

Multi-objective Optimal Placement of Distributed Generation Using Bee Colony Optimization

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Abstract— In this paper, the proposed bee colony optimization (BCO) is used to determine optimal placement and number of the distributed generation (DG) to simultaneously minimize the real power loss and violation function of contingency analysis subject to power balance constrains, and power generation limits. The simulation results on the IEEE 30 bus system show that BCO can obtain the optimal solution with less computing time than simulated annealing (SA), genetic algorithm (GA) and tabu search algorithm (TSA). The average computing time of BCO is 82.62%, 74.40% and 83.83% less than GA, SA and TSA, respectively.

Keywords- Distributed Generation, Multi-objective Optimal Placement, Bee Colony Optimization.

1. INTRODUCTION

Electric power grids have brought substantial benefits to the Southeast Asia Region as well as Greater Mekong Subregion (GMS) and hold the potential to provide further benefits if strengthened and extended. The benefits include more reliable power supply, lower electricity costs to consumers, and reduced environmental impacts. Power grid enhancements can make electric supply more reliable by improving the ability of economies to cope with the outage of specific generating units or types of generating units, as well as by limiting the scope of power outages. Enhanced power grids can lower electricity costs by reducing needs for electric generating capacity and allowing cheaper fuel to be substituted for more expensive fuel. Grids lower needs for generating capacity by allowing peak demand in one area to be served in part by spare capacity in a neighbouring area where demand is not at its peak. Grids lower fuel costs by allowing generation from nuclear, hydro and coal-fired power plants to displace generation from gas-fired plants.

A plan for power grid interconnections in Southeast Asia has been elaborated under the auspices of the Association of South East Asian Nations (ASEAN). The plan initially included fourteen cross-border projects, supported by national power utilities. These are shown as 14 projects in the Figure 1 below. The power grid master plan is extremely ambitious relative to transmission capacity in place, even though several elements of the plan build upon existing interconnections. The planned 700 MW link between Singapore and Peninsular Malaysia, to be completed by 2010, will add to an existing 500 MW link. The planned interconnections between Thailand and Laos, to add 2,015 MW of transmission capacity in 2008 and another 1,578 MW in 2010, will build upon earlier links of 75 MW in 1972, 45 MW and 214 MW in 1998 and 126 MW in 1999 [1].

Particular support has been evident for components of the ASEAN Power Grid to be located in the Greater Mekong Subregion that includes Cambodia, Laos, Myanmar, Thailand and Vietnam as well as Yunnan Province in southern China. A Greater Mekong Subregion transmission study was performed by the Mekong River Commission in 1996. Finally, an Inter-Governmental Agreement (IGA) on Regional Power Trade in the Greater Mekong Subregion was signed by ministers of the subregion's six economies in November 2002. The IGA set up a Regional Power Trade Coordination Committee to establish rules governing regional power trade. It is anticipated that power trade pursuant to the agreement will allow members to coordinate and cooperate in the planning and operation of their systems to minimize costs while maintaining satisfactory reliability; fully recover their costs and share equitably in the resulting benefits; and promote reliable and economical electric service to the customers of each country.

Conversely, a few proposed new power links in the Greater Mekong Subregion, see Figure 2, go beyond what as been proposed in the broader ASEAN context. The 500 kV lines in northeastern Thailand would be reinforced by 2015 to accommodate greater power flows southward. A 230 kV line would be built by 2019 from Lower Sre Pok to Sambor and Phnom Penh in Cambodia, as well as from Sambor to Tan Dinh in Vietnam. A 500 kV HVDC transmission line would link the Jinghong and Nuozhadu hydro projects in the Yunnan province of China to Thailand by 2013, while a 230 kV line would link the Malutang hydro plant in Yunnan with Vietnam by 2019 [2].

In this paper, integrated electricity system planning is reviewed in section 2. The metaheuristic optimization methods are reviewed in section 3. Section 4 shows the problem formulation of minimizing the real power loss along with violation of system contingency. The solution algorithm based on the BCO approach is shown in section 5. In section 6, simulation result showing multi-

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objective optimal placement of DG is demonstrated. The validity of the solution algorithm is verified by comparing the searching results with those by the BCO. Lastly, conclusion is given in section 7.



Source: ASEAN Centre for Energy. Key: Existing lines solid, proposed lines dashed.

Fig. 1. Southeast Asian Power Grid Endorsed by ASEAN Leaders.

2. INTEGRATED ELECTRICITY SYSTEM PLANNING

International power grid interconnections provide links between the electricity transmission systems of two or more adjoining countries and thus allow those countries to share power generation resources. As different countries are differently endowed with natural resources, energy trade among countries for centuries has helped to reduce energy prices and increase energy supply in importing countries, while providing a means of income for exporting countries.

International grid interconnections can be as modest as the one-way transfer of a small amount of electricity from one country to another, or as ambitious as the full integration of the power systems and markets of all of the countries in a region. Whatever the scale, international power grid interconnections can help to contribute toward the process of sustainable development. Grid interconnections can help to increase the supply and/or reliability of electricity [3].

The need to embed the consideration of power interconnection and generation projects into the broader consideration of electricity system planning, and even overall energy sector planning but deserves special additional mention. All costs and benefits of a long-term project like the power interconnection and generation must be measured relative to other means of providing the same energy services. As technology progresses, the number of other means of providing those energy services is growing rapidly, including not only construction of new large power plants, but also on-site renewable or fossil-fueled distributed generation for businesses and homes, energy efficiency improvements, fuel switching, and even alternative social organizations.



Source: Doorman et al. Note: Existing substations are shown as filled circles, planned substations as empty circles. Hydro plants are shown as squares with a diagonal slash, fossil-fuelled plants as squares with a horizontal slash.

Fig. 2. Extended Power Cooperation Scenario for Greater Mekong Subregion.

Distributed generation (DG) is a small generator spotted throughout a power system network, providing the electricity locally to load customers. DG is an alternative for industrial and commercial customers. DG makes use of the latest modern technology which is efficient, reliable, and simple enough so that it can compete with traditional large generators in some areas. Placement of DG is an interesting research area due to economical reason. Appropriate size and optimal location are the keys to achieve it.

Recently, the need for more flexible electric systems, changing in the regulatory and economic scenarios is providing impetus to the development of DG. Various kinds of DG are becoming available and it is expected that will grow in future years [4-7].

The local DG has some merits from the viewpoint of location limitations as well as transient and voltage stability in power system. The exact solution of the DG allocation can be obtained by a complete enumeration of all feasible combinations of placement and capacity rating of DG, which could be very large number and various sizes, while the load flow is run for each feasible combination to evaluate the quality of solution. However, the high dimension of the feasible solution is the real difficulty in solving the problem. This paper presents methodology for optimal placement and number of DG in distribution systems by solving an optimization problem of system contingencies and real power loss.

3. REVIEW METAHEURISTIC OPTIMIZATION METHODS

Recently, the metaheuristic optimization methods are being successfully applied to combinatorial optimization problems in power systems. Methods and procedures of the DG placement are varied according to objective and the problem solution viewpoints. In [8], a GA based DG allocation method is presented where the power losses in an existing network is minimized. In [9], Rau and Wan employ gradient and second order methods to determine the optimal DG location for the minimization loss, line loading and reactive power requirement in the network. Kim et al in [10] suggest a combination of fuzzy nonlinear goal programming and genetic algorithm techniques to locate DG and minimize overall power losses. In [11], Nara et al apply tabu search method to the same problem. Griffin et al in [12] demonstrate an iterative method that provides an approximation for the optimal placement of DG for loss minimization. In [13], Kim et al apply Hereford ranch algorithm to optimal placement of fixed capacity DG in order to minimize the losses of network. Celli et al in [14] propose a multiobjective formulation for the sizing and sitting of DG units into distribution feeders for simultaneous minimization of cost of network upgrading, losses, energy not supplied and customer energy. Willis in [15] offers a "2/3 rule" to place DG on a radial feeder with uniformly distributed load, where it is suggested to install DG of approximately 2/3 capacity of the incoming generation at approximately 2/3 of the length of line. El-Khattam et al in [16] use a heuristic approach to determine the optimal DG size and location in distribution feeders from an investment point of view. Wang and Nehrir in [17] present analytical approaches for determining optimal location of DG units with unity power factor in power system to minimize the power losses. In [18], Harrison and Wallace employ an optimal power flow technique to maximize DG capacity with respect to voltage and thermal constraints. Popovic et al in [19] use a sensitivity analysis to maximize DG capacity in the network without violation of security constraints. Keane and O'Malley in [20] present a method based on linear programming to determine the optimal allocation of DG with respect to technical constraints. In [21] Carpenellis et al propose a methodology based on multi-objective programming and decision theory which to find the best development plan for the system by using the DG as a development option. In [22], Borges and Falcao propose a methodology for optimal DG allocation and sizing in order to minimize the network losses and to guaranteeing acceptable reliability level and voltage profile.

In the literatures, several optimization techniques have

been applied to DG placement, such as genetic algorithm (GA) [8], [10], [14], [21], [22], [27], tabu search algorithm (TSA) [11], [24-26], simulated annealing (SA) [28], heuristic algorithms [12], [16] and analytical based methods [9], [15], [17]. This paper presents a model to determine optimal location of DG in a distribution system in order to minimize the electrical losses and violation of system contingency, i.e. line overload and bus overvoltage, which they is solved using bee colony optimization (BCO) [23], [29-30] as the optimization tool by comparing with GA, SA and TSA. In this algorithm, DG is considered as constant power sources. The methods proposed are applied to the IEEE 30-bus test system to demonstrate their effectiveness.

4. PROBLEM FORMULATION

The problems of the system in the future are shortage of reactive power support, undervoltage at various buses, increased system losses and the tendency of voltage collapse initiation. Addition of proper DG in the system can overcome these problems. The contingency is analyzed to assess the ability of the network to provide electric power of sufficient quality to connected customers. DG optimization to alleviate the problem of the system is determined.

The main objective here is to minimize the real power loss along with violation of system contingency while subjected to power balance constraints and power generation limit. This is a case of nonlinear combinatorial problem with multiple objectives. This multi-objective optimization problem is converted to a single objective problem with the help of suitable weights, and the mathematical formulation of the problem is expressed as equation (1).

Minimize
$$\omega_{l}P_{l}(S) + \omega_{2}Vf_{contin}(S)$$
 (1)

subject to:

$$P_i = |V_i| \sum_{j=1}^{N} |Y_{ij}| |V_j| \cos(\theta_i - \theta_j - \delta_{ij})$$
⁽²⁾

$$Q_i = \left| V_i \right| \sum_{j=1}^{N} \left| Y_{ij} \right| \left| V_j \right| \sin(\theta_i - \theta_j - \delta_{ij})$$
⁽³⁾

$$P_{Gi,\min} \le P_{Gi} \le P_{Gi,\max}, \forall_i \in NG$$
(4)

$$Q_{Gi,\min} \le Q_{Gi} \le Q_{Gi,\max}, \forall_i \in NG$$
(5)

where

$$Vf_{contin}(S) = Vvf_{contin}(S) + Olf_{contin}(S)$$
 (6)

Weights considered in Equation (1) reflect the relative priority of each term present in the objective function. In the present work, the weight is used to convert multiobjective optimization problem to a single objective problem. Since the main objective is to achieve a small quantity of power loss and violation of system contingency (voltage violation and line overloading), penalty is imposed to the both terms. Varying these weights can lead to alternative solutions. The experimental results of the optimal values of weight for the IEEE 30 bus system are shown in section 6.

5. BEE COLONY OPTIMIZATION

A great number of traditional engineering models and algorithms used to solve complex problems are based on control and centralization. Various natural mechanisms (social insect colonies) show that very simple individual organisms can create systems able to perform highly complex tasks by dynamically interacting with each other. Bee swarm behavior in nature is, first and foremost, characterized by autonomy and distributed functioning and self-organizing [23]. In the last couple of years, the researchers started studying the behavior of social insects in an attempt to use the swarm intelligence concept in order to develop various artificial systems.

Bee in the Nature

Self-organization of bees is based on a few relatively simple rules of individual insect's behavior. In spite of the existence of a large number of different social insect species, and variation in their behavioral patterns, it is possible to describe individual insects' as capable of performing a variety of complex tasks [31]. The best example is the collection and processing of nectar, the practice of which is highly organized. Each bee decides to reach the nectar source by following a nestmate who has already discovered a patch of flowers. Each hive has a so-called dance floor area in which the bees that have discovered nectar sources dance, in that way trying to convince their nestmates to follow them. If a bee decides to leave the hive to get nectar, she follows one of the bee dancers to one of the nectar areas. Upon arrival, the foraging bee takes a load of nectar and returns to the hive relinquishing the nectar to a food storer bee. After she relinquishes the food, the bee can (a) abandon the food source and become again uncommitted follower, (b) continue to forage at the food source without recruiting the nestmates, or (c) dance and thus recruit the nestmates before the return to the food source. The bee opts for one of the above alternatives with a certain probability. Within the dance area, the bee dancers "advertise" different food areas. The mechanisms by which the bee decides to follow a specific dancer are not well understood, but it is considered that "the recruitment among bees is always a function of the quality of the food source" [31]. It is also noted that not all bees start foraging simultaneously. The experiments confirmed, "new bees begin foraging at a rate proportional to the difference between the eventual total and the number presently foraging".

The basic principles of collective bee intelligence in solving combinatorial optimization problems were for a first time used in [29] and [30]. The authors introduced the Bee System and tested it in the case of Traveling Salesman Problem. The Bee Colony Optimization Metaheuristic that has been proposed in this paper represents further implementing it to solve combinatorial optimization problems of optimal placement of distributed generation.

Bee Colony Optimization Meta-heuristic

The BCO is a relatively new member of swarm intelligence. Within the BCO, agents called - artificial bees collaborate in order to solve difficult combinatorial optimization problem. All artificial bees are located in the hive at the beginning of the search process. During the search process, artificial bees communicate directly. Each artificial bee makes a series of local moves, and in this way incrementally constructs the solution of the problem. Bees are adding components to the current partial solution until they create one or more feasible solutions. The search process is composed of iterations.

The first iteration is finished when bees create for the first time one or more feasible solutions. The best discovered solution during the first iteration is saved, and then the second iteration begins. Within the second iteration, bees again incrementally construct solutions of the problem, etc. There are one or more partial solutions at the end of each iteration. The analyst-decision maker prescribes the total number of iterations.

When flying through the space our artificial bees perform forward pass or backward pass. During forward pass, bees create various partial solutions. It is executed via a combination of individual exploration and collective experience from the past. After that, backward pass is performed of returning to the hive. In the hive, all bees participate in a decision-making process. Every bee can obtain the information about solutions' quality generated by all other bees. In this way, bees exchange information about quality of the partial solutions created. Bees compare all generated partial solutions. Based on the quality of the partial solutions generated, every bee decides whether to abandon the created partial solution and become again uncommitted follower, continue to expand the same partial solution without recruiting the nestmates, or dance and thus recruit the nestmates before returning to the created partial solution. Depending on the quality of the partial solutions generated, every bee possesses certain level of loyalty to the path leading to the previously discovered partial solutions. During the second forward pass, bees expand previously created partial solutions, and after that perform again the backward pass and return to the hive. In the hive bees again participate in a decision-making process, perform third forward pass, etc. The iteration ends when one or more feasible solutions are created.

The advantage of BCO in solving optimization problems is that bee colony is as dynamical system gathering information from an environment and adjusting its behavior in accordance to it. They established a robotic idea on the foraging behavior of bees. Usually, all these robots are physically and functionally identical, so that any robot can be randomly replaced by the others. The swarm possesses a significant tolerance; the failure in a single agent does not stop the performance of the whole system. They also developed a minimal model of forage selection that leads to the emergence of collective intelligence which consists of three essential components: food sources, employed foragers and unemployed foragers. The model defines two leading modes of the behavior: recruitment to a nectar source and abandonment of a source.



Fig. 3. Flow chart of the BCO algorithm.

Comparison with the other algorithms such as GA and SA suggests that BCO works more efficiently due to the parallelism of the multiple independent bees. For TSA, BCO algorithms work more efficiently due to TSA records the closest results to the best known solutions and have the most number of best solutions. Further, it also manages to achieve best results in the shortest execution time. These spectacular results are attributed to the efficient critical block neighborhoods. Moreover, a tabu list that keeps track of the most recent tabu moves prevents the search algorithm to be locked in local minimums.

Algorithm

Like Dynamic Programming, the BCO also solves combinatorial optimization problems in stages. Each of the defined stages involves one optimizing variable. The flowchart of the artificial BCO algorithm is given in Figure 3.

6. SIMULATION RESULTS

The test system is the 30-bus system, which has total load 232.3 MW and 77.3 MVar. The total active power loss and reactive power loss without DG is 4.77 MW and 0.60 MVar, respectively. The maximum number of DG is 2.

The parameters of BCO are set as follow; number of bees = 20, maximum of iteration = 50, number of partial solution = 5, and maximum generation (run) = 1000.

The simulation results on the IEEE 30-bus system show that BCO can obtain the optimal solution with the least computing time comparing with GA, SA and TS. The average computing time of BCO is 82.62%, 74.40% and 83.83% less than GA, SA and TS respectively. Table 1 compares the results of BCO and other heuristic methods.

 Table 1. Comparison results of BCO with other heuristic search methods based on 1,000

Heuristic Approaches	Average Total CPU Time (sec)		
GA	7.0293		
SA	4.7729		
TSA	7.5553		
BCO	1.2219		

 ω_1 and ω_2 as well as normalization of $P_L(S)$ and $Vf_{contin}(S)$ to the same based for calculation of multiobjective optimization has been concluded and presented in Table 2. The results show that the optimal value of ω_1 and ω_2 for the IEEE 30 bus system is 0.3 and 0.7, respectively.

The results of each single objective optimal placement of minimizing system loss and violation function of contingency analysis are summarized in Table 3 and 4, respectively. When single objective of minimizing system loss is considered, the optimal placement of DG is of bus 19 and 20, which the system loss is reduced 27% comparing with system without DG. Meanwhile, when considering single objective of minimizing violation function of contingency analysis, the optimal placement of DG is of bus 19 & 21, which violation function of contingency analysis is reduced 43.75% comparing with system without DG.

Table 2.	Weight factor and normalization for finding			
multi-objective optimization				

ω	W ₂	min Loss	min Cont.	P _L (S)	Vf _{contin} (S)	Opt. Eq.(1)	Bus
0.3	0.7	3.74	4.14	0.78	0.56	0.63	19,21
0.4	0.6	3.74	4.14	0.78	0.56	0.65	19,21
0.5	0.5	3.74	4.14	0.78	0.56	0.67	19,21
0.6	0.4	3.48	4.68	0.73	0.64	0.69	19,20
0.7	0.3	3.48	4.68	0.73	0.64	0.70	19,20

The effect of location and number of DG to each single objective optimal placement of minimizing real power loss and violation function of contingency analysis are presented in Figure 4 and 5, respectively.

Table 3. The simulation results of the single objective optimal placement of minimizing real power loss

System with 2 DG	Min. Power Loss		Max. Power Loss		
DG Size (MW)	Loss (MW)	DG Location (Bus)	Loss (MW)	DG Location (Bus)	
2 x 10	3.48	19 & 20	4.81	2 & 27	
Comparing with system without DG (4.77 MW)	System loss reduced 27%		System loss increased 1.26%		

Table 4. The simulation results of the single objective optimal placement of minimizing violation function of contingency analysis

System with 2 DG	Min. Contingency		Max. Contingency	
DG Size (MW)	System Cont. (p.u.)	DG Location (Bus)	System Cont. (pu)	DG Location (Bus)
2 x 10	4.14	19 & 21	8.16	23 & 27
Comparing with system without DG (7.36 MW)	System contingency reduced 43.75%		System contingency increased 10.87%	

In Table 5, the optimal placement of DG to achieve multi-objective of minimizing real power loss together with violation function of contingency analysis is of Bus 19 and 21, which it can significantly reduce the system loss from 4.77 MW to 3.74 MW or 22% reduction, while violation function of contingency analysis can be reduced from 7.36 p.u. to 4.14 p.u. or 43% reduction, when comparing to the system without DG. The effect of DG allocation to the multi-objectives optimal placement is demonstrated in Figure 6.

 Table 5. The simulation results of the multi-objective optimal placement of DG

Number of DG DG Size (MW)	2 DG 2 x 10
1. Without DG in the system: - System loss (MW) - System contingency (p.u.)	4.77 7.36
 2. With DG in the system: Optimal placement (Bus No.) System loss (MW) System contingency (p.u.) 	19 & 21 3.74 4.14



Fig. 4. Effect of allocation of DG to the single objective optimal placement of minimizing real power loss.

7. CONCLUSION

In this paper, the efficiency and success of BCO approach implemented to determine the multi-objective optimal placement of DG to simultaneously minimize the real power loss and violation function of contingency analysis has been demonstrated. The effectiveness of the BCO to solve the DG allocation problem has been illustrated through the IEEE 30-bus system, which it is executed with the BCO comparing to other heuristic search methods of GA, SA and TSA. Comparison with the other algorithms such as GA suggests that BCO algorithms work more efficiently due to the parallelism of the multi-bees. The result proves that the BCO is the

best against GA, SA and TSA in terms of computing time and number of iteration, which average computing time of BCO is 82.62%, 74.40% and 83.83% less than GA, SA and TSA, respectively.



Fig. 5. Effect of allocation of DG to the single objective optimal placement of minimizing violation function of contingency analysis.



Fig. 6. Effect of allocation of DG to the multi-objective optimal placement.

NOMENCLATURE

- P_i active power at bus *i*,
- Q_i reactive power at bus *i*,
- P_{Gi} active power generation at generator number *i*,
- Q_{Gi} reactive power generation at generator number *i*,
- $|V_i|$ voltage magnitude at bus *i*,
- $|V_j|$ voltage magnitude at bus j,
- $|Y_{ij}|$ magnitude of the the *i*-*j*th element of the bus admittance matrix,
- δ_{ij} angle of the *i*-*j*th element of the bus admittance matrix,
- θ_i phase angle of the voltage V_i ,

- θ_j phase angle of the voltage V_j ,
- *NG* set of generation bus indices,
- N set of bus indices,
- $P_L(S)$ real power loss of solution **S**,
- *S* solution of number and location of the DG,
- ω_l weight factor of the real power loss,
- ω_2 weight factor of the violation function of contingency analysis,
- $Vf_{contin}(S)$ violation function of contingency analysis of solution **S**,
- *Vvf_{contin}(S)* voltage violation function of contingency analysis of solution **S**,
- $Olf_{contin}(S)$ overloaded line function of contingency analysis of solution **S**.

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