Optimal Microgrid Design for Load Management and Enhancing Distribution System Reliability

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Abstract
Recently, the penetration level of distribution generation (DG) and energy storage system (ESS) has been increased in power system, and it can effect on the system reliability, voltage profiles, and power losses. This paper proposes an approach to evaluate distribution system reliability and a procedure for allocation of DG and ESS. The main objective is minimizing energy not supplied (ENS) and system costs. The procedure is based on considering a probabilistic model for DG and load units, as well as defining some probabilistic indices. The multi-objective problem is formulated and solved using particle swarm optimization (PSO). In a standard IEEE 33-bus radial distribution system, firstly the size and location of DG units are determined and then the advantage of installing ESS to improve the reliability and system losses is assessed. The simulation results verify the effectiveness and validity of the proposed method.

Keywords: Distributed generation (DG), energy storage system (ESS), microgrid, reliability, PSO.

Introduction
In the last few decades, with the increase the rate of electricity consumption environmental pollution and cost of fossil fuels have manifested the need for new planning, operation, and control strategies in the power distribution systems. This can change the conventional distribution systems into multiple modern, interconnected distribution systems, called microgrids. In the other words, microgrids are small electrical distribution systems which connect several electricity consumers to distributed generators and storage units [1]. There are several papers related to microgrids and distribution generation (DG) and their benefits [2-4]. Microgrids including distributed generation units and energy storage system reduce the electrical distance between generation and loads, improving energy efficiency, reducing the system losses, and increasing power system reliability. In microgrids the active power can may be produced by renewable energy units, such as wind turbines (WT) or photovoltaic (PV) modules, while the intermittent characteristics of them will adversely affect the entire grid. In the other words, because of the stochastic nature of the power, generated from renewable-based customer owned WT and PVs, distribution utilities cannot rely solely on such sources as a means of improving system reliability. In [5]-[9], discussions related to reliability and their assessment, modeling and analyzing of DGs are addressed. Microgrid systems might utilize energy storage system (ESS) units as a backup source for supporting the network against disturbances. ESS is a technology that can support the incorporation of smart grids because of its capacity to enable successful islanding and to facilitate the integration of high penetration levels of DGs. ESSs can also provide additional benefits for distribution utilities, such as demand side management, reliability enhancement, and cost reduction as well as being used as an efficient expansion alternative through peak load shaving. The primary goal of this paper is to propose a systematic approach for optimal allocation of
DGs to improve the reliability indices and subsequently, by adding ESSs, reduce the total system losses costs while further improving the reliability indices of the whole system. The system used for the case study is a 33-bus radial distribution system. The optimum microgrid infrastructure is determined by solving an optimization problem. In addition, an approach is proposed for allocating ESSs in a distribution system. The proposed design is based on recently developed IEEE standard 1547.4–2011, which presents a microgrid structure as building blocks of active distribution systems [10]. The rest of this paper is organized as follows: in section II, the concept of reliability indices in microgrids is explained and then the models used for DGs and ESSs as well as mathematical formulating of the problem are presented. PSO algorithm is briefly introduced section III. The results of using PSO for optimal allocation of DGs and ESSs are presented in Section V. Finally, section VI concludes the paper.

Assessment system reliability
The objective function, which includes maximization of reliability and minimization costs of constructed microgrids, is formulated in this section. These indices include system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI), customer average interruption duration index (CAIDI), average service availability index (ASAI), average service unavailability index (ASUI), ENS, and average energy not supplied (AENS) [11]. ENS is calculated by summing the energy interrupted at all nodes over the entire study period, as formulated in (1),

$$ ENS = \frac{1}{N_y} \sum_{i=1}^{N} \sum_{h=1}^{8760} P_{SI,i} \times P_{DI,i} $$

where $P_{SI}$ is the portion of load to be shed, that is equal to 1 if the load is totally shed.

It is assumed that there are overall candidate buses for installing DGs. The goal of the first problem is to optimally allocate different kind of DGs. It is necessary to find the optimum locations and sizes of DG/load uncertainties. The objection function under this condition can be described as (2)

$$ F = \text{Annual Energy not supplied} $$

$$ = \sum_{n=1}^{N} ENS_n \times p_n \times h_n $$

In (2), $N$ is the number of states for a year. $ENS_n$ is the energy not supplied for every hour of the year, $p_n$ is the probability of the related state and is the time segment of the related state, which is one hour for this research. So, minimizing the total energy not supplied to the system is reached by optimally allocating the DGs.

Modeling of DGs, ESS, and System Reliability Assessment
In order to optimally design microgrids with maximum reliability, characteristics of all the system components, such as the uncertain nature of DG units and loads, should be modeled properly. In this research, DG units are modeled with typical combination of most commonly used DG units in distribution systems, which are PV modules, wind turbines, and biomass generators (BM). Other types of DGs could also be modeled with similar approaches. In this section, the steps taken to model the DG units, loads, ESSs are presented. Hourly wind speed and solar irradiance data are modeled by Weibull and Beta probability density function (PDF), respectively.

ESS Modeling
To improve the reliability of distribution systems ESS can be employed. A probabilistic approach for sizing ESSs is presented in [12] and sizing ESS for isolated micro-grid applications is proposed in [13]. Determining the optimal ESS charging/discharging is related to the instant load state; for example, the ESS is assumed to be in state of charging/discharging less/more than 51% of the peak load.

When the system is restored, ESS units are permitted to be charged up to their maximum power rates as long as system constraints are not violated. The characteristic equations that govern the energy stored in each ESS unit at a given hour (h) are as follows:
\[ E_{\text{ESS}_h} = E_{\text{ESS}_{h-1}} + P_{\text{ESS}_{h}}^{\text{ch}} \times \eta_{\text{ESS}} - P_{\text{ESS}_{h}}^{\text{dis}} \]

\[ 0 \leq E_{\text{ESS}_h} \leq E_{\text{ESS}_i} \]  

\( \text{ch, dis} \) refer to charging and discharging, respectively and \( \eta_{\text{ESS}} \) is the round-trip efficiency of the ESS. The following objective function minimizes the total cost comprised of the annual installation and maintenance costs of the ESS units in addition to the annual interruption costs.

\[ \text{Minimize } \sum_{i=1}^{N} \left[ (C_P + C_M \times PVF) \times P_{\text{ESS}_i}^{\text{rated}} + (C_E + C_R) \times E_{\text{ESS}_i}^{\text{rated}} \right] \]

where \( C_P \) is capital power cost of the ESS, \( C_E \) is capital energy cost of the ESS, \( C_M \) is annual operation and maintenance cost of the ESS, \( E_{\text{ESS}_i}^{\text{rated}} \) is ESS rated capacity, \( N \) is total number of system buses, \( P_{\text{ESS}_i}^{\text{rated}} \) is ESS rated charging/discharging power. The fixed capital costs are annualized by dividing them by the present value function (PVF), can be calculated as follows [14]:

\[ PVF = \frac{(1 + IR')^n - 1}{IR'(1 + IR')} \]

where \( n \) is lifetime of the equipment and \( IR' \) is effective interest rate, based on the following formula:

\[ IR' = \frac{IR - F}{1 + F} \]

Where \( F \) is inflation rate and \( IR \) is interest rate.

Voltage limits and ESS size constraints are:

\[ V_{\text{min}} \leq V_{\text{LVRT}} \leq V_{\text{max}} \quad \forall i, s, yr \]

\[ P_{\text{ESS}}^{\text{rated}} = x_i \times \text{discrete step} \quad \forall i \in B \]

\[ E_{\text{ESS}}^{\text{rated}} = y_i \times \text{discrete step} \quad \forall i \in B \]

\[ P_{\text{ESS}}^{\text{max}} \leq P_{\text{ESS}} \quad \forall i \in B \]

\[ E_{\text{ESS}}^{\text{max}} \leq E_{\text{ESS}} \quad \forall i \in B \]

**PV Modeling**

The output of each PV module depends on the amount of solar irradiance, ambient temperature and characteristics of the module itself. For calculating the output power of PV, each day is divided into 24 hours, each having a probability density functions (PDF) for solar irradiance. For estimating the output, solar irradiance for each hour is modeled by Beta probability distribution function, and so the probabilistic function of the output power of PV modules can be generated easily [15]. Beta PDF depends on solar irradiance (kW/m²) and parameters of the Beta distribution \((\alpha, \beta)\). \( \alpha \) and \( \beta \) are calculated by utilizing the mean \((\mu)\) and standard deviation \((\sigma)\) of random variable. So, the Beta PDF for the PV model is described in (13).

\[ f_b(s) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \times s^{\alpha-1} \times (1 - s)^{\beta-1} \]

\[ 0 \leq s \leq 1, \alpha \geq 0, \beta \geq 0 \]

\[ \beta = (1 - \mu) \times \left( \frac{\mu \times (1 + \mu)}{\sigma^2} - 1 \right) \]

\[ \alpha = \frac{\mu \times \beta}{1 - \mu} \]

Initially, the Beta PDF is generated for each state, and then the output power during the different states is calculated for this segment using the following:

\[ T_{cy} = T_{n} + s_{ay} \left( \frac{N_{by} - 20}{0.8} \right) \]

\[ I_v = s_{av} \left[ I_{sc} + K_i(T_c - 25) \right] \]

\[ V_y = V_{oc} - K_v \times T_{cy} \]
\[ P_{Sy} (s_{av}) = N \times FF \times V_y \times I_y \] (18)

\[ FF = \frac{V_{MPP} \times I_{MPP}}{V_{oc} \times I_{sc}} \] (19)

In the equations above:
- \( T_c \) is cell temperature during state,
- \( T_a \) is ambient temperature,
- \( K_i \) is voltage temperature coefficient,
- \( K_v \) is current temperature coefficient,
- \( N_{OT} \) is nominal operating temperature of cell,
- \( FF \) is fill factor,
- \( I_{sc} \) is short circuit current in A,
- \( V_{oc} \) is open-circuit voltage in V,
- \( I_{MPP} \) is current at maximum power point in A,
- \( V_{MPP} \) is voltage at maximum power point in V,
- \( P_{Sy} \) is output power of the PV module during state, and
- \( s_{av} \) is average solar irradiance of state.

**Wind Turbine Modeling**

The output power of wind turbines depends on wind speed and parameters of the wind-power conversion curve [16], [17]. For estimating the output, WT is modeled by the Weibull PDF in which the wind speed for each hour of the day is modeled by using historical data. A day is further divided into 24-hour time segments, each having a PDF for wind speed and so the probabilistic function of the output power can be generated. The Rayleigh PDF for the WT model is described in (20).

\[ f(v) = \left( \frac{2v}{c^2} \right) \times \exp \left[ -\left( \frac{v}{c} \right)^2 \right] \] (20)

The mean value of wind speed is calculated using the historical data for each state, and then the scale index is calculated as (21).

\[ v_m = \int_0^\infty vf(v)dv \] (21)

\[ = \int_0^\infty v \left( \frac{2v}{c^2} \right) \times \exp \left[ -\left( \frac{v}{c} \right)^2 \right] dv = \frac{\sqrt{\pi}}{2}c \]

\[ c \approx 1.128v_m. \]

\[ P_{W}(v_{aw}) = \begin{cases} P_{rated} \times \frac{v_{aw} - v_{ci}}{v_t - v_{ci}} & 0 \leq v_{aw} \leq v_{ci} \\ P_{rated} & v_{cl} \leq v_{aw} \leq v_{r} \\ 0 & v_r \leq v_{aw} \leq v_{co} \end{cases} \] (22)

Where \( v_r \) is cut in speed, \( v_{rated} \) is rated speed, and cut-off, \( v_{ci} \) is speed of the wind turbine, \( P_{W} \) is output power of the wind turbine during state, and \( v_{aw} \) is average wind speed of state.

The output power of WT for a segment each having a special PDF is calculated, using the following equation (22)

**Optimization Algorithm**

In PSO, each particle can be presented by its current velocity and position which searches the problem space. The speed of each particle is adjusted by its own previous best experience and the historical best experience of other adjacent particles as well [18-19].

The velocity and the position of each particle are represented by (23) and (24), respectively.

\[ V_i = [V^1_i, V^2_i, ... , V^D_i] \] (23)

\[ X_i = [X^1_i, X^2_i, ... , X^D_i] \] (24)

where \( V \) is the speed and \( X \) is the position of the particle, \( i \) represent the individual particle and \( D \) represents the problem dimension. The vector of previous best position of each particle and its adjacent particles in the problem space is represented in (25), while (26) represents the best position vector which is found considering the objective function.
\[ p_{Best_i} = [p_{Best_1}, p_{Best_2}, ..., p_{Best_M}] \]  
\[ (i = 1, 2, ..., M) \]

\[ g_{Best} = [g_{Best_1}, g_{Best_2}, ..., g_{Best_D}] \]

In each iteration, if the current best position were optimum comparing with previous positions, \( p_{Best} \) will be updated and \( g_{Best} \) is found. The procedure for PSO algorithm can be summarized in a flowchart as shown in Fig. 1.

\[ V_i^d = \omega \times V_i^d + c_1 \times \text{rand}_1^d \times (p_{Best_i}^d - X_i^d) + c_2 \times \text{rand}_2^d \times (g_{Best}^d - X_i^d) \]  

Figure 1: Flowchart of the proposed methodology.

In this paper, the PSO problem considers the DG units and the network as the particles and the search space respectively.

**Case Study**

A 33-bus radial distribution system, as shown in Fig. 2, is employed as a case study to verify the proposed method. The load data of the feeder is taken from [20]. The system peak demand is 3720kw at base year. The reliability data of system component drawn from [21] and the reliability parameters of the substation and the system feeders which are further summarized in Table I [19].

<table>
<thead>
<tr>
<th>Component</th>
<th>Sustained Failure Rate</th>
<th>Repair Time (Hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Substations</td>
<td>0.6/100</td>
<td>24</td>
</tr>
<tr>
<td>Cables</td>
<td>3.5/100</td>
<td>18</td>
</tr>
</tbody>
</table>

Table 1: Component Reliability Data [19]

It is assumed that the candidate ESSs are available in discrete sizes in steps of 100 kVA/kWh. The annual capital and maintenance costs for ESS are presented in table 2. In this research, IR= 5%, F= 1% and n=30 years [19].

<table>
<thead>
<tr>
<th>Capital power cost (S/kW)</th>
<th>175</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital energy cost (S/kW)</td>
<td>305</td>
</tr>
<tr>
<td>Capital replacement cost (S/kW)</td>
<td>305</td>
</tr>
<tr>
<td>Annual O&amp;M cost (S/kW)</td>
<td>15</td>
</tr>
<tr>
<td>Number of charge/discharge cycles</td>
<td>3200</td>
</tr>
</tbody>
</table>

Table 2: Capitals and Maintenance Costs of ESSs Technologies [19]
Three DG types are utilized in the system for the case study:
DG1 is a 1 MW wind turbine with power curve parameters as shown in Table II. The reliability parameters of the substation and the system feeders and Wind Turbine Parameters showed in Tables 1 and 3 respectively.

<table>
<thead>
<tr>
<th>Cut-in speed (m/s)</th>
<th>Cut-out speed (m/s)</th>
<th>Cut-in speed (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>25</td>
<td>4</td>
</tr>
<tr>
<td>14</td>
<td>25</td>
<td>4</td>
</tr>
</tbody>
</table>

In [22], the probabilistic wind-based DG model is developed utilizing both the wind speed and the wind turbine data in which the Rayleigh PDF is used for wind speed modeling. DG2 is a 0.5 MW PV unit. The PSO optimization algorithm for allocation is solved using DIgSILENT software.

The following cases are studied:
The results of this research are summarized in this section in which the DG and the ESS units are optimally allocated in order to achieve load management, improve system reliability and minimize system losses. The impact of pre-allocated DG types is also studied through the following five different scenarios:

Scenario A: no DG, represents the base case in which the total ENS and SAIFI and CAIDI are only comprised of the costs associated with energy losses. The next four scenarios present the impact of allocating DGs and ESSs.

Scenario B: In a wind based DG scenario, only the wind turbine is assumed to be present in the system. The reliability improvement and reduction of losses costs can apparently be observed comparing with the results of scenario A, due to the integration of wind based DG.

Scenario C: In a wind and solar based DGs scenario, the system is assumed to be equipped with both WT and PV units. The results of scenario C shows a further improvement in system reliability and a further reduction in costs, comparing with scenario B.

Scenario E: In a wind and solar DGs and ESS based scenario, due to load management capability of ESSs, i.e. charging at off-peak and discharging at on-peak, the cost are reduced comparing with previous scenarios while the reliability is improved.

The above results are summarized numerically in Table IV. As shown in this table, in scenario E, amount of ENS reduces from 4.61 kWh to 1.9 kWh, amount of SAIFI from 2.05 kWh to 0.36 kWh, and amount of CAIDI from 5.06h to 2.62h. In case 5, amount of ENS reduces from 4.61 kWh to 1.9 kWh, amount of SAIFI from 2.05 kWh to 0.33 kWh, and amount of CAIDI from 5.06h to 2.26 h.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>DG type</th>
<th>Location</th>
<th>ENS (kWh)</th>
<th>SAIFI (h)/yr</th>
<th>CAIDI (h)</th>
<th>Cost ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>No DG</td>
<td>--</td>
<td>4.61</td>
<td>2.05</td>
<td>5.06</td>
<td>830660.63</td>
</tr>
<tr>
<td>B</td>
<td>Wind based</td>
<td>18</td>
<td>2.39</td>
<td>0.36</td>
<td>3.36</td>
<td>713448.58</td>
</tr>
<tr>
<td>C</td>
<td>Wind based</td>
<td>18</td>
<td>1.94</td>
<td>0.37</td>
<td>2.8</td>
<td>649970.97</td>
</tr>
<tr>
<td></td>
<td>Solar based</td>
<td>33</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>Wind based</td>
<td>18</td>
<td>1.90</td>
<td>0.36</td>
<td>2.62</td>
<td>639756.36</td>
</tr>
<tr>
<td></td>
<td>Solar based</td>
<td>33</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ESS</td>
<td>25</td>
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</table>
Conclusions
This paper presented a systematic and optimized strategy for designing microgrids in a distribution system. The design takes into account the reliability and the losses costs to develop a proper objective function in order to determine the optimal allocated DG and ESS. A step by step adding up DG approach in the form of 4 scenarios is presented to evaluate the impact of DGs and ESS units on reliability indices improvement and losses reduction. Due to load management capability of ESSs, i.e. charging at off-peak and discharging at on-peak, the costs are reduced comparing with the scenarios in which the ESS is not present. It was showed that the results were dependent on the system under study, type and size of existing DGs and ESS.

References