Mohammed Albadi[1,*], Hisham Soliman[1], Mahmood Awlad Thani[2], Ahmed Al-Alawi[1], Said Al-Ismaili[1], Ahmed Al-Nabhani[1], Haitham Baalawi[1]

J. Electrical Systems 13-4 (2017): 678-688

Regular paper

Optimal Allocation of PV Systems to Minimize Losses in Distribution Networks Using GA and PSO: Masirah Island Case Study

Journal of Electrical Systems

This study addresses the issue of photovoltaic (PV) systems optimal allocation in electric distribution network. A case study of using particle swarm optimization (PSO) and genetic algorithms (GA) is presented. The objective function of the problem is to minimize system losses while improving voltage profile. The study considers the network of Masirah Island, Oman, as a case study system. The study includes two stages. In the first stage, the test system is modeled and simulated using the MATLAB load flow toolbox. In the second stage, both PSO and GA optimization tools are used to find the optimal allocation of PV systems. Both algorithms resulted in similar values for both the objective function value and decision variables. Simulation results shows that technical real power losses represent 2.1% of the total load. However, the optimal allocation of PV systems at five buses can reduce losses by 50%.

Keywords: Loss Minimization; Photovoltaic Systems; Particle Swarm Optimization; Genetic Algorithms.

Article history: Received 14 December 2016, Accepted 2 October 2017

1. Introduction

Distributed generation (DG) units are small-scale generation facilities that are connected close to the consumers [1]. DG units can be classified into two types: fuel-based and renewable-based. Renewable-based DG units include photovoltaic (PV) systems and wind turbines. Several factors are driving the growing capacity of renewable energy in the power sector, including improvements in renewable technologies that result in lower costs, policies that encourage the utilization of renewable energy, regulations that provide better access to financing, security and environmental concerns related to other energy resources, and growing demand. It is reported that PV systems and wind turbines capacities represented about 77% of all new renewable energy installations in 2015 [2].

Several studies have demonstrated that Oman has outstanding solar and wind resources [3-7]. Although the current contribution of renewable-based DG units is small, it is expected to increase in the coming years [8]. Al Mazyounah PV project (303kW), which is connected to Al Mazyounah distribution system in May of 2015, is the first IPP PV project in Oman [8, 9]. Al Mazyounah PV system is connected to the system powerhouse the include diesel generators.

[*] Corresponding author: Sultan Qaboos University, Electrical and Computer Engineering, P.O. Box 33, Muscat 123, Oman, Email : mbadi@squ.edu.om; mohammed.albadi@gmail.com

[1] Sultan Qaboos University, Electrical and Computer Engineering

[2] Rural Areas Electricity Company, P.O. Box: 1166, Muscat 133, Oman

The large-scale deployment of DG in distribution systems introduces several issues and uncertainties related to energy security, environmental concerns, economic efficiency [10-12]. However, DG units can provide numerous benefit DG owners, utilities, and all other members of society. These benefits include, but not limited to, deferring/avoiding transmission/distribution system expansion, supporting system voltage, providing ancillary services, improving reliability, and reducing emissions [11, 13]. Moreover, the presence of any generation units, including DG, in distribution systems changes the power flow; therefore, affects power losses [9, 11, 14]. To maximize the benefits of renewable-based generation facilities in distribution systems, it is necessary to consider the size (installed capacity) and the location (point of connection).

The main contributions of the article include the followings:

- Modelling and simulating the Masirah Island power system using the MATLAB load flow toolbox.
- Optimizing size and location of the PV systems for loss minimization using Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) techniques.
- Comparing between PSO and GA performance.

Following this introduction, the article presents a short survey about the two optimization tools: GA and PSO. Section four describes the Masirah Island power system as well as network modelling and performance simulation before the installation of PV systems. Simulation results and discussions are presented in section five. In section six, the main conclusions of the study are presented.

2. Notation

The notation used throughout the paper is stated below.

AI	Artificial intelligence
DG	Distributed generation
DPS	Dhofar power system
GA	Genetic algorithms
MIS	Main interconnected system
PSO	Particle swarm optimization
PV	Photovoltaic
RAEC	Rural areas electricity company
P_i	Real power equation at bus i
Q_i	Reactive power equation at bus i
$\|V_i\|$	Voltage magnitudes at bus i in per unit
δ_i	Angle o$f\ V_i\ in\ r$adian
$\|Y_{ij}\|$	Magnitude of Y_{bus} element in per unit
θ_{ij}	Angle of Y_{bus} element in radian
$S_{L\,ij}$	Power losses in the branch i-j in per unit
X_{lb}^n	Best particle position in the current iteration
X_{gb}^n	Best particle position of all previous iterations
v_{id}^n	Speed of particle i during iteration number n in dimension index d
x_{id}^n	Position of particle i during iteration number n in dimension index d
c_1	Individual learning rate
c_2	Group learning rate

3. Optimization Techniques

To optimally allocate DG units in distribution systems, different techniques and methods have been used [15-19]. These methods include analytical techniques, classical optimization techniques, artificial intelligence (meta-heuristic) techniques, and hybrid techniques [20]. Artificial intelligence (AI) optimization methods have been used extensively in recent years. AI methods are conceptually different from the mathematical programming-based techniques. AI methods are considered as modern methods of optimization. Most of these AI optimization methods are based on certain characteristics and behaviors of biological, neurobiological, molecular, and insect swarm systems. Particle swarm optimization (PSO), GA, ant colony optimization, simulated annealing, and neural network-based methods are examples of AI algorithms.

3.1 Particle Swarm Optimization

Researchers developed PSO optimization based on the behavior of a group of living organisms, such as a swarm of insects [21-23]. The PSO algorithm starts with a population of proposed solutions (particles) to the desired problem and uses them to test the search space. A particle, i, is defined as a moving particle that has a position coordinate $X_i = (x_{i1}, x_{i2}, \dots, x_{in})^T$ in an N-dimension hyperspace. For each dimension, each particle in the population has an adjustable velocity (change in position) $V= (v_{i1}, v_{i2}, \dots, v_{in})^T$, according to which they change positions in the search space. A performance index or an objective function is used to evaluate each individual particle solution. The value of the objective function of the best particle position of the current population, the local best, X_{lb} is calculated and stored. Similarly, the value of the objective function of the best particle position of all previous iterations, the global best, X_{gb}, is calculated and stored. Both X_{lb} and X_{gb} are used for changing the new particle speed and position [24]. The following equations describe the particles' speeds and positions:

$$v_{id}^{n+1} = v_{id}^{n} + c_1 r_1 (X_{lb}^{n} - x_{id}^{n}) + c_2 r_2 (X_{gb}^{n} - x_{id}^{n}) \tag{1}$$

$$x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n} \tag{2}$$

where, i is current particle, d is the current dimension index, n is the iteration number, and c_1r_1 and c_2r_2 are bounded positive uniform distribution random numbers that are used to prevent the PSO algorithm being trapped in a local minimum. The r_1 and r_2 are uniformly distributed random numbers in the range between 0 and 1. c_1 and c_2 are the cognitive (individual) and social (group) learning rates, respectively. c_1 and c_2 represent the relative importance of the position of the particle itself to the position of the group. The values of c_1 and c_2 are typically assumed to be 2 so that c_1r_1 and c_2r_2 ensure that the particles would overfly the target about half the time. To prevent search divergence, the speed of the particle is bounded to $\pm V_{max}$. A smaller swarm size is necessary to reduce the total number of function evaluations that are needed to find a solution. However, if a swarm size is too small, more iterations are required to reach a solution. Typically, 20-40 particles are a good size for the swarm. In this study, the PSO parameters are set as following: a=1.5, b=1.5, V_{max}=2, and swarm size=40.

3.2 Genetic Algorithms

Genetic algorithms have been used extensively for serval power system applications [25-27]. They are based on the principles of natural genetics and natural selection. The basic process for a genetic algorithm is as follows [24]:

Step 1: Initialization - Create an initial population. This size of the population can range from few individuals to thousands.

Step 2: Evaluation - the "fitness" value for each individual is calculated based on the desired objective.
Step 3: Selection - To constantly improve the populations' overall fitness, bad designs are discarded and only the best individuals in the population are kept. There are a few different selection methods that aim to make it more likely that fitter individuals will be selected for the next generation.
Step 4: Crossover - During crossover, new individuals are created by combining aspects of the selected individuals. Combining certain traits from two or more individuals might create an even "fitter" offspring that inherits the best traits from each of its parents.
Step 5: Mutation - randomness is added to the populations' genetics. This induce small random changes to an individual's genome.
Step 6: Repeat! - After creating a new generation, start again from step two until a termination condition is reached.
In this study, the GA parameters are set as following: population size=50, elite count=5% of population, and crossover fraction=0.8. Constraint-dependent functions are considered for both mutation and crossover functions.

4. Masirah Island System Data and Modelling

4.1 Masirah Island Power System Data

The public electricity network on Masirah island, located 15 km off the eastern coast of Oman, is operated by the Rural Areas Electricity Company (RAEC). RAEC is a closed Omani joint-stock company registered under the Commercial Companies Law of the Sultanate of Oman. RAEC commenced its operations on May 1st of 2005 after restructuring the electricity market and related water sector activities according to the Royal Decree 78/2004 [28]. RAEC serves small scattered communities that are not connected to the Main Interconnected System (MIS) or the Dhofar Power System (DPS) [8]. Its license and business activities include generation, transmission, and distribution [28].

The electric power demand of the island is supplied using diesel-powered generators. The peak electrical load was about 12.04 MW power in 2014. Figure 1 depicts the Masirah Island power system network data during peak load. The network consists of 12 diesel generators and three main feeders that have a total of 126 buses. The system includes four transformers (10MVA, 33/11 kV) that are used to step up and step down the voltage. The remaining 57 transformers are service transformers of different sizes (11/0.415 kV). Table 1 shows the transformer data and parameters. The values of per unit resistance (R) and reactance (X) for different transformers are calculated based on X/R ratio and per unit impedance (Z).

The conductors that are used in the Masirah power system include 1/C and 3/C cable types of different sizes: $185mm^2$, $240mm^2$, $300mm^2$, and $500mm^2$. Additionally, an ACSR overhead line conductor is used in the Island. Table 2 shows the conductors' parameters. The load data of the study were supplied by the RAEC based on 2014 peak load conditions.

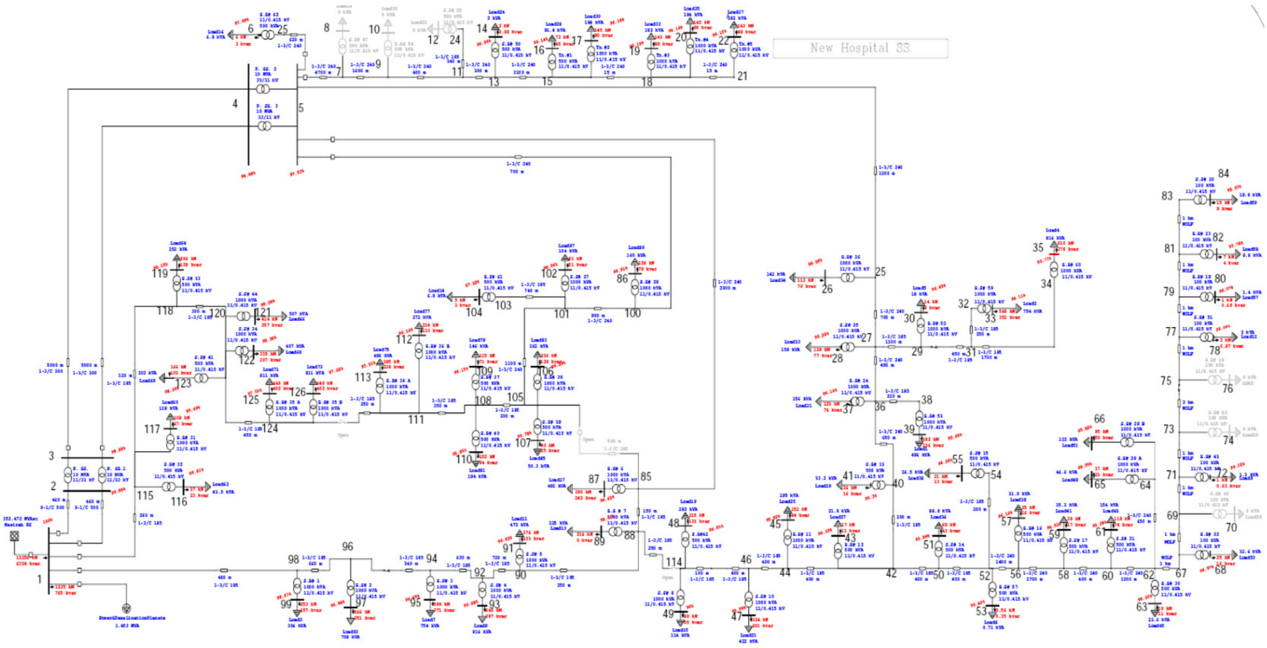

Figure 1. Masirah Island power system network

Table 1: Rating and number of each transformer

Size (MVA)	Numbers	X/R ratio	%Z	%X	%R
10	4	15.5	7.5	7.48	0.48
1	33	5.57	4.75	4.68	0.84
0.5	23	5.1	4.75	4.66	0.91
0.1	9	2.32	4.75	4.36	1.88

Table 2: Conductor data used in the Masirah Island system

Conductor Type	Size (mm^2)	R (Ω/km)	X (Ω/km)	B (S/km)
3/C XLPE Cable	185	0.128	0.112	0.0001351
3/C XLPE Cable	240	0.098	0.109	0.0001495
3/C XLPE Cable	300	0.08	0.105	0.0001646
1/C XLPE Cable	500	0.051	0.1	0.0001945
WOLF ACSR OHL	150	0.1828	0.221	0

4.2 Power Flow Modelling

Actual network, load, and generation data are used to build power flow model of the system. Using this model, voltages at different buses and line flows in the network are calculated by solving the following power balance equations:

$$P_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\delta_i - \theta_{ij} - \delta_j) \tag{3}$$

$$Q_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\delta_i - \theta_{ij} - \delta_j) \tag{4}$$

where $|Y_{ij}|$ is the magnitude of the Y-bus element between buses i and j; and θ_{ij} is the corresponding Y-bus angle; $|V_i|$ and $|V_j|$ are the magnitudes of the voltage at bus i and j, respectively; δ_i and δ_j are the associated angles.

Iterative techniques such as the Newton-Raphson, the Gauss-Seidel, and the fast-decoupled are commonly used to solve the above nonlinear equations [29]. To solve the power flow for the test system, the Newton-Raphson method is applied using a MATLAB software package toolbox [30]. The data required for the toolbox include branch data and bus data matrixes. In the bus data matrix, the type of each bus and the voltage magnitude of voltage-controlled buses as well as generation and load data are given. In the branch data matrix, information about all the connections between buses are given. System losses can be calculated once the power flow problem is solved. The losses in any branch i-j can be determined by the flowing equation:

$$S_{L\,ij} = P_{L\,ij} + jQ_{L\,ij} = S_{ij} + S_{ji} \tag{5}$$

where $S_{ij} = V_i\, I_{ij}^{*}$ and $S_{ji} = V_j\, I_{ji}^{*}$.

4.3 Model Verification

A summary of the power flow simulation results is presented in Table 3. The network exhibits a net capacitive element behavior as the reactive power of the load is higher than that of the generation. This behavior is shown by the negative value of the reactive power losses. This result is attributable to two reasons: one, most of the lines used in the system are underground cables, and two, the network is lightly loaded. Simulation results shows that technical real power losses are 253 kW or 2.1% of the total load.

Table 3: Simulation summary

	P (MW)	*Q (MVAR)*
Generation	12.297	5.430
Demand	12.044	7.330
Losses	0.253	-1.900

A comparison between the simulated voltage profile and data received from RAEC is presented in Figure 2. The results show a good match between the data received and the simulation results. According to the Omani Distribution Code, the voltage profile should be within 6% of the nominal value in distribution networks (33 kV, 11 kV, and 415 V) [31]. It is worth noting that the 6% limit is violated at some buses.

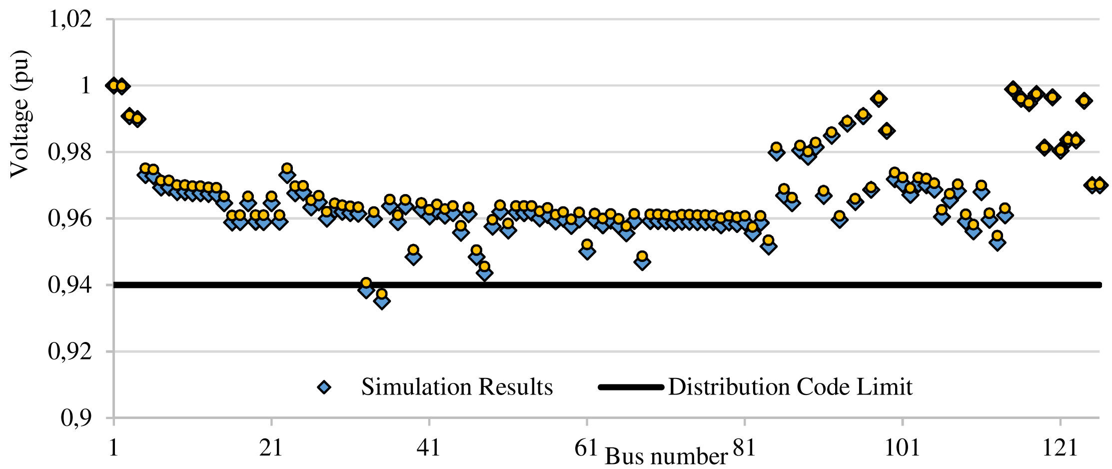

Figure 2. Model verification

5. Results and Discussion

As seen from the voltage profile, the voltage level at several buses is lower than the limit specified by the Omani Distribution Code. The five buses that have the lowest voltage levels are considered as candidates for the connection of a power source to boost the voltage.

5.1 Optimal Size of PV System

At first, both algorithms, GA and PSO, were applied to the five candidate buses to find the optimum size PV systems at each bus. Both techniques resulted in similar values for both the objective function value and decision variables as seen in Figure 4.

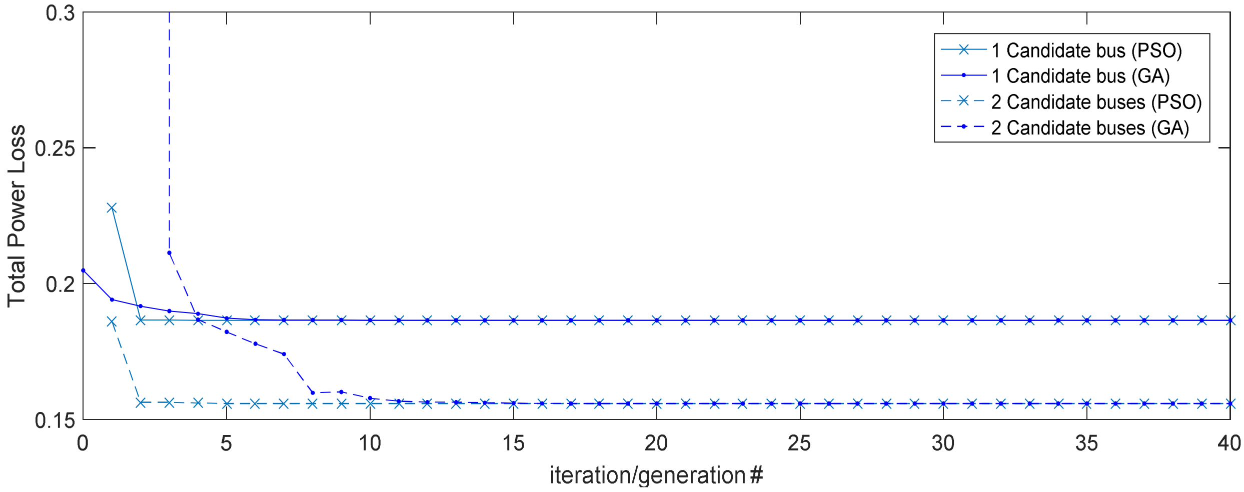

Figure 4. Objective function convergence

Table 4 summarizes the results for all the scenarios. With the optimal allocation of PV systems at all five candidate buses, system losses can be reduced by about 50% through the optimum deployment of 3.86 MW PV systems. Then, the number of candidate buses was reduced by dropping out the bus that had the lowest capacity. The losses can be reduced by 26% if a 2 MW DG is connected at bus 33.

Table 4: Optimal size and locations of PV systems

Location / Scenario	Bus 33	Bus 35	Bus 39	Bus 48	Bus 68	Total Size (MW)	P_{loss} (MW)	P_{loss} Reduction
5 Candidate buses	1.088	1.056	1.082	0.566	0.069	3.861	0.126	50.3%
4 Candidate buses	1.098	1.065	1.096	0.575	0	3.833	0.127	49.9%
3 Candidate buses	1.191	1.145	1.238	0	0	3.574	0.136	46.4%
2 Candidate buses	1.567	0	1.480	0	0	3.047	0.156	38.4%
1 Candidate bus	1.982	0	0	0	0	1.982	0.187	26.3%
Base-case	0	0	0	0	0	0	0.253	0.0%

5.2 Voltage Profile Improvement

The simulation results of the system voltage profile for different scenarios are presented in Figure 5. The results demonstrate the enhancement of the voltage profile and reveal that the voltage level is within the 6% limit at all buses for all scenarios.

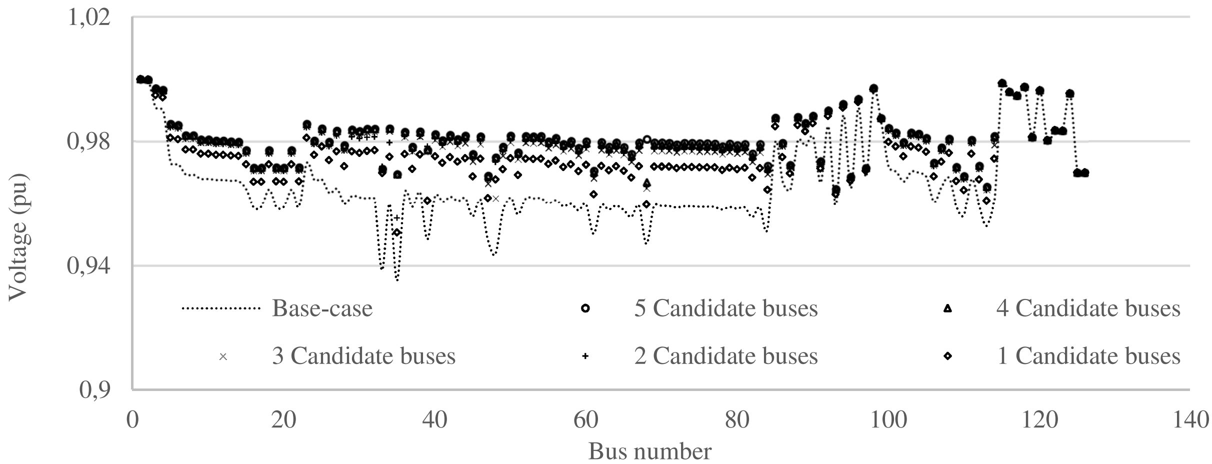

Figure 5. Voltage profile for different scenarios

5.3 Losses as a Function of PV Size

A case study of the distribution network power losses as a function of the size of PV system installed at bus 33 is presented in Figure 6. Simulation results show that power losses is reduced from 0.253 MW with no PV system installed to 0.187 MW with a 1.982 MW PV system. Increasing the PV system capacity beyond this value results in higher power system losses.

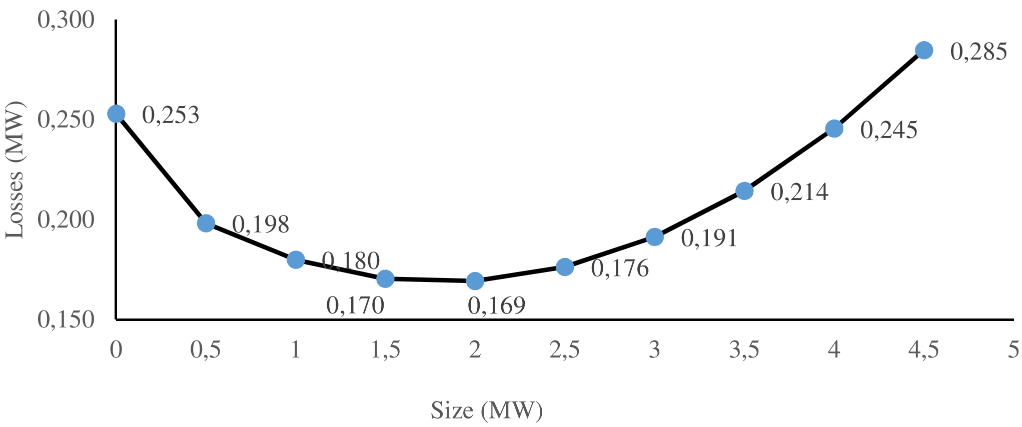

Figure 6. Changes in system losses with PV system size at bus 33

5.4 PSO and GA Convergence Comparison

Table 5 shows the number of iterations required to reach the final solution, to the nearest four decimal places. The results show that as the number of decision variables increases, the required number of iterations for the problem to converge increases. Figures 7 and 8 illustrate the value of system power losses with PSO iterations and GA generations, respectively. It is worth noting that PSO converges faster that GA for this specific problem. However, that these results might differ with different set of PSO and GA parameters.

Table 5: Iterations to reach final solution

Scenario	PSO Iterations	GA Generation
5 Candidate buses	28	71
4 Candidate buses	8	35
3 Candidate buses	8	20
2 Candidate buses	5	16
1 Candidate bus	4	7

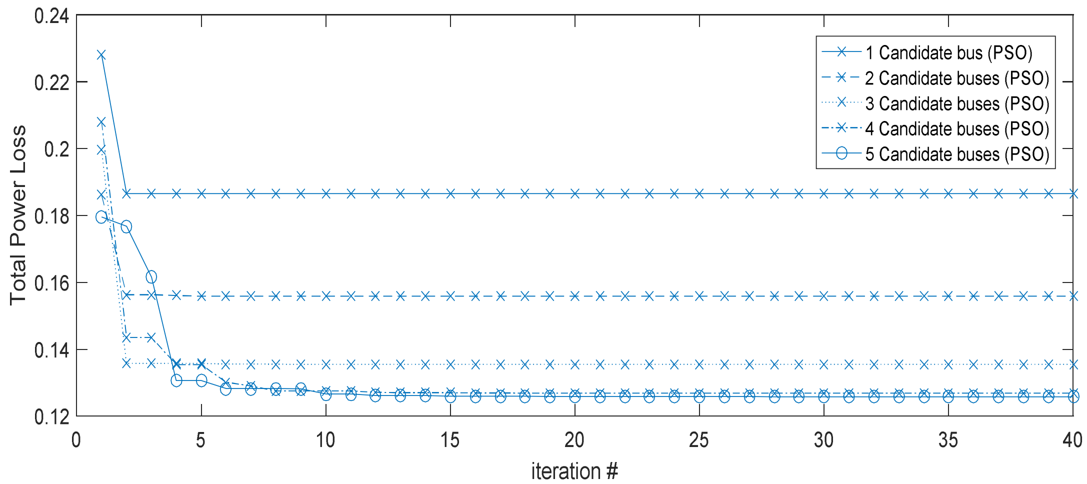

Figure 7. System power losses as a function of PSO iterations for different scenarios

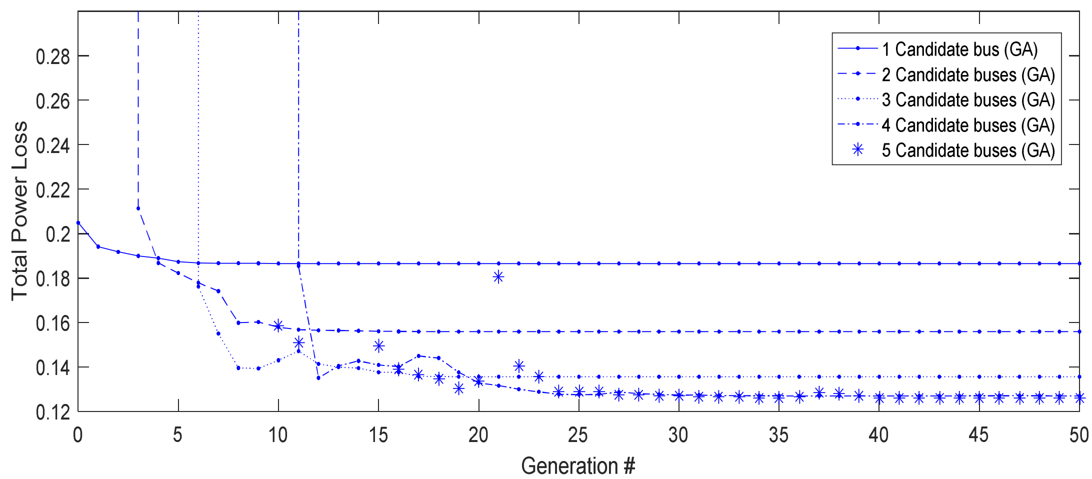

Figure 8. System power losses as a function of GA generations for different scenarios

6. Conclusions

This article presents a case study that models and simulates the Masirah Island distribution system and optimally allocates the PV system in the network using two optimization algorithms. The system model is achieved using MATLAB load flow toolbox and is verified by comparing its output to that of the system operator data. Simulation results reveal that technical power losses represent 2.1% of the total load and that voltage limits are violated at some buses. Based on the voltage profile, five buses are considered as candidates for point of connection for PV systems. To minimize losses, both PSO and GA are used to find the optimal size and location of PV systems. Similar results of the objective function and decision variables are obtained using both optimization techniques. However, the PSO technique reaches the final solution faster than the GA technique for this specific problem. The optimal allocation of PV systems at 5 buses can reduce losses by 50%. With the optimal-sized PV system installed at only 1 bus, losses can be reduced by 26%.

ACKNOWLEDGMENTS

The authors would like to thank the Rural Area Electricity Company for providing the system data and for their support in achieving this work.

References

[1] T. Ackermann, G. Andersson, and L. Söder, "Distributed generation: a definition," Electric power systems research, vol. 57, pp. 195-204, 2001.

[2] REN21, "Renewables 2016 Global Status Report," REN21 Secretariat, Paris2016.

[3] AER, "Study on Renewable Energy Resources, Oman," COWI and Partners LLC MuscatMay 2008.

[4] A. Al-Badi, M. Albadi, A. Al-Lawati, and A. Malik, "Economic perspective of PV electricity in Oman," Energy, vol. 36, pp. 226-232, 2011.

[5] A. Al-Badi, "Wind power potential in Oman," International Journal of Sustainable Energy, vol. 30, pp. 110-118, 2011.

[6] A.-Y. Sultan, Y. Charabi, A. Gastli, and S. Al-Alawi, "Assessment of wind energy potential locations in Oman using data from existing weather stations," Renewable and Sustainable Energy Reviews, vol. 14, pp. 1428-1436, 2010.

[7] M. H. Albadi, A. Al-Busaidi, and E. El-Saadany, "Seawater PHES to Facilitate Wind Power Integration in Dry Coastal Areas–Duqm Case Study," International Journal of Renewable Energy Research (IJRER), vol. 7, pp. 1363-1375, 2017.

[8] M. H. Albadi, "Electricity sector in Oman after 10 years of reform: Status, trends, and future perspectives," The Electricity Journal, vol. 30, pp. 23-30, 2017/08/01/ 2017.

[9] M. Albadi, A. Al-Hinai, N. Al-Abri, Y. Al-Busafi, and R. Al-Sadairi, "Optimal allocation of solar PV systems in rural areas using genetic algorithms: a case study," International Journal of Sustainable Engineering, vol. 6, pp. 301-306, 2013.

[10] J. P. Lopes, N. Hatziargyriou, J. Mutale, P. Djapic, and N. Jenkins, "Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities," Electric power systems research, vol. 77, pp. 1189-1203, 2007.

[11] M. Albadi and E. El-Saadany, "The role of distributed generation in restructured power systems," in Power Symposium, 2008. NAPS'08. 40th North American, 2008, pp. 1-6.

[12] M. A. Zehir, A. Batman, M. A. Sonmez, A. Font, D. Tsiamitros, D. Stimoniaris, et al., "Impacts of microgrids with renewables on secondary distribution networks," Applied Energy, 2017.

[13] B. Singh and J. Sharma, "A review on distributed generation planning," Renewable and Sustainable Energy Reviews, vol. 76, pp. 529-544, 2017.

[14] F. S. Abu-Mouti and M. El-Hawary, "Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm," IEEE transactions on power delivery, vol. 26, pp. 2090-2101, 2011.

[15] A. Khare and S. Rangnekar, "A review of particle swarm optimization and its applications in solar photovoltaic system," Applied Soft Computing, vol. 13, pp. 2997-3006, 2013.

[16] M. P. HA, P. D. Huy, and V. K. Ramachandaramurthy, "A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms," Renewable and Sustainable Energy Reviews, vol. 75, pp. 293-312, 2017.

[17] M. Albadi, H. Soliman, E. El-Saadany, M. A. Thani, A. Al-Alawi, S. Al-Ismaili, et al., "Optimal allocation of PV systems in distribution networks using PSO," in Modeling, Simulation, and Applied Optimization (ICMSAO), 2017 7th International Conference on, 2017, pp. 1-5.

[18] A. A. Hassan, F. H. Fahmy, A. E.-S. A. Nafeh, and M. A. Abu-elmagd, "Genetic single objective optimisation for sizing and allocation of renewable DG systems," International Journal of Sustainable Energy, vol. 36, pp. 545-562, 2017.

[19] P. S. Georgilakis and N. D. Hatziargyriou, "Optimal distributed generation placement in power distribution networks: models, methods, and future research," IEEE Transactions on Power Systems, vol. 28, pp. 3420-3428, 2013.

[20] P. Prakash and D. K. Khatod, "Optimal sizing and siting techniques for distributed

generation in distribution systems: A review," Renewable and Sustainable Energy Reviews, vol. 57, pp. 111-130, 2016.
[21] Y. Del Valle, G. K. Venayagamoorthy, S. Mohagheghi, J.-C. Hernandez, and R. G. Harley, "Particle swarm optimization: basic concepts, variants and applications in power systems," IEEE Transactions on evolutionary computation, vol. 12, pp. 171-195, 2008.
[22] J. Kennedy and R. Eberhart, "Particle swarm optimization," in IEEE International Conference on Neural Networks - Conference Proceedings, 1995, pp. 1942-1948.
[23] R. C. Eberhart and Y. Shi, "Particle swarm optimization: Developments, applications and resources," in Proceedings of the IEEE Conference on Evolutionary Computation, ICEC, 2001, pp. 81-86.
[24] S. S. Rao and S. Rao, Engineering optimization: theory and practice: John Wiley & Sons, 2009.
[25] K. Nara, A. Shiose, M. Kitagawa, and T. Ishihara, "Implementation of Genetic Algorithm for Distribution Systems Loss Minimum Re-Configuration," IEEE Transactions on Power Systems, vol. 7, pp. 1044-1051, 1992.
[26] S. Gerbex, R. Cherkaoui, and A. J. Germond, "Optimal location of multi-type FACTS devices in a power system by means of genetic algorithms," IEEE Transactions on Power Systems, vol. 16, pp. 537-544, 2001.
[27] G. Celli, E. Ghiani, S. Mocci, and F. Pilo, "A multiobjective evolutionary algorithm for the sizing and siting of distributed generation," IEEE Transactions on Power Systems, vol. 20, pp. 750-757, 2005.
[28] RAEC. (2016). Rural Area electricity Company. Available: http://www.reefiah.com/.
[29] H. Saadat, Power System Analysis: McGraw- Hill, 1999.
[30] T. MathWorks. (2016). MATLAB - The Language of Technical Computing. Available: https://www.mathworks.com/products/matlab/
[31] MJEC, MZEC, and MEDC, "The Distribution Code, Version 1.000," ed, 2005