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Optimal Allocation and Sizing of Distributed Generation with Soft Computing Technique for Loss Reduction

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Abstract – This article presents an evaluation of the optimal location and dimensioning of distributed generation in electrical energy distribution systems. For such evaluation, the Shuffled Frog-Leaping Algorithm has been considered. In the problem of optimal location and dimensioning, two objectives have been considered: the minimization of active losses and the improvement of the voltage profile. To compare the effectiveness of the implemented methods, IEEE-33 bus test distribution system is used. The correct location and dimensioning of the distributed generation allowed to substantially improve the network voltage profile and reduce losses for the test system.

Keywords – Active Power Losses, Centralized Generation, Distributed Generation, Reactive Power Losses, Voltage Profiles, etc.

1. INTRODUCTION

Electric power systems around the world are evolving towards a scenario where the presence of generation units close to demand is increasingly common. This generation is currently known as distributed generation [1]. The reasons for this trend are the product of various international energy policies that support the connection of electricity generation based on alternative sources or on high-efficiency technologies [2], [3]. The main advantages of DG over centralized generation are low environmental impacts and low investment costs. Additionally, DG can help reduce electrical losses, alleviate congestion problems in transmission lines, expand the power profile, improve system constancy, then also reduce electricity costs for the final consumer.

The optimal location & sizing of new DG units is influenced by technical and economic factors, including the increase in the price of energy at peak hours. In this case, the DG can deliver energy during these hours, making prices to consumers lower. There are many aspects that must be considered when conducting DG planning and operation studies (development of the current profile, minimization of losses, improvement of system reliability, etc.). Most planning studies include the ideal area and estimating of new conveyed age units.

In the process of restructuring electrical systems worldwide, the criterion of considering the management of distribution networks as natural monopolies has been maintained. Traditional regulatory schemes such as cost of service regulation have been replaced by new performance-based regulatory schemes in which non-discrimination and free access to networks is a fundamental pillar of the reform process. Unfortunately, an open access policy must be applied on a network that produces energy losses. Consequently, these losses must be transparently allocated between consumers and distributed generation. Electrical losses have a non-linear behavior with respect to power flows and it is difficult to determine the responsibility of each power injection for the overall losses of the system.

Given this situation, several and different loss allocation systems have remained projected in the literature, mainly referring to transmission systems [4]. However, few technical publications devoted to the allocation of losses in distribution systems are observed taking into account the increasing penetration of distributed sources.

Generally, circulation misfortunes have been considered as an extra burden then have been distributed proportionally among all consumers in the network, generally using average values. However, the presence of distributed generation dramatically changes the paradigm of loss allocation. The degree of penetration of the distributed energy sources can contribute globally to avoid losses or rather to increase them.

In this sense, different methodologies have been proposed in the literature for the designation of dynamic misfortunes in circulation networks with appropriated age, basically divided into two groups. First, methods such as postage [5], MW-km [5] and proportional participation [6] [7] have been proposed based on an arbitrary allocation between generators and consumers, typically 50: 50%. Recently, a modification to the proportional participation method [8] has been proposed based on the allocation of 100% of network losses to consumers, neglecting the effect of generators. Subsequently, the effect of the generators is calculated and the losses produced or avoided are assigned to the generators as a penalty or incentive in the use of the network.

Secondly, marginal methods have been proposed [9] [10 [11] that have been widely discussed in transmission systems in order to send efficiency signals to economic agents. As a result, it seeks to compensate those agents that contribute to the reduction of losses (losses avoided) and to penalize those agents that produce increases in the overall losses of the system.
In order to establish a general evaluation of the impact of each allocation methodology.

Metaheuristic techniques provides the path to change the procedures of subsidiary heuristics to achieve superior solutions efficiently, employing successful search strategies and bioinspired algorithms. Some of the most commonly used mono-objective techniques are: artificial bee colony algorithm [12], ant colony optimization [13], genetic algorithm [14], particle swarm optimization [15], simulated annealing [16], Tabu search [17] and immune algorithms [18]. The objective of this paper is to contribute to the discussion on the effectiveness of metaheuristic method for the optimal location and dimensioning of DG. To this end, Shuffled Frog-Leaping Algorithm (SFLA) has been implemented and to test the efficiency of this method, different tests have been carried out on an IEEE-33 bus distribution test system. Section two describes the implementation of proposed approach. Results are presented in section three trailed by the conclusive remarks in the section four.

2. PROPOSED METHODOLOGY

A. Problem Formulation

The optimal location then dimensioning problem of DG remains formulated for two objectives: the maximization of net social benefit and the maximization of profit for the owner of the DG. The local marginal prices obtained from the optimal power flow solution remain utilized as pointers to distinguish the applicant bars where to locate the DG.

B. Maximization of Net Social Benefit

The optimal location then sizing problem of DG addressed from the network operator's point of view is to maximize the net social benefit subject to network constraints. Net social benefit is characterized as the absolute advantage of shoppers less the all-out expense of creation [19] and can be represented by equation (1).

$$\max\left[\sum_{i=1}^{nd}[F_i(P_{di})] - \sum_{i=1}^{ng}[G_i(P_{gi})]\right] \quad (1)$$

$$F_i(P_{di}) = a_{Di} + b_{Di}P_{di} - c_{Di}(P_{di})^2 \quad (2)$$

$$G_i(P_{gi}) = a_{Gi} + b_{Gi}P_{gi} - c_{gi}(P_{gi})^2 \quad (3)$$

Where,

nd : Number of loading bars;

ng : Number of generators;

P_{di} : Power demanded in bar i;

P_{gi} : Power delivered by generator i;

$F_i(P_{di})$: Demand benefit function i;

$G_i(P_{gi})$: Generator i benefit function;

a_{Di}, a_{Gi} : Independent coefficients of the benefit functions of demand and generator i respectively.

b_{Di}, b_{Gi} : First order coefficients of the profit functions of demand and generator i respectively.

c_{Di}, c_{Gi}: Second order coefficients of the demand benefit function and the generator i respectively.

The maximization problem described in (1) can be formulated as a minimization problem by changing the sign of the objective function as shown in (4).

$$\min\left[\sum_{i=1}^{ng}\left[G_i(P_{gi})\right] - \sum_{i=1}^{nd}\left[F_i(P_{di})\right]\right] \quad (4)$$

This problem remains subject towards equality & inequality restrictions. The equality constraints correspond to the active then reactive power balance equations for each of the bars in the system as shown in (5) and (6).

$$P_{gi} - P_{di} - P(V,\theta) = 0 \quad (5)$$

$$Q_{gi} - Q_{di} - Q(V,\theta) = 0 \quad (6)$$

Where,

P_{gi} : Active power generated in bar i;

Q_{gi} : Reactive power generated in bar i;

P_{di} : Active power demanded in bar i;

Q_{di} : Reactive power demanded in bar i;

$P(V,\theta)$: Active power calculated on bar i;

$Q(V,\theta)$: Reactive power calculated in bar i.

The expressions for the injections of active & reactive power calculated according to the angles & voltages of the network, are given according to (4) and (5).

$$P_i(V,\theta) = V_i \sum_{j=1}^{nb}\left[V_j\left\{g_{ij}\cos(\theta_i - \theta_j) - b_{ij}\sin(\theta_i - \theta_j)\right\}\right] \quad (7)$$

$$Q_i(V,\theta) = V_i \sum_{j=1}^{nb}\left[V_j\left\{g_{ij}\sin(\theta_i - \theta_j) - b_{ij}\cos(\theta_i - \theta_j)\right\}\right] \quad (8)$$

Where:

nb : Number of buses in the system;

V_i : Magnitude of voltage at bar i;

θ_i : Angle in the bar i;

g_{ij} : Conductance of line ij;

b_{ij} : Susceptance of the ij line.

The inequality constraints are the generation limits (active & reactive power), the power flow limits on the lines then the voltage limits on the nodes. These restrictions are represented in equations (9) to (13).

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \quad (9)$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \quad (10)$$

$$S_{ij} \leq S_{ij}^{max} \quad (11)$$

$$S_{ji} \leq S_{ji}^{max} \quad (12)$$

$$V_{i}^{min} \leq V_{i} \leq V_{i}^{max} \quad (13)$$

The model described by equations (4) - (13) corresponds to a mixed, highly dimensional and non-convex integer nonlinear programming problem that presents multiple local optimums, which justifies the use of proposed Shuffled Frog-Leaping Algorithm (SFLA) aimed at its solution in this paper. Below is a brief description of the SFLA technique.

C. Shuffled Frog-Leaping Algorithm (SFLA)

This optimization technique projected by Muzaffar Eusuff & Kevin Lansey in 2003, consists of modeling the behavior of groups of frogs, in particular the way in which these amphibians search for food (insects) [20].

The SFLA algorithm has jump rules to what will first be a local search for each individual frog, and combination rules for the different groups of frogs (leaves) for a global search [21] [22]; Each leap of the frog produces a change of position within the solution space and is intended to approach the best possible. The steps of the algorithm are:

- **Step 1:** Initial information is provided, such as the number of jumps per frog s, the number of frogs per leaf m, the number of variables in the NV problem, the allowed search space ASS, the number of leaves k_l and for completion the number of iterations.
- **Step 2:** The iterations are started, a random population of frog jumps is generated and evaluated in the cost function to determine their fitness and thus order them in descending order.
- **Step 3:** A distribution of leapfrogging (partition) is made among the leaves, in such a way that the first frog jump is assigned to the first leaf, the second jump to the second leaf and so on.
- **Step 4:** The best & worst frog leaps (best fitness value and worst fitness value) of each leaf are identified, as well as the frog leap with the best overall fitness.
- **Step 5:** Update the worst frog jumps using the best jumps on each leaf, such that:

  $$wsF_m^{k+1} = wsF_m^k + r^k(bsF_m^k - wsF_m^k) \quad (14)$$

  Where k is the current generation of population, wsF is the worst frog, bsF is the best frog and the corresponding leaf m. The best frogs on each leaf are updated with the best global frog.

  $$bsF_m^{k+1} = bsLF^k + r^k(bsGF^k - bsLF^k) \quad (15)$$

  Where $bsLF$ is the best local frog jump and $bsGF$ is the best global frog jump.
- **Step 6:** A leaf combination is performed (reassignment of leaf jumps).
- **Step 7:** The completion criteria is reviewed, if it is met, the results are presented and the program ends; if not met, return to Step 2 [20].

3. SIMULATION RESULTS

The graphs below represent the results obtained:

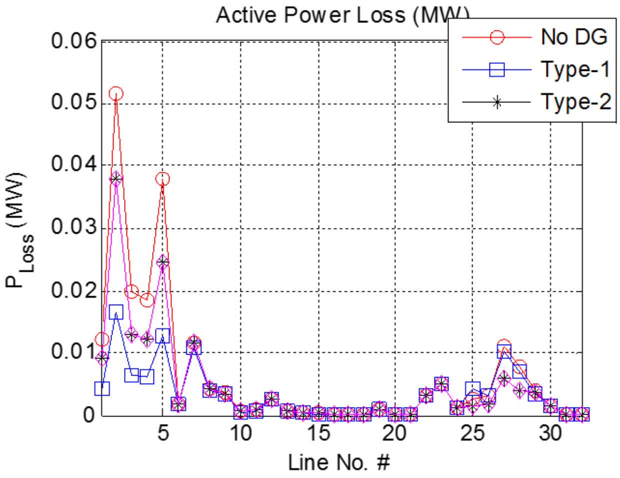

Figure 1: Active power loss comparison for DG (Type-1, Type-2) & without DG placement

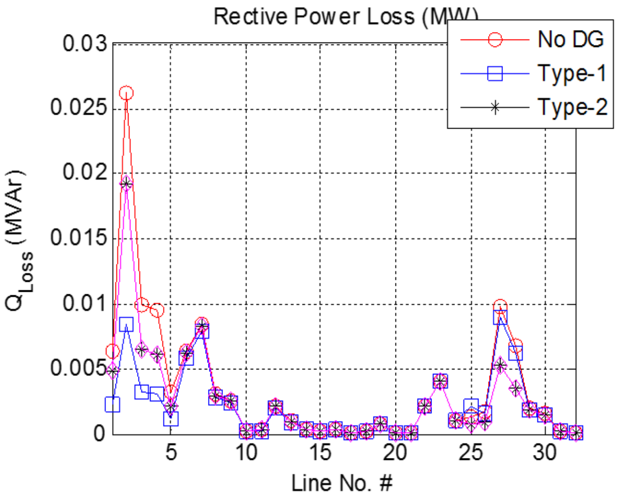

Figure 2: Reactive power loss comparison for DG (Type-1, Type-2) and without DG placement

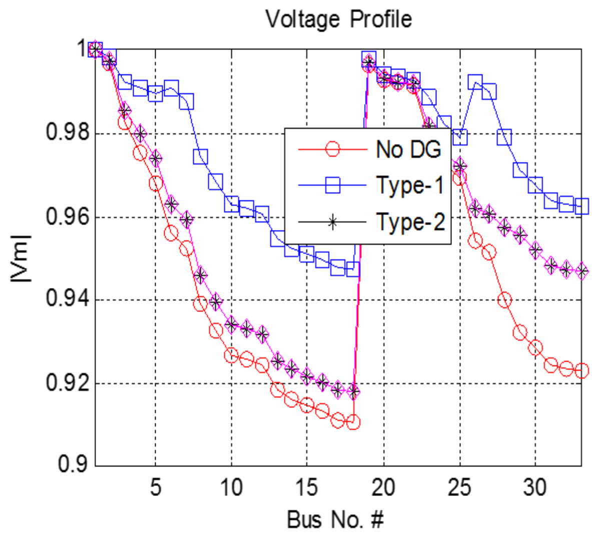

Figure 3: Voltage profile for DG (Type-1, Type-2) and without DG placement

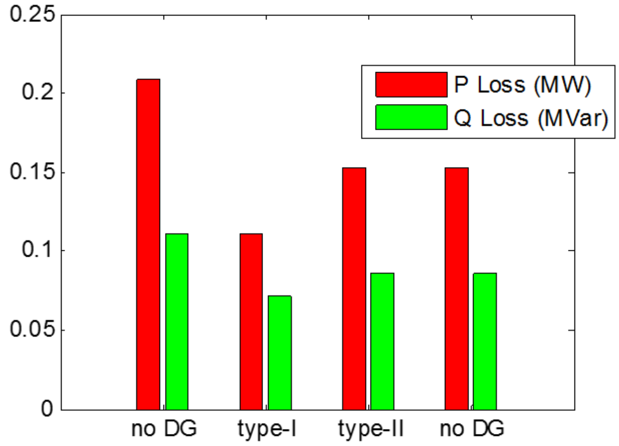

Figure 4: Bar graph for active and reactive power loss minimization with DG (Type-1, Type-2) and without DG placement

Table 1: Comparative results

Type of DG Bus	Bus No.	Power loss without DG placement		Power loss without optimal DG placement	
		Active power loss P(MW)	Reactive power loss Q(MVAr)	Active power loss P(MW)	Reactive power loss Q(MVAr)
Type-1	26	2.489	-	0.112	0.072
Type-2	26	-	1.317	0.153	0.086

4. CONCLUSION

In this paper, DG allocation is accomplished using a metaheuristic optimization algorithm, i.e. Shuffled Frog-Leaping Algorithm. The outcome of proposed approach clearly shows that the minimization of active power loss is done for the radial distribution network. One more advantage of this approach is that it increases the voltage at weak buses which defines the optimal size and location of distribution generation unit.

In a later work, other aspects may be included in the model, such as variability in demand, investment costs, and geographic or environmental restrictions imposed by certain DG technologies.

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