so as to reduce the possibilities of the system being overloaded. This is because a technology that sheds more than or less than the required optimal load amount will not control the instability of the voltage but can instead lead to the collapse of the system voltage and frequency [5].

In case of a contingency that leads to a section of the grid operating as an island, the isolated generators should operate in frequency and voltage control mode to provide constant voltage to local loads so as to maintain the voltage and frequency within the island. Otherwise, this may affect the power system operation and pose safety risks to the maintenance personnel [19]. In this paper, loads connected to the different buses are assigned priority indices based on Fast Voltage Stability Index (FVSI). Then, ABC algorithm is used to evaluate the amount of load to be shed to ensure there is balance between power generated and connected loads within an islanded microgrid.

The rest of the paper is structured as follows. Section 2 introduces the formulation of the problem for the proposed load prioritization and shedding scheme using ABC algorithm, while Section 3 discusses the methodology used in this approach. The study simulation results and their discussions are presented in Section 4. And finally, the paper conclusion is highlighted in Section 5.

2. Problem Formulation

2.1. Structure of Islanded MG. Figure 1 is the structure of an islanded MG that was used in this study. It comprises RESs supplying loads locally, while the rest of the system is connected to the main grid through a transformer.

2.2. Load Prioritization. In this study, loads and buses were assigned priority indices which determines their order of shedding in case of a contingency. Fast Voltage Stability Index (FVSI) was used to determine the weak buses and rank them in order of their priority as expressed by the following equation:

$$\mathrm{FVSI} = \frac{4Z^2 Q_r}{V_i^2 X}, \tag{1}$$

where X is the reactance of the line, V_i^2 is the square of the sending end voltage, Z is the impedance of the line, and Q_r is the receiving end reactive power.

FVSI is an essential tool that helps in identifying weak buses and lines that are critically loaded and how close the system is to voltage collapse [20]. It is proven to be a good indicator for voltage stability in a power system. It is a sensitive index and hence an indicator of the best location to perform load shedding. This information is useful when making decisions on which loads and buses to shed in case of a contingency. The higher the value of FVSI, the weaker the bus or line. Other indices include New Voltage Stability Index (NVSI), LQP, and Lmn. FVSI is the simplification of Lmn, while LQP is the simplification of NVSI. FVSI, Lmn, and LQP are found to be sensitive to the changes in reactive power, while NVSI is prone to the changes in real power load [21].

2.3. Load Shedding. In this study, ABC algorithm was applied in shedding loads. This system is designed to calculate power imbalance in the island and then determine the minimum amount of load to shed and ensure as many loads as possible remain connected to the system.

The main objective when microgrids operating as islands due to loss of mains is to ensure the supplied power and

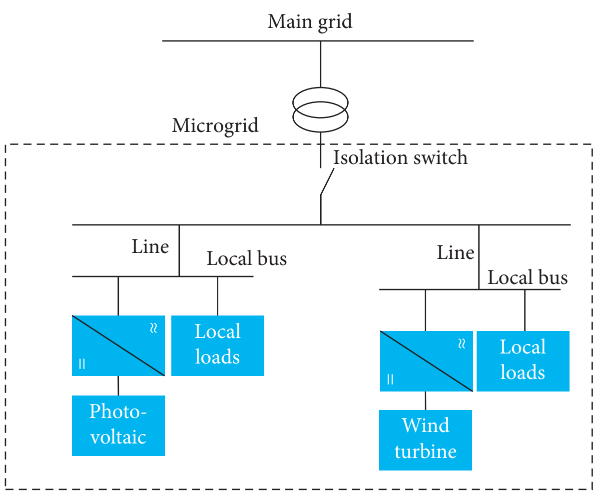

Figure 1: Structure of an islanded MG.

connected loads are equal, hence adequately supplied. This can be expressed by the following function:

$$P = \sum_{i=1}^{N} \left[\alpha_i \left(P_{di} - \overline{P_{di}} \right)^2 + \beta_i \left(Q_{di} - \overline{Q_{di}} \right)^2 \right], \quad (2)$$

where P is the power to be shed, P_{di} and Q_{di} are the active and reactive powers that are supplied to the load, N is the total number of the buses in the system, $\overline{P_{di}}$ and $\overline{P_{di}}$ are active and reactive loads connected, and α_i and β_i are weights associated with bus priority in the system.

At the same time, the power losses in the system should be minimal as expressed by the following equation:

$$\text{Loss} = \min \left[\sum_{k=1}^{N_{\mathrm{TL}}} G_k \left(V_i^2 + V_j^2 - 2 V_i V_j \cos \alpha_{ij} \right) \right], \quad (3)$$

where G_k is the conductance of the k^{th} branch connected between the i^{th} and j^{th} buses.

The system equality and inequality constraints can be expressed by (4)–(8). Equations (4) and (5) are equality constraints for active and reactive powers, whil (7) and (8) are constraints for minimum and maximum powers in the system:

$$P_{G-D} = V_i \sum_{j=1}^{N} V_j \left(G_{ij} \cos \delta_{ij} + B_{ij} \cos \delta_{ij} \right), \quad (4)$$

$$Q_{G-D} = V_i \sum_{j=1}^{N} V_j \left(G_{ij} \cos \delta_{ij} - B_{ij} \cos \delta_{ij} \right), \quad (5)$$

$$V_{gi}^{\min} \le V_{gi} \le V_{gi}^{\max}, \quad (6)$$

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max}, \quad (7)$$

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max}, \quad (8)$$

where G_{ij} is the conductance between bus i and j, V_{gi} is the bus voltage, P_{gi} and Q_{gi} are the active and reactive power generated at bus i, and P_{G-D} and Q_{G-D} are the active and reactive power flow between generation and demand points.

2.4. ABC Algorithm. Artificial Bee Colony (ABC) algorithm is based on the behavior of the bees colony when looking for quality food sources (nectar). It is a metaheuristic optimization algorithm that was proposed by Karaboga from Erciyes University of Turkey [22]. The algorithm has been applied to solve a number of optimization problems, especially in engineering [23]. This is because it is robust and can be implemented very easily. Unlike other stochastic methods of optimization, this algorithm has excellent performance in exploration. However, it performs poorly when it comes to exploitation.

This algorithm is divided into three groups as was observed from the behavior of a swarm of bees as follows.

(i) *The Employed Bees Group*. This group is equal to the possible solutions of the problem. They continuously update the rest of the bees in the hive about the quantity, quality, and the direction of the food source through the performance of a waggle dance. The duration of the waggle dance depends on the quality and quantity of food source.

(ii) *The Onlooker Bees Group*. These are a group of bees which pick on a food source to exploit based on the information provided by the employed bees waggle dance.

(iii) *The Scout Bees Group*. The work of this group is to look for new sources of food for exploitation.

2.5. ABC Control Parameters. The parameters of this algorithm are set as follows:

(i) NP: this is the total number of the bee population.

(ii) The total number of the available sources of food is set as *NP*/2, that is, half of the bee colony size.

(iii) Limit: this is the number of trials for a given source of food before an employed bee abandons it and becomes a scout bee.

(iv) Max cycle: this is the number of foraging cycles before an algorithm stops.

The algorithm can be summarized into four steps as elaborated below.

(1) Initialization of the artificial bee stage where the bee colony size, the number of food sources, and limit of iterations parameters are set. The fitness of a food source can be expressed by the following equations:

$$(\text{fitness})_i = \frac{1}{1 + f_i}, \quad \text{if } f_i \ge 0, \quad (9)$$

$$(\text{fitness})_i = 1 + \text{abs}(f_i), \quad \text{if } f_i \le 0. \quad (10)$$

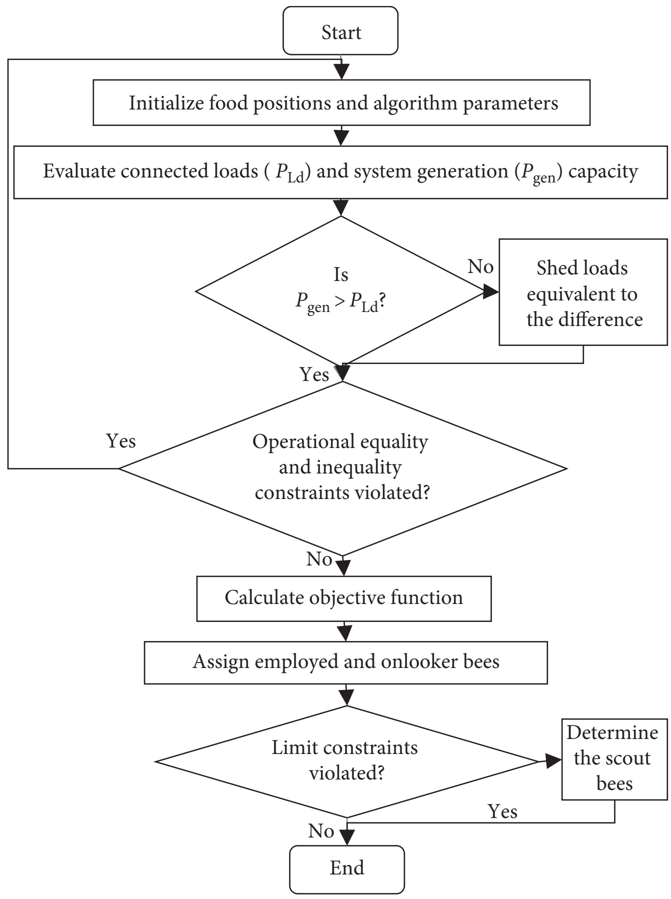

Figure 2: System flow chart.

(2) The employee bee stage where a new fitness value is evaluated and compared with the previous one. The two values are compared and the inferior one is discarded. The new food sources are arrived at using the following equation:

$$V_{i,j} = X_{i,j} + Q_{i,j}\left(X_{i,j} - X_{k,j}\right). \tag{11}$$

All food sources have the potential of being selected based on the fitness value of employed bee i, j as shown by the following equation:

$$P_i = \frac{\mathrm{fit}_i}{\sum_{j=1}^{SN} \mathrm{fit}_j}. \tag{12}$$

(3) The onlooker bee stage where the onlooker bees decide which food sources to exploit based on the probability as in stage 2 above.

(4) The scout bee stage where if the food source does not improve after a set number of trials, that food source is left and the bee becomes a scout. The scout bee then goes out to search for new food sources randomly using the following equation:

$$X_{i,d} = X_d^{\min} + r\left(X_d^{\max} - X_d^{\min}\right). \tag{13}$$

(5) The food with highest value of fitness is selected at this stage and printed.

3. Methodology

This proposed prioritization and optimal load shedding for MGs with RESs using ABC algorithm was done on the standard IEEE 30-bus system. This system has six generators located at buses 1, 2, 5, 8, 11, and 13; two static VAR sources are located at buses 10 and 24, thirty buses, forty-one lines, four tap changing transformers at lines 6–9, 6–10, 4–12, and 28–27 branches and twenty-one loads. It has a total of 283.400 MW and 126.200 MVAR base load.

First, the connected loads and buses were assigned priority indices to be used to determine which loads to shed based on their priority. This was based on FVSI values. Using ABC algorithm, the optimal amount of load to be shed within an island was determined. Both loss of generation and overload contingencies were analyzed using this algorithm. In each of the test cases, Newton–Raphson load flow was done to give the status of the bus voltage and line currents.

The simulation was carried out on MATLAB/SIMULINK platform on an AMD 4C + 6G 2.10 GHz processor with 4 GB RAM. The flow chart in Figure 2 was used in this study.

Table 1: Weak buses ranking using FVSI.

Bus number	FVSI	Rank	Loading limit
5	0.6820	1	149.778
10	0.2205	2	9.222
30	0.1900	3	16.854
24	0.0987	4	13.833
7	0.0855	6	36.252

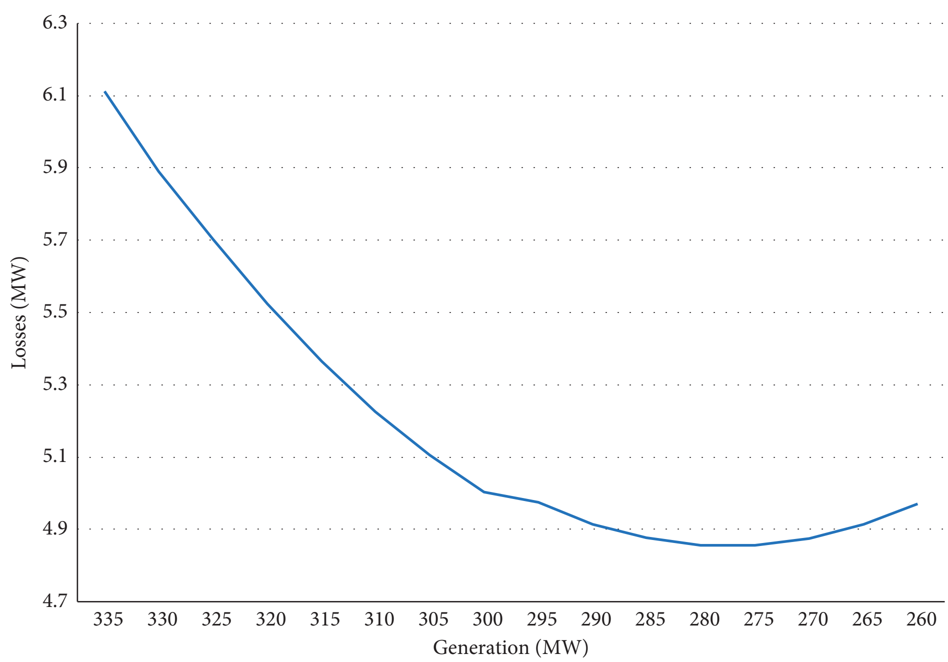

Figure 3: Line losses versus generation deficit.

4. Simulation Results and Analysis

Using FVSI, the weak buses with their maximum loading limit were identified and arranged as shown in Table 1.

4.1. Generation Contingencies. Loss of generation scenarios ranging from 0 to 75 MW at intervals of 5 MW were simulated while keeping the load demand constant at 328.4 MW. The line losses, convergence characteristics, and the amount of load to be shed by ABC algorithm at each instant were observed. This is as shown by Figures 3–7.

Figure 3 shows the system loss for the 30-bus system for a generation deficit contingency. The active power generation is varied from 335 MW to 260 MW at intervals of 5 MW. From the observation, this approach shows a considerable reduction in power losses. However, it shows an increase in losses as the generation deficit increases.

Using this algorithm, the suggested amount of load to be disconnected so as to bring the system to a stable operating point was evaluated. This was recorded as shown in Figure 4.

Figure 5 shows the convergence characteristic for a 283.4 MW load with 190 MW generation. The system converges after 23 iterations.

Keeping the load demand constant at 328.4 MW, the amount of load to be shed under various generation contingencies and their appropriate buses were monitored. This is as shown in Table 2.

Figure 6 is the generation contingency characteristics when power generation is reduced from 322 to 290 MW. From the observation, the suggested load to be shed increases proportionally from 14.844 MW to 46.002 MW.

The line losses decrease as the generation contingency increases. This is evidenced in Figure 7 where the losses are 8.484 MW when the power of 322 MW is being produced and reduces to 7.602 at 290 MW power generation.

4.2. Overload Contingencies. To test the performance of the proposed approach in load shedding, the system was subjected to an overloading contingency of 85.02 MW on weak buses just like the case in [8]. This approach suggests a total of 30.491 MW of load to be shed. This is shown in Figure 8. This indicates that the approach performs better than particle swarm optimization (PSO) but not as good as genetic algorithm (GA) and GA-PSO hybrid working on the same conditions. GA-PSO hybrid exploits the advantages of both GA and PSO and overcoming of individual drawbacks of each of these algorithms applied separately. Hence, it gives the

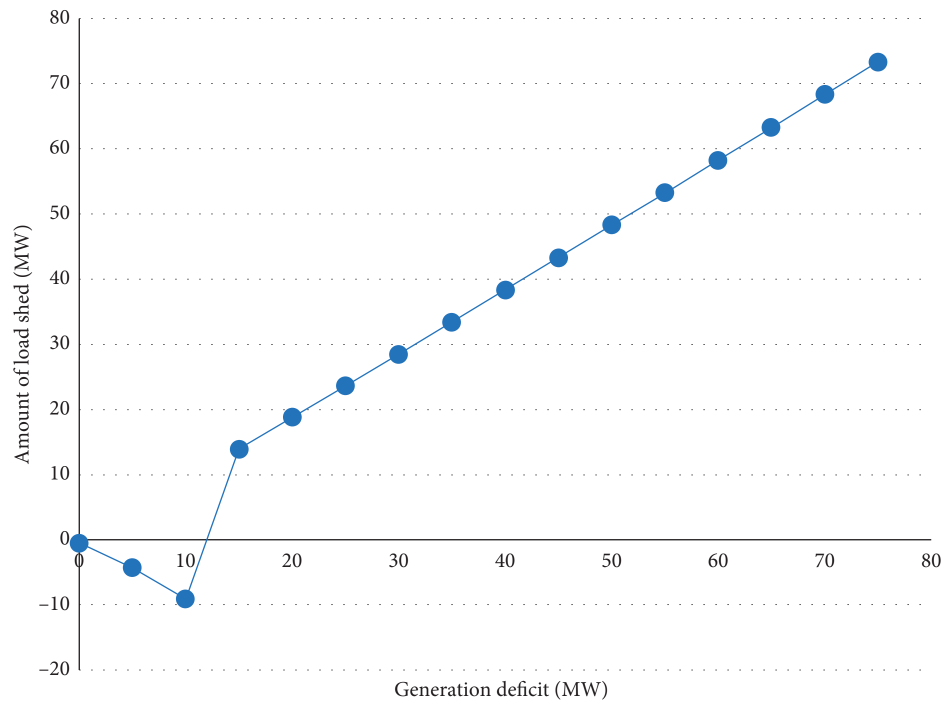

FIGURE 4: Load to shed versus generation deficit.

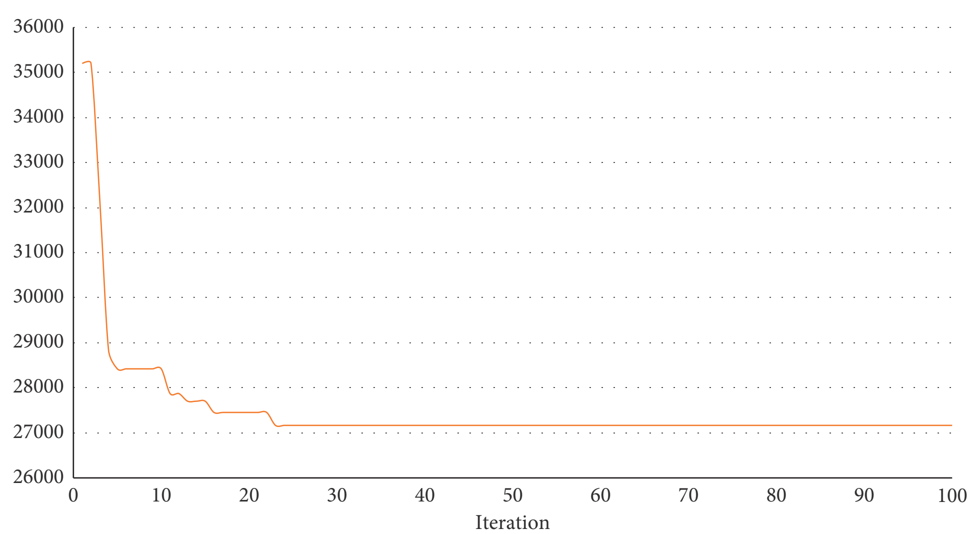

FIGURE 5: Convergence characteristics at 315 MW generation and 328.4 MW load.

lowest amount of load to shed in this analysis. Similarly, it is expected that the overall efficiency will be greatly improved with the GA-ABC hybridization and hence have even less amount of load to be shed when put into the same application.

Figure 9 shows the voltage magnitude characteristics during the contingency and after load shedding using ABC algorithm in a standard IEEE 30-bus system. These are compared against the voltage characteristics for normal operating condition. This shows that load shedding using ABC algorithm can reliably restore deteriorating voltages close to normal operating conditions.

Figure 10 shows an observation of the line active and reactive power losses before, during the overload contingency, and after load shedding. When compared to the losses recorded by [6], this approach records lower losses, which is in line of minimizing system losses and load to be shed. From the figure, a total of 17.318 MW and 19.734 MVAR losses are recorded after load shedding using this approach which is close to 17.599 MW and 22.244 MVAR that is recorded during normal operating condition. 22.719 MW and 42.639 MVAR losses are recorded during overload contingency.

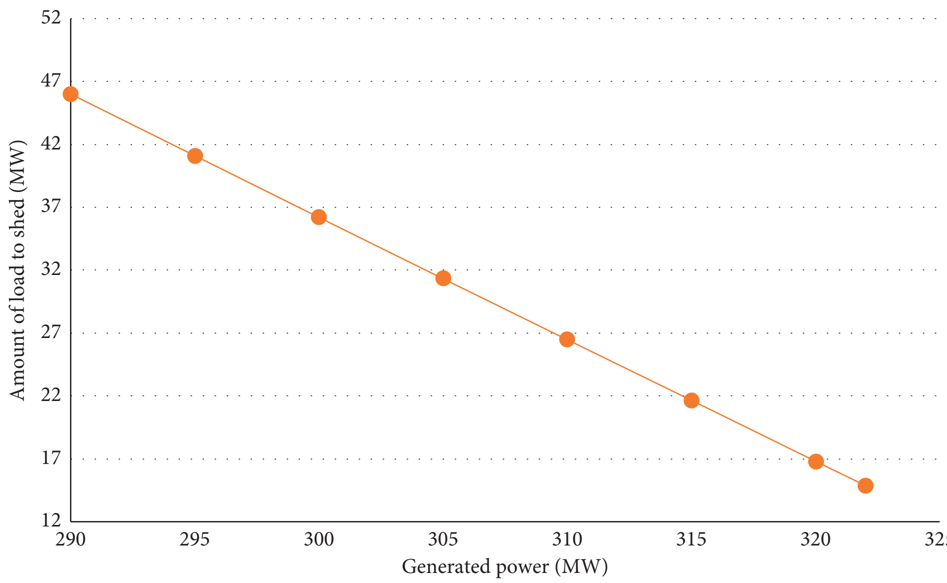

Figure 6: Generation contingency characteristics.

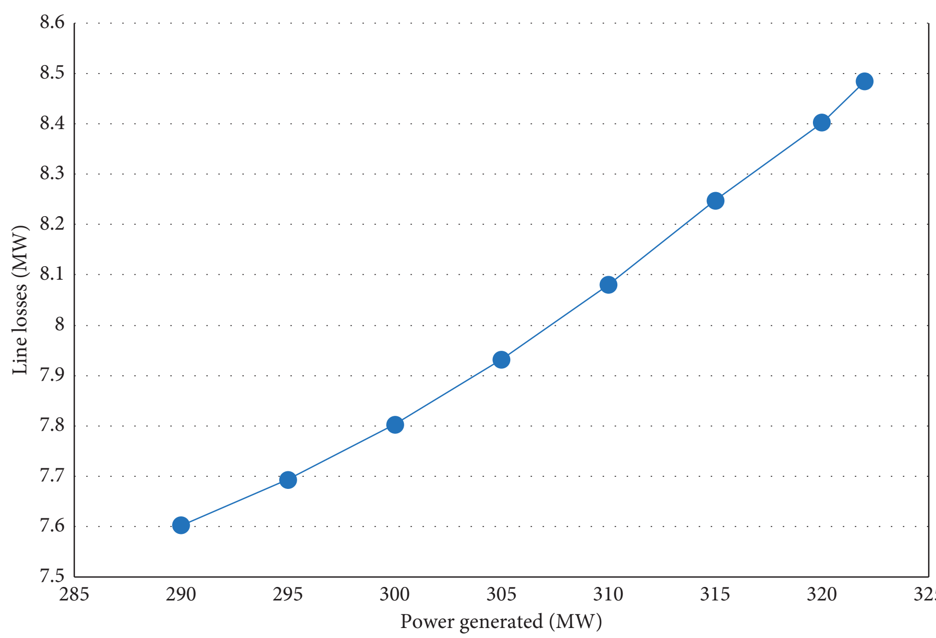

Figure 7: Losses versus generated power.

Table 2: Load to be shed under different generation contingencies.

Generated power (MW)	Losses (MW)	Amount of load to shed (MW)	Bus to shed
322.000	8.484	14.884	30
320.000	8.402	16.802	30 and 29
315.000	8.248	21.648	30 and 29
310.000	8.080	26.480	30, 29, and 26
305.000	7.932	31.332	30, 29, 26, and 24
300.000	7.803	36.203	30, 29, 26, and 24
295.000	7.693	41.093	30, 29, 26, and 24
290.000	7.602	46.002	30, 29, 26, 24, and 23

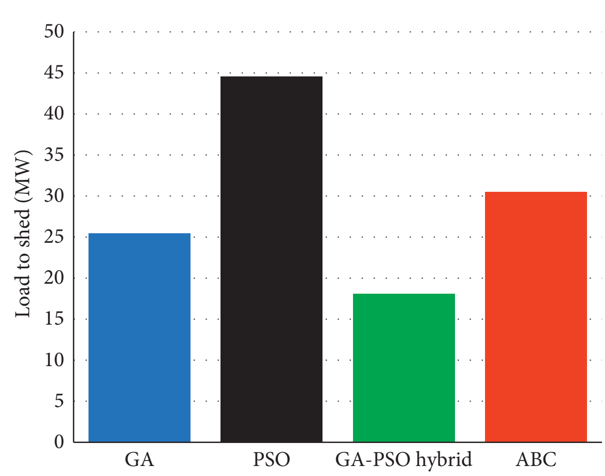

Figure 8: Amount of load to shed comparisons.

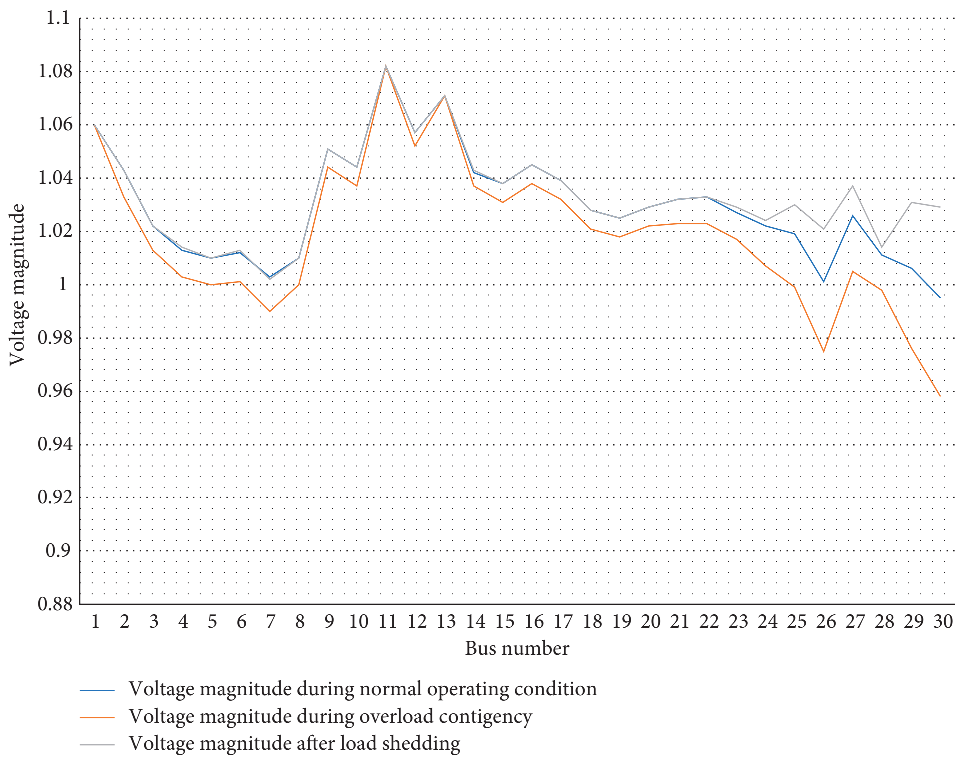

Figure 9: Bus voltage measurement.

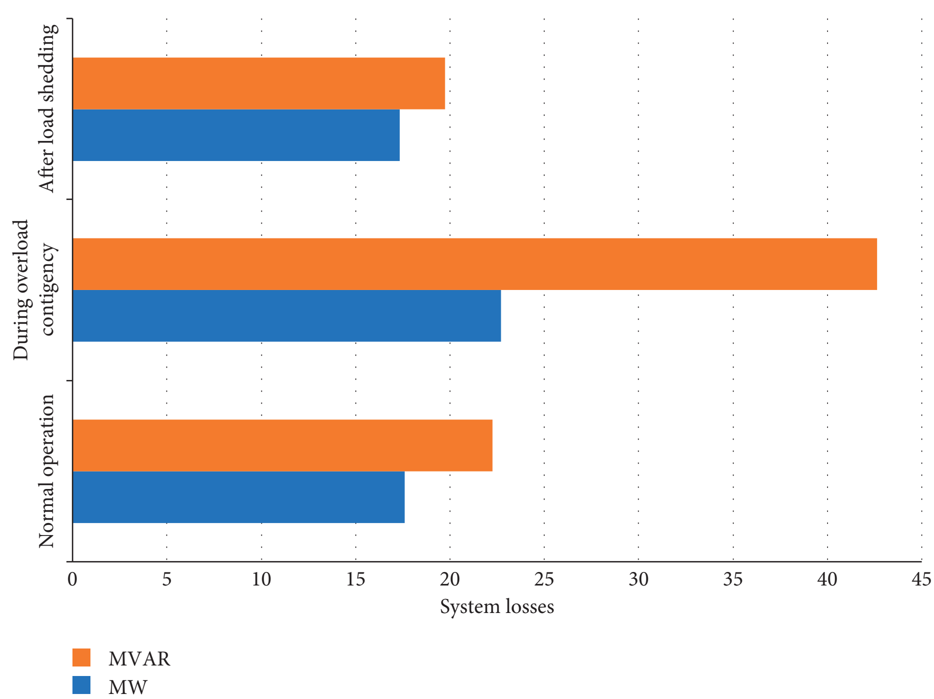

Figure 10: System losses.

Table 3: Overload contingency characteristics.

Connected load (MW)	Excess load to shed (MW)	Buses to shed
335.4	9.550	
340.4	14.603	30
345.4	19.664	30 and 29
350.4	24.733	30 and 29
353.4	27.778	30, 29, and 26
358.4	32.800	30, 29, 26, and 24
363.4	37.880	30, 29, 26, and 24
368.4	42.969	30, 29, 26, and 24
373.4	48.066	30, 29, 26, 24, and 23

In order to shed as minimal load as possible based on the priority attached, Table 3 shows the amount of load to be shed from respective buses based on their bus priority index.

5. Conclusion

In this study, load prioritization and optimal shedding using ABC algorithm have been presented for islands with RESs. IEEE 30-bus system was used to show the possibility of this approach and its validation. As it can be seen from these results, the proposed load shedding strategy was applied satisfactorily, and at the same time the objective function was minimized while satisfying the system's operational constraints. The results obtained also show that as minimal power as possible can be shed in case of a contingency, that can lead to islanding operation. This is due to superior convergence characteristics of ABC algorithm in optimal load shedding in MGs with high penetration of RESs. It can, therefore, be concluded that this approach can be used in the determination of minimal amount to be shed to prevent voltage collapse and frequency instability.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research was supported by the Pan African University Institute for Basic Sciences, Technology and Innovation in the form of a postgraduate student research funding.

References

[1] M. Dreidy, H. Mokhlis, and S. Mekhilef, "Application of meta-heuristic techniques for optimal load shedding in islanded distribution network with high penetration of solar PV generation," *Energies*, vol. 10, no. 2, 150 pages, 2017.

[2] IEEE, *IEEE Guide for Design, Operation, and Integration of Distributed Resource Island systEms with Electric Power Systems*, IEEE, Piscataway, NJ, USA, 2011.

[3] L. Bin, W. Jingpeng, B. Hailong, and Z. Huiying, "Islanding detection for microgrid based on frequency tracking using extended kalman filter algorithm," *Journal of Applied Mathematics*, vol. 2014, Article ID 186360, 11 pages, 2014.

[4] S. Fatma and K. Salah, "Optimal load shedding for voltage collapse prevention using improved harmony search algorithm," in *Proceedings fo the Nineteenth International Middle East Power Systems Conference (MEPCON)*, Menoufia University, Cairo Egypt, pp. 19–21, December 2017.

[5] M. L. Raja, W. M. Mohd, N. A. Muhammad, A. J. Touqeer, S. Suhaib, and K. P. Manoj, "An improved algorithm for optimal load shedding in power systems," *Energies*, vol. 11, pp. 1–16, 2018.

[6] R. Mageshvaran and T. Jayabarathi, "Steady state load shedding to prevent blackout in the power system using artificial bee colony algorithm," *Jurnal Teknologi*, vol. 74, no. 1, pp. 113–124, 2015.

[7] M. L. Raja, W. M. Mohd, and N. A. Muhammad, "A critical review of the state-of-art schemes for under voltage load shedding," *International Transactions on Electrical Energy Systems*, vol. 29, no. 5, pp. 1–26, 2019.

[8] M. L. Raja, W. M. Mohd, K. P. Manoj, and N. Q. Kashif, "Optimal load shedding under contingency conditions using voltage stability index for real-time applications in power systems," *ARPN Journal of Engineering and Applied Sciences*, vol. 13, no. 22, pp. 8693–8704, 2018.

[9] J. A. Laghari, H. Mokhlis, A. H. A. Bakar, and H. Mohamad, "Application of computational intelligence techniques for load shedding in power systems: a review," *Energy Conversion and Management*, vol. 75, pp. 130–140, 2013.

[10] J. Tang, J. Liu, F. Ponci, and A. Monti, "Adaptive load shedding based on combined frequency and voltage stability assessment using synchrophasor measurements," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 2035–2047, 2013.

[11] J. Jafar, M. Saad, M. Hazlie, L. Javed, and B. Ola, "Application of hybrid meta-heuristic techniques for optimal load shedding planning and operation in an islanded distribution network integrated with distributed generation," *Energies*, vol. 11, no. 5, pp. 1–25, 2018.

[12] A. Estebsari, E. Pons, T. Huang, and E. Bompard, "Techno-economic impacts of automatic undervoltage load shedding under emergency," *Electric Power Systems Research*, vol. 131, pp. 168–177, 2016.

[13] A. El-Zonkoly, M. Saad, and R. Khalil, "New algorithm based on CLPSO for controlled islanding of distribution systems," *International Journal of Electrical Power & Energy Systems*, vol. 45, no. 1, pp. 391–403, 2013.

[14] S. A. M. Javadian, M.-R. Haghifam, S. M. T. Bathaee, and M. Fotuhi Firoozabad, "Adaptive centralized protection scheme for distribution systems with DG using risk analysis for protective devices placement," *International Journal of Electrical Power & Energy Systems*, vol. 44, no. 1, pp. 337–345, 2013.

[15] J. A. Laghari, H. Mokhlis, M. Karimi, A. H. Abu Bakar, and H. Mohamad, "A new under-frequency load shedding technique based on combination of fixed and random priority of loads for smart grid applications," *IEEE Transactions on Power Systems*, vol. 30, no. 5, pp. 2507–2515, 2015.

[16] M. M. Hosseini-Bioki, M. Rashidinejad, and A. Abdollahi, "An implementation of particle swarm optimization to evaluate optimal under-voltage load shedding in competitive electricity markets," *Journal of Power Sources*, vol. 242, pp. 122–131, 2013.

[17] A. Ahmadi and Y. Alinejad-Beromi, "A new integer-value modeling of optimal load shedding to prevent voltage instability," *International Journal of Electrical Power & Energy Systems*, vol. 65, pp. 210–219, 2015.
[18] M. Ojaghi, M. Azari, and A. Valujerdi, "Robust UVLS scheme to improve transmission line performance considering interruption cost and voltage stability index," in *Proceedings of the IEEE International Conference On Industrial Technology (ICIT)*, Busan, South Korea, March 2014.
[19] M. S. Almas and L. Vanfretti, "RT-HIL implementation of the hybrid synchrophasor and goose-based passive islanding schemes," *IEEE Transactions on Power Delivery*, vol. 31, no. 3, pp. 1299–1309, 2016.
[20] R. Kanimozhi, K. Selvi, and K. M. Balaji, "Multi-objective approach for load shedding based on voltage stability index consideration," *Alexandria Engineering Journal*, vol. 53, no. 4, pp. 1–9, 2014.
[21] R. Verayiah, A. Mohamed, H. Shareef, and I. Zainal Abidin, "Performance comparison of voltage stability indices for weak bus identification in power systems," in *Proceedings of the 4th International Conference on Energy and Environment 2013 (ICEE2013)*, Selangor, Malaysia, May 2013.
[22] D. Karaboga, B. Gorkemli, C. Ozturk, and N. Karaboga, "A comprehensive survey: artificial bee colony (abc) algorithm and applications," *Artificial Intelligence Review*, vol. 42, no. 1, pp. 21–57, 2012.
[23] A. Selcuk, "A transition control mechanism for artificial bee colony (ABC) algorithm," *Computational Intelligence and Neuroscience*, vol. 2019, Article ID 5012313, 24 pages, 2019.