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 show 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.
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 benefits to 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
- \( \delta_i \): Angle of \( V_i \) in radian
- \( |Y_{ij}| \): Magnitude of \( Y_{bus} \) element in per unit
- \( \theta_{ij} \): Angle of \( Y_{bus} \) element in radian
- \( S_{ij} \): Power losses in the branch \( i-j \) in per unit
- \( X_{ib}^n \): 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 \( X_i = (x_{i1}, x_{i2}, ..., x_{in})^T \) in an N-dimension hyperspace. For each dimension, each particle in the population has an adjustable velocity (change in position) \( V_i = (v_{i1}, v_{i2}, ..., v_{in})^T \), 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:

\[
\begin{align*}
v_{id}^{n+1} &= v_{id}^n + c_1 r_1 (X_{lb}^n - x_{id}^n) + c_2 r_2 (X_{gb}^n - x_{id}^n) \\
x_{id}^{n+1} &= x_{id}^n + v_{id}^n
\end{align*}
\]  

(1)  

(2)

where, \( i \) is current particle, \( d \) is the current dimension index, \( n \) is the iteration number, and \( c_1 r_1 \) and \( c_2 r_2 \) 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 \( c_1 r_1 \) and \( c_2 r_2 \) 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 several 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: 185mm², 240mm², 300mm², and 500mm². 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

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

Table 2: Conductor data used in the Masirah Island system

<table>
<thead>
<tr>
<th>Conductor Type</th>
<th>Size (mm²)</th>
<th>R (Ω/km)</th>
<th>X (Ω/km)</th>
<th>B (S/km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3/C XLPE Cable</td>
<td>185</td>
<td>0.128</td>
<td>0.112</td>
<td>0.0001351</td>
</tr>
<tr>
<td>3/C XLPE Cable</td>
<td>240</td>
<td>0.098</td>
<td>0.109</td>
<td>0.0001495</td>
</tr>
<tr>
<td>3/C XLPE Cable</td>
<td>300</td>
<td>0.08</td>
<td>0.105</td>
<td>0.0001646</td>
</tr>
<tr>
<td>1/C XLPE Cable</td>
<td>500</td>
<td>0.051</td>
<td>0.1</td>
<td>0.0001945</td>
</tr>
<tr>
<td>WOLF ACSR OHL</td>
<td>150</td>
<td>0.1828</td>
<td>0.221</td>
<td>0</td>
</tr>
</tbody>
</table>

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:

\[ P_i = \sum_{j=1}^{n} |V_i||V_j|^*Y_{ij}\cos(\delta_i - \theta_{ij} - \delta_j) \]  
\[ Q_i = \sum_{j=1}^{n} |V_i||V_j|^*Y_{ij}\sin(\delta_i - \theta_{ij} - \delta_j) \]

where \( |Y_{ij}| \) is the magnitude of the \( Y \)-bus element between buses \( i \) and \( j \); and \( \theta_{ij} \) is the corresponding \( Y \)-bus angle; \( |V_i| \) and \( |V_j| \) are the magnitudes of the voltage at bus \( i \) and \( j \), respectively; \( \delta_i \) and \( \delta_j \) 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 matrices.
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:

\[
S_{L \, ij} = P_{L \, ij} + jQ_{L \, ij} = S_{ij} + S_{ji}
\]

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>
<thead>
<tr>
<th></th>
<th>(P , (MW))</th>
<th>(Q , (MVAR))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation</td>
<td>12.297</td>
<td>5.430</td>
</tr>
<tr>
<td>Demand</td>
<td>12.044</td>
<td>7.330</td>
</tr>
<tr>
<td>Losses</td>
<td>0.253</td>
<td>-1.900</td>
</tr>
</tbody>
</table>

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.

![Simulation Results vs. Distribution Code Limit](image)

**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](image)

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

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.
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.

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 than GA for this specific problem. However, these results might differ with different set of PSO and GA parameters.

Table 5: Iterations to reach final solution

<table>
<thead>
<tr>
<th>Scenario</th>
<th>PSO Iterations</th>
<th>GA Generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 Candidate buses</td>
<td>28</td>
<td>71</td>
</tr>
<tr>
<td>4 Candidate buses</td>
<td>8</td>
<td>35</td>
</tr>
<tr>
<td>3 Candidate buses</td>
<td>8</td>
<td>20</td>
</tr>
<tr>
<td>2 Candidate buses</td>
<td>5</td>
<td>16</td>
</tr>
<tr>
<td>1 Candidate bus</td>
<td>4</td>
<td>7</td>
</tr>
</tbody>
</table>
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