Journal of Electrical and Computer Engineering

Applications of Heuristics and Metaheuristics in Power Systems

Guest Editors: Ruben Romero, Edgar M. C. Franco, and Massoud Rashidinejad

Applications of Heuristics and Metaheuristics in Power Systems

Journal of Electrical and Computer Engineering

Applications of Heuristics and Metaheuristics in Power Systems

Guest Editors: Ruben Romero, Edgar M. C. Franco, and Massoud Rashidinejad

Editorial Board

The editorial board of the journal is organized into sections that correspond to the subject areas covered by the journal.

Contents

Hindawi Publishing Corporation
Journal of Electrical and Computer Engineering
Volume 2012, Article ID 658507, 2 pages
doi:10.1155/2012/658507

Editorial

Applications of Heuristics and Metaheuristics in Power Systems

Ruben Romero,[1] Edgar M. C. Franco,[2] and Massoud Rashidinejad[3]

[1] *University of the State of São Paulo (UNESP), Ilha Solteira, SP, Brazil*
[2] *State University of Western Paraná (UNIOESTE), Foz do Iguazu, PR, Brazil*
[3] *Shahid Bahonar University of Kerman 76169, Kerman, Iran*

Correspondence should be addressed to Ruben Romero, ruben@dee.feis.unesp.br

Received 11 March 2012; Accepted 11 March 2012

The electricity industry has undergone profound changes in recent years, resulting in significant changes in economic relations in the generation, transmission, and distribution sectors. This is also leading to important changes in operations management and planning processes relating to different sectors of generation, transmission, distribution, and commercialization of electricity.

In this context, the optimization techniques for application in electrical system operation and planning are becoming increasingly important, especially with the growth in size and complexity of new mathematical models related to optimization problems of electric power systems.

In the optimization of operation and planning problems of electric power systems, optimization techniques used are from the field of operations research. These techniques can be classified into two major groups: (1) exact methods and (2) approximate methods.

Exact methods can be analytical or classical optimization techniques. Analytical exact methods have virtually no application in large and complex problems, and classical optimization techniques include the use of optimization techniques such as linear programming, nonlinear programming, mixed integer linear, and mixed integer nonlinear.

Approximate methods include heuristics and metaheuristics. It should be noted that the larger and more complex the mathematical model of a problem, the more efficient the metaheuristics when compared with other optimization techniques. This special issue presents various optimization proposals related to the operation and planning of power systems using heuristics and metaheuristics.

One paper addresses the problem of multicriteria reconfiguration of distribution network with distributed generation according to the criterion of minimum power loss under normal conditions and the criterion of power supply reliability under postemergency conditions. In this case an specialized ant colony algorithm is used to solve the problem for minimum loss reconfiguration of distribution network. Additionally, some interesting results are presented with data from the Central Power System of Mongolia.

Another paper presents a novel mathematical model for transmission network expansion planning. The main contribution is to consider phase shifter as new elements of the transmission system expansion together with other traditional components such as transmission lines and conventional transformers. There are few proposals of this kind in the specialized literature. It should be noted that the results of this kind of expansion planning require lower investment since the redistribution of the power flow as a result of the phase shifter allows for better use of the transmission lines capacity.

One of the papers assesses the reliability of distribution systems using artificial intelligence methods. The paper presents an artificial neural networks (ANNs) version for evaluating the reliability of distribution power systems. In this case, ANN is used to predict the reliability of the power system using historical data, and the method is constructed according to the back-propagation learning rule. At the same time, the system average interruption frequency index (SAIFI), and the system average interruption duration index (SAIDI) of the real distribution system are computed and compared with results generated by a network method. The results presented are promising.

An evolutionary optimization of electric power distribution planning by means of the dandelion code has been manifested in one of the papers. In this paper, the problem is solved using a genetic algorithm that, with the help

of a coding based on the dandelion code permits solving larger instances of the problem. Using this optimization technique, the authors can solve large size problems such as, for example, electrical networks with 4000 buses and 20 substations.

One other paper describes a specialized genetic algorithm for solving the static and multistage transmission network expansion planning. In this case, an initial population is generated using fast and efficient heuristic algorithms, a better implementation of the local improvement phase is implemented, and an efficient solution of linear programming problems is proposed. Critical comparative analysis is made between the proposed genetic algorithm and traditional genetic algorithms. Results using some known systems show that the proposed specialized genetic algorithm presents higher efficiency in solving the static and multistage transmission network expansion planning.

The final paper on this issue presents two multiobjective optimization methods for congestion management in deregulated power systems. The paper proposes two effective methods for transmission congestion alleviation in deregulated power systems. Congestion or overload in transmission networks is alleviated by rescheduling of generators and/or load shedding. The two objectives that are optimized in this paper, transmission line overload and congestion cost, are conflicting. Multiobjective fuzzy evolutionary programming and nondominated sorting genetic algorithm-II methods are used to solve this problem. The quality and usefulness of the algorithm are tested on the IEEE30 bus system.

Ruben Romero
Edgar M. C. Franco
Massoud Rashidinejad

Hindawi Publishing Corporation
Journal of Electrical and Computer Engineering
Volume 2012, Article ID 527258, 10 pages
doi:10.1155/2012/527258

Research Article

Transmission Network Expansion Planning Considering Phase-Shifter Transformers

Celso T. Miasaki,[1] Edgar M. C. Franco,[2] and Ruben A. Romero[3]

[1] *Mathematics Department, FUNEC, Av. Mangará, 477, Santa Fe do Sul, SP 15755-000, Brazil*
[2] *Engineering and Applied Sciences Center (CECE), UNIOESTE, Av. Tarquinio Joslin dos Santos 1300, Foz do Iguazu, PR 85870-000, Brazil*
[3] *Electrical Engineering Department (DEE), UNESP, Av. Brasil 1200, Ilha Solteira, SP 15385-000, Brazil*

Correspondence should be addressed to Edgar M. C. Franco, emfranco@unioeste.br

Received 3 October 2011; Accepted 16 January 2012

Academic Editor: Massoud Rashidinejad

This paper presents a novel mathematical model for the transmission network expansion planning problem. Main idea is to consider phase-shifter (PS) transformers as a new element of the transmission system expansion together with other traditional components such as transmission lines and conventional transformers. In this way, PS are added in order to redistribute active power flows in the system and, consequently, to diminish the total investment costs due to new transmission lines. Proposed mathematical model presents the structure of a mixed-integer nonlinear programming (MINLP) problem and is based on the standard DC model. In this paper, there is also applied a specialized genetic algorithm aimed at optimizing the allocation of candidate components in the network. Results obtained from computational simulations carried out with IEEE-24 bus system show an outstanding performance of the proposed methodology and model, indicating the technical viability of using these nonconventional devices during the planning process.

1. Introduction

Transmission network planning begins with the establishment of power demand growth scenarios, in accordance with forecasts along the time. Given these scenarios, one can verify the eventual need to broaden and to strengthen the network. In case electric service conditions are not satisfied, there should be proposed a plan that has coherence among the power supply availability, demand, and installation of new equipments in the network. Integration of these new equipments in the network, aimed at maintaining suitable technical and operating conditions, requires planning of the allocation of such reinforcement.

Main objective of the transmission expansion planning is to obtain the *optimal expansion plan*, while fulfilling operating and economic constraints.

Formulation of a mathematical representation for the transmission expansion planning problem begins with some assumptions, where accuracy and complexity are considered in the model construction. Regularly, the problem is represented by a Mixed-Integer Nonlinear Programming (MINLP) problem that presents many local optima solutions for real-life systems. This high number is due to the possible expansion plans that shows the association of the specified optimal operational mode. Therefore, a basic problem consists in defining the least-cost expansion alternative that satisfies all operating constraints.

In static long-term transmission expansion planning (typically with a planning horizon of more than 5 years), all investments are carried out in a single-year planning horizon, whereas for the multistage it is divided into several stages.

Static planning is aimed at searching *where* and *what* type of circuits should be constructed for the network to operate properly. This type of planning applies some simplifications; for instance, voltage magnitudes constraints are neglected, albeit in short-term planning are essential. Voltage and stability problems are not taken into account in this

approach either. Even though considering these simplifications, the problem still remains complex with unknown optima solutions for various real-life systems.

In the technical literature, DC and transportation models are static mathematical models often used to solve the transmission expansion planning problem. These models consider only the addition of transmission lines (TLs) and conventional transformers.

Here a novel transmission expansion strategy is proposed. An improved model considers the inclusion of a new kind of device, in this case, a flexible alternating current transmission system (FACTS) device.

The literature concerning the use of FACTS devices is wide. However, most papers treat only the operational improvement by using FACTS devices [1–3]. This topic is considered as the operation planning, in which FACTS devices are used, for example, to redistribute the active power flow in order to eliminate congestion problems and/or to optimize the power dispatch. In this way, the PS is considered a FACTS device with the characteristic of redistributing the active power flow.

Feasibility of employing the PS as a candidate component in the long-term transmission expansion planning process is analyzed regarding a static and centralized planning model. Nevertheless, the present model can be extended to the multistage planning [4], to the competitive planning [5], or to the planning with security constraints [6].

Instead of trying to consider all functions concerning the planning problem in a single model, this work is focused solely on the core of the network synthesis; for which the mathematical modeling and the solution technique is addressed.

The proposed model is based on the DC model, which is the most employed one in planning problems; consequently, only the active power flow is considered. Other aspects such as performance analysis (reliability and stability analysis, reactive planning, AC power flow, and short-circuit calculation) relevant to transmission expansion are beyond the scope of this paper. Nonetheless, in general, after obtaining a basic solution, all those analyses can be carried out.

2. Mathematical Model

This section introduces the classical mathematical model and the proposed one.

2.1. Classical Model. The mathematical formulation of the DC model for transmission network expansion planning problem, when considering solely the installation of transmission lines and/or conventional transformers, assumes the following form:

$$\text{Minimize} \quad v = \sum_{(i,j)} c_{ij} n_{ij} \tag{1}$$

subject to

$$S \cdot f + g = d, \tag{2}$$

$$f_{ij} - \gamma_{ij} \cdot \left(n_{ij}^0 + n_{ij}\right) \cdot \left(\theta_i - \theta_j\right) = 0, \tag{3}$$

$$\left| f_{ij} \right| \leq \left(n_{ij}^0 + n_{ij}\right) \cdot \overline{f}_{ij}, \tag{4}$$

$$0 \leq g_i \leq \overline{g_i}, \tag{5}$$

$$0 \leq n_{ij} \leq \overline{n_{ij}}, \tag{6}$$

$$n_{ij} \quad \text{Integer}, \tag{7}$$

$$f_{ij} \quad \text{Unbounded}, \tag{8}$$

$$\theta_j \quad \text{Unbounded}, \tag{9}$$

$$(i, j) \in \Omega. \tag{10}$$

The objective function (1) represents the investment cost due to new transmission lines during the specified planning horizon.

The first set of constraints (2) represents Kirchhoff's Current Law (KCL) equations (one constraint per bus), and the second one (3) represents Kirchhoff's Voltage Law (KVL) (one constraint per branch). In this model, the transmission lines or regular transformers are represented without distinction by decision variables n_{ij}.

Set of constraints (4) refers to the capacity of transmission circuits (lines and/or transformers) in terms of the required absolute value since the power flow can flow in both ways.

Constraint (5) represents the limits for generation buses and (6) represents the limits for the added circuits at each candidate path i-j. Remaining constraints refer to the self-characteristics of the variables.

From the operational research standpoint, system (1)–(10) is a MINLP whose resolution is complex, especially for large-size electric systems. Main source of complexity in the problem is due to variables n_{ij} that need to be integer.

For some types of algorithms utilized for the transmission network planning problem, it is more suitable to carry out alterations to the basic modeling for allowing the application of the solution techniques. An alteration commonly used is the insertion of new variables that represent the load shedding associated with all load buses of the system. This resource can also be seen as an artificial generation aimed at turning the problem always viable during computational implementations [7]. Note that this artificial generation, from the mathematical standpoint, is solely an increase in the number of variables of the original problem. Additionally, all variables corresponding to the artificial generators in the final solution should be equal to zero, so both problems (original and modified) will have equivalent solutions.

2.2. Model with Phase Shifters. When PS is considered in the transmission network planning problem, the DC model assumes the following form:

$$\text{Minimize} \quad v = \sum_{(i,j)} c_{ij} n_{ij} + \sum d_{ij} \cdot \left(n_{ij}^0 + n_{ij}\right) \cdot \delta_{ij} + \alpha \sum r_k \tag{11}$$

subject to

$$S \cdot f + g + r = d, \tag{12}$$

$$f_{ij} - \gamma_{ij} \cdot \left(n_{ij}^0 + n_{ij}\right) \cdot \left(\theta_i - \theta_j + \varphi_{ij} \cdot \delta_{ij}\right) = 0, \tag{13}$$

$$\left|f_{ij}\right| \leq \left(n_{ij}^0 + n_{ij}\right) \cdot \overline{f}_{ij}, \tag{14}$$

$$0 \leq g_i \leq \overline{g_i}, \tag{15}$$

$$0 \leq n_{ij} \leq \overline{n_{ij}}, \tag{16}$$

$$0 \leq r_{kj} \leq d_k, \tag{17}$$

$$n_{ij} \quad \text{Integer}, \tag{18}$$

$$f_{ij} \quad \text{Unbounded}, \tag{19}$$

$$\theta_j \quad \text{Unbounded}, \tag{20}$$

$$\varphi_{ij} \quad \text{Unbounded}, \tag{21}$$

$$\delta_{ij} \quad \text{Unbounded}, \tag{22}$$

$$(i, j) \in \Omega. \tag{23}$$

The objective function (11) corresponds to the investment cost. First two terms refer to the costs due to the insertion of transmission lines and PS, respectively. Last term refers to a penalty for the configuration under analysis, due to the presence of artificial generation. The penalty parameter α should be properly weighted in order to turn those configurations less attractive with artificial generation.

In constraint (12), corresponding to KCL, vectors g and r indicate existent and artificial generations, respectively.

Installation of PS in one or more lines can be represented as the combination of the buses' angles and the angle supplied by the equipment.

Angle between terminal voltages of a transmission line can be modified by installing a PS. Therefore, power flow equations (KVL) are affected when these devices are inserted. Thus, the function of PS appears in the KVL, which redirects the active power flow.

The PS is considered a component with negligible reactance that can be placed in series with a transmission line or a conventional transformer.

In this work, the angular difference of the PS was considered an unbounded variable; however, a limit can be set without modifying the mathematical model significantly.

Presence of variable $\delta_{ij} \in \{0, 1\}$ in (13) makes this relation even more nonlinear in relation to the DC model and, consequently, more complex since four types of variables (n_{ij}, θ_j, φ_{ij}, and δ_{ij}) are multiplied.

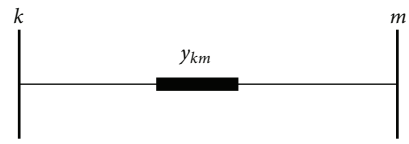

Figure 1: Transmission line.

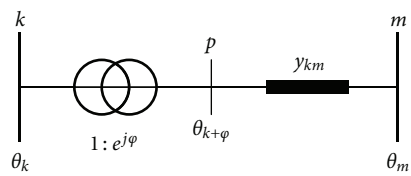

Figure 2: Transmission line and phase-shifter transformer.

Table 1: Lines data of the 3 buses system.

Line	Reactance (pu)	Maximum flow (MW)
1-2	0.333	35
1–3	0.500	40
2-3	0.500	40

Set of constraints (14), (15), (16), and (17) refers to the transmission capacity of the circuits, limits of generation buses, limits of circuits added in each candidate path i-j, and limits of artificial generation buses, respectively. Remaining constraints refer to the characteristics of variables.

Therefore, the proposed mathematical model is more complex than the classical one, due to the characteristics of a PS.

In traditional models, a transmission line or a conventional transformer in a path k-m can be represented in Figure 1.

The PS is considered with zero impedance connected in series with a transmission line or a conventional transformer in path k-m as shown in Figure 2.

It is also considered that when a path k-m is selected, the PS is allocated to every transmission line present in path k-m. Therefore, the number of PS at each selected path is equal to $n\text{PS}_{ij} = (n_{ij}^0 + n_{ij}) \cdot \delta_{ij}$. The PS can be allocated in existing transmission lines as well as in those created during the optimization process.

Problem (11)–(23) represents a MINLP, which is more complex than the model (1)–(10). However, metaheuristic techniques employed for (1)–(10) can also be applied to (11)–(23) after performing some modifications.

2.3. Illustrative Example: 3-Bus System. An example consisting of a network with three buses is presented in order to illustrate the application of the PS. System data is shown in Tables 1 and 2.

Results obtained by performing the linearized DC power flow are illustrated in Figure 3.

Table 2: Generation and demand data of the 3-buse system.

Bus	Generation (MW)	Demand (MW)
1	70	0
2	0	60
3	0	10

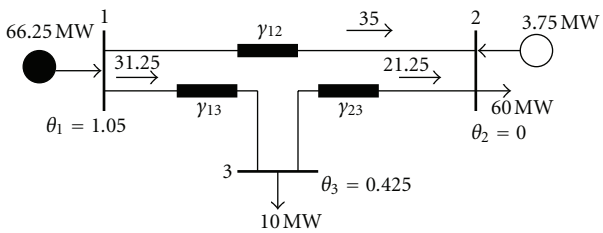

Figure 3: Three-bus system.

Notice that there is a load shedding of $r_2 = 3.75$ MW at bus 2. Therefore the system is not operating adequately and new transmission lines are required. On the other hand, lines 1–3 and 2-3 are operating below their capacity. In this case, there is no possibility of increasing the transmitted power through the lines without overloading line 1-2. An interesting solution for this problem is to install a PS at 1–3 (see Figure 4), so the system operates without load shedding.

Thus, this example shows how a PS is able to redirect the active power flow. This property will be employed in the long-term transmission planning, in which basic components are transmission lines, conventional transformers, and PS.

2.4. Phase-Shifter Transformer Features. PSs have the ability to redirect active power flows in the network. This feature provides a dynamic operational mode since it makes increasing the utilization of existing circuits possible. Consequently, as it can be verified from relation (13), the PS acts directly on KVL.

Another important aspect is the use of relaxed models. In general, optimal solutions for relaxed models are not feasible for more accurate or constrained ones. Thus, it is probable that the optimal solution obtained by the transportation model, where the KVL (13) is relaxed (dropped), presents the KVL constraints violated in the DC model. With the inclusion of PS in determined positions, a feasible solution obtained with transportation model becomes also feasible for the DC model since the KCL constraints are already satisfied for both models. However, an efficient inclusion should be carried out in order to satisfy the optimality conditions of the DC model, once there exist expansion proposals with lower costs. It is worthwhile to notice that if PS costs are equal to zero, then the optimal solution for the transportation model and the DC model presents the same added lines, that is, presents the same topology for both mathematical models. Only difference with the conventional approach is that some PS are included in order to satisfy the KVL.

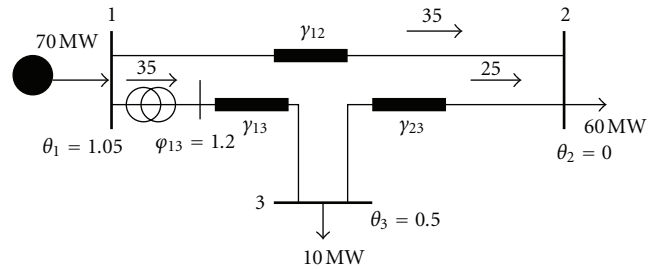

Figure 4: Load flow solution with a phase shifter.

The primary objective of this work is to verify the operation of PS and the technical feasibility of considering such type of equipment in long-term transmission expansion planning. In case a reduced-cost PS is employed, the optimal solution will be the same of the transportation model with addition of PS. On the other hand, higher costs will inhibit the presence of PS in the optimal solution, tending to the solution given by classical DC model. Finally, if the costs are competitive to transmission lines, an intermediary solution will be provided.

3. Solution Mathodology

Metaheuristic algorithms are specially suited for problems that present large search space with many local optima, such as the transmission expansion planning problem. The nonlinearity of the problem concerning the KVL is higher than the conventional model, thus degenerating even more the performance of more accurate methods. For instance, simulated annealing, genetic algorithms, and tabu search represent efficient methods for solving such problems. This work employed a modified version of the genetic algorithm presented in [4, 8] for solving the mathematical optimization problem. Indeed, extra modifications become necessary in order to guarantee the acceptable performance of the genetic algorithm.

4. Genetic Algorithm

This section presents the genetic algorithm developed for the planning problem considering the addition of PS.

4.1. Encoding. Each individual in a population (chromosome) is a proposed solution for the problem. In this work, an individual is encoded considering only the integer and binary variables. Remaining variables (continuous variables) are obtained from the linear programming (LP) solution. Thus, transmission lines and transformers are represented by decimal encoding (variable n_{ij}), whereas the PSs are represented by binary variables (δ_{ij}).

An example of this chromosome of length $2nl$ is shown in Figure 5. The first nl positions show the number of transmission lines added for each configuration and the last nl positions indicate whether a PS was added or not in each path. The existing transmission lines are not coded but they

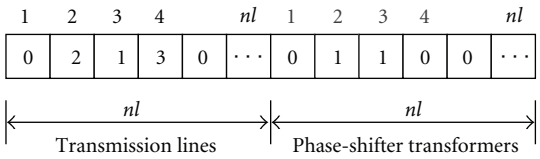

Figure 5: Encoding proposal (chromosome).

are taken into account when operational variables are calculated, as well as when PSs are added in series to the transmission lines at each path. It can be noticed that in path 2, two transmission lines have been added with the corresponding PS. In path 3, one transmission line and the necessary number of PSs have been added, and so on.

In [8], an excellent performance of the genetic algorithm was obtained with the coding above, which is also in accordance with the coding proposals suggested for genetic algorithms presented in [4, 9, 10].

4.2. Objective Function and Infeasibility. The objective function of any solution proposal is found by solving an LP problem. The LP determines the exact values of the operational variables, which makes verifying the operation feasibility of a determined investment proposal possible, that is, whether the system presents load shedding to the implemented expansion proposal. Considering that an investment proposal s is characterized by variables n_{ij}^s and δ_{ij}^s, the load shedding is obtained by solving the following LP problem:

$$\text{Minimize} \quad w^s = \sum_{k \in \Gamma} r_k \tag{24}$$

subject to

$$S \cdot f + g + r = d, \tag{25}$$

$$f_{ij} - \gamma_{ij} \cdot \left(n_{ij}^0 + n_{ij}^s\right) \cdot \left(\theta_i - \theta_j + \varphi_{ij} \cdot \delta_{ij}^s\right) = 0, \tag{26}$$

$$\left|f_{ij}\right| \le \left(n_{ij}^0 + n_{ij}^s\right) \cdot \overline{f}_{ij}, \tag{27}$$

$$0 \le g_i \le \overline{g_i}, \tag{28}$$

$$0 \le r_k \le d_k, \tag{29}$$

$$f_{ij} \quad \text{Unbounded}, \tag{30}$$

$$\theta_j \quad \text{Unbounded}, \tag{31}$$

$$\varphi_{ij} \quad \text{Unbounded}, \tag{32}$$

$$(i, j) \in \Omega. \tag{33}$$

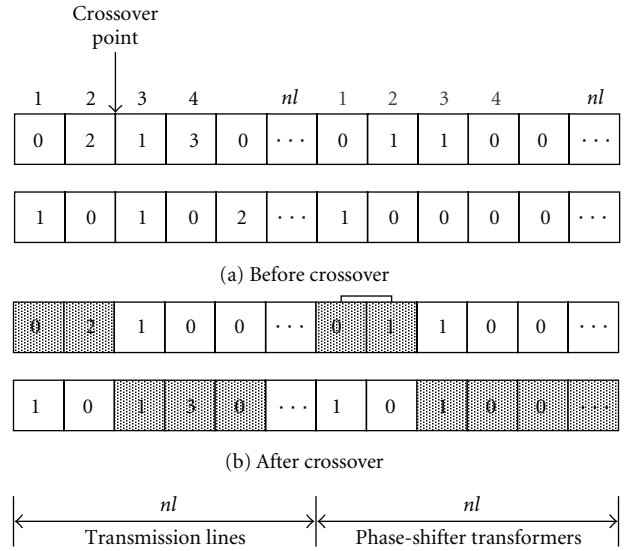

Figure 6: Single point crossover.

For each solution proposal, the objective function is calculated with the following expression:

$$v^s = \sum_{(i,j) \in \Omega} c_{ij} n_{ij}^s + \sum d_{ij} \cdot \left(n_{ij}^0 + n_{ij}^s\right) \cdot \delta_{ij}^s + \alpha \cdot w^s. \tag{34}$$

In the genetic algorithm, every solution proposal is considered, including the infeasible ones. The infeasible configurations (with load shedding) are eliminated gradually by selection process, since these configurations are penalized by parameter α in the objective function.

4.3. Selection Process. The selection is based on tournament with $k = 2$, that is, a game where two topologies of the current population participate. Recent publications show that selection by tournament is the most efficient method as long as parameter k is set adequately.

4.4. Crossover. The single point crossover was employed in this work. The crossover point is chosen randomly and a descendant, which has a parcel of its parents from the crossover point, is created. The random point was generated from an interval of 1 to $(nl - 1)$, that is, considering only the first half of the chromosome. In the second part the same operation is executed as shown in Figure 6. The objective of the operation is to transmit the existing information, which is present in both sectors of the chromosome to only one descendant in order to avoid quality degeneration.

4.5. Mutation. The mutation operator acts in the following form. Considering transmission lines, the application of mutation operation means the addition or removal of one transmission line added during the optimization process ($n_{ij} + 1$ or $n_{ij} - 1$). For PS, it means the change of an allele, that is, inclusion or exclusion of the PS in the path.

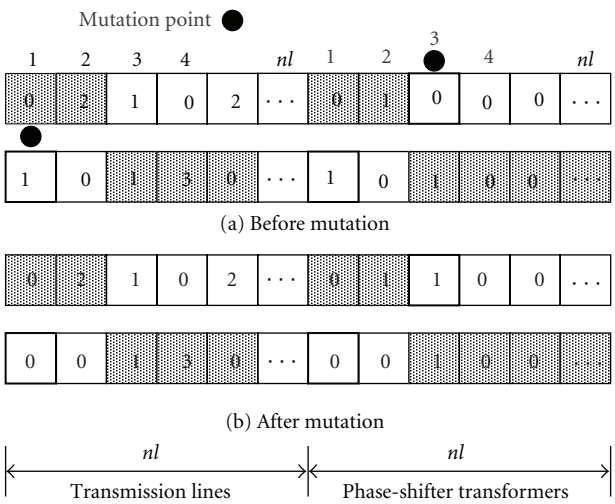

Figure 7: Mutation.

The mutation operation should be executed respecting the following conditions:

(1) the maximum number of transmission lines in the path;

(2) before adding a PS in the selected path, the existence of a transmission line must be checked; if it is an empty path, a transmission line has also to be added;

(3) when a transmission line is removed, the corresponding PS is removed, in case it exists.

Concluding, a PS can only be inserted to an existing transmission line, whereas the number of PS is equal to the number of transmission lines in a branch. In Figure 7, two cases of mutation are presented. The first case shows the random addition of PS to an existing transmission line, and the second case, mutation is applied to the transmission line that is removed (in this case there is no transmission line in the base topology); then the PS is removed in order to keep the process coherent.

4.6. Proposed Genetic Algorithm. The general structure of the implemented genetic algorithm is similar to that presented in [8], except for some modifications. The basic structure of the algorithm is the following.

(1) Set the control parameters and generate the initial population. Make the initial population the current population.

(2) Calculate the objective function of the current population by solving one LP for each element (topology) of the current population. Update the incumbent solution whenever possible.

(3) If the stopping criterion is satisfied, stop the process. Otherwise go to step 4.

(4) Execute selection by tournament with $k = \{2; 3\}$.

(5) Execute one point crossover.

(6) Implement specialized mutation.

(7) Form the current population and go to step 2.

Some details of the algorithm are presented in the next section.

4.7. Details and Improvement of the Genetic Algorithm. We present, briefly, details of the algorithm and some improvements made to the genetic algorithm.

4.7.1. Generation of the Initial Population. Generation of the initial population is made by a controlled random process. Basically, it defines the number of paths in which the transmission lines are added and the maximum number of PS. Regarding transmission lines are defined randomly number of branches where the lines are inserted, position, and number of transmission lines (subject to the limits of added lines). In the case of PS, the number of branches and the position are selected randomly. In general, experience in transmission planning indicates that the number of branches to be added should be small, whereas the number for PS should be even smaller.

The performance coefficient (35) can be employed for ranking the most interesting transmission lines. Observe that lines with a larger capacity that is also cost-effective have the priority in the addition:

$$\mathrm{PC}_{ij} = \frac{\overline{f_{ij}}\gamma_{ij}}{c_{ij}}. \tag{35}$$

After ranked, the circuits are separated into two groups with different size (75%, 25%), whereas the largest one presents the most interesting transmission lines in terms of capacity usage. The initial population is formed by 80% up to 100% of elements belonging to the largest group. Another option to the initial population generation is to employ constructive heuristic algorithms as in [11, 12].

4.7.2. Control Parameters: Crossover and Mutation Rates. The employed crossover rate was $R_C = 0.8$. Two mutation rates were employed: $R_M = 0.1$ or $R_M = 0.6$ (the value depends on the current population diversification level). The mutation rate is defined differently from the classical concept and it applies for an entire solution proposal (topology). For example, a rate of 0.1 means that there is 10% of probability for a topology to suffer mutation. The population size varied from 40 to 200 elements.

4.7.3. Mutation Details. Mutation is executed in the following way: the power flow of each topology is stored in four matrices considering the load level of each circuit. They are separated in intervals of 25, 50, 75, and 100% of capacity. The load level is calculated by means of the relationship (36):

$$\mathrm{FC}_{ij} = \frac{f_{ij}}{\left(n_{ij}^{0} + n_{ij}\right) \cdot \overline{f_{ij}}}. \tag{36}$$

Mutation operation is executed based on the probability of 70% of circuit removal and 30% of circuit addition. In case

Table 3: Five transmission expansion plans considering low-cost phase-shifter transformers.

Circuits	Plan P_0		Plan P_1		Plan P_2		Plan P_3		Plan P_4	
	TL	PS	TL	PS	TL	PS	TL	PS	TL	PS
$\mathbf{n}_{01\text{-}03}$								1		
$\mathbf{n}_{03\text{-}09}$						1				
$\mathbf{n}_{04\text{-}09}$						1				
$\mathbf{n}_{03\text{-}24}$					1					
$\mathbf{n}_{06\text{-}10}$	1		1		1		1		1	
$\mathbf{n}_{07\text{-}08}$	2		2		1		2		2	
$\mathbf{n}_{08\text{-}09}$		1		1						
$\mathbf{n}_{08\text{-}10}$									1	
$\mathbf{n}_{10\text{-}12}$					1					1
$\mathbf{n}_{11\text{-}14}$		1		1						
$\mathbf{n}_{12\text{-}23}$				1				1		
$\mathbf{n}_{13\text{-}23}$										1
$\mathbf{n}_{14\text{-}16}$	1		1		1				1	
$\mathbf{n}_{15\text{-}16}$								1		
$\mathbf{n}_{16\text{-}17}$			2		2			1	1	
$\mathbf{n}_{16\text{-}19}$			1		1					
$\mathbf{n}_{17\text{-}18}$			1		1					
$\mathbf{n}_{17\text{-}22}$								1		
$\mathbf{n}_{19\text{-}22}$						2				
$\mathbf{n}_{13\text{-}14}$							1	1		
Partial cost	**102**	**4**	**226**	**6**	**310**	**8**	**110**	**14**	**188**	**4**
Total cost	**106**		**232**		**318**		**124**		**192**	

that circuit addition operation is selected, a random selection is carried out over the branches from the matrix with most loaded branches (up to 75%). If the matrix is empty, the next load level matrix is searched. For the circuit removal operation, the search starts from the least loaded branches (matrices with branches on 25% and 50% of its capacity). With this strategy, transmission lines with low utilization are removed from the system, whereas in regions where higher utilization is observed lines are inserted.

4.7.4. Stopping Criterion. The algorithm stops when a defined total number of iterations is reached or when there is no improvement of the incumbent solution after a specified number of iterations.

4.7.5. Elitism and Diversification Control. The population diversity is controlled by changing the mutation rate. A measurement of diversity is given by (37):

$$R_{\text{Div}} = \frac{\text{Pop} - \text{NR}}{\text{Pop}}. \tag{37}$$

The diversification rate is calculated after mutation. If this rate is below 50%, there is used a mutation rate of 0.6; otherwise a rate of 0.1 is considered. This mechanism was applied aimed at maintaining diversity and at exploring new search spaces.

Another strategy used was the elitism, in which the parent topologies are compared with the descendants and then the two best topologies are preserved in the current population.

5. Tests and Results

In order to analyze the performance of the proposed genetic algorithm and to demonstrate viability of the mathematical model with PS, tests were carried out with the IEEE-24 bus system. This system has 41 circuit paths, 8550 MW of load, generation capacity of 10215 MW, and five different generation plans whose data is present in [5].

For all simulations, a fixed cost for the PS was adopted, that varies among 2 and 120 million of dollars. In all the tests was used a value of $\alpha = 10^6$ US$/MW.

The simulations were divided in three stages. In the first stage, equipments of low value were added. In the following stage, equipments of high value were added. Finally, in the last stages, intermediate costs were adopted; that is, in each stage different values were fixed for the PS.

5.1. Low-Cost Phase Shifters. With the purpose of testing the algorithm, the first simulations set the cost of PS as low as $d_{ij} = 2 \times 10^6$ (US$). Table 3 shows the results obtained.

Table 4: Five transmission expansion plans considering high-cost phase-shifter transformers.

Circuits	Plan P_0		Plan P_1		Plan P_2		Plan P_3		Plan P_4	
	TL	PS	TL	PS	TL	PS	TL	PS	TL	PS
$\mathbf{n}_{01\text{-}05}$			1		1					
$\mathbf{n}_{03\text{-}24}$			1		1				1	
$\mathbf{n}_{06\text{-}10}$	1		1		1		1		1	
$\mathbf{n}_{07\text{-}08}$	2		2		1		2		2	
$\mathbf{n}_{09\text{-}11}$									1	
$\mathbf{n}_{10\text{-}12}$	1				1		1		1	
$\mathbf{n}_{11\text{-}14}$									1	
$\mathbf{n}_{14\text{-}16}$	1		1		1		1		1	
$\mathbf{n}_{15\text{-}24}$			1		1					
$\mathbf{n}_{16\text{-}17}$			2		2		1		1	
$\mathbf{n}_{16\text{-}19}$			1							
$\mathbf{n}_{17\text{-}18}$			2		2					
$\mathbf{n}_{20\text{-}23}$							1			
Partial cost	**152**	**0**	**390**	**0**	**392**	**0**	**218**	**0**	**346**	**0**
Total cost	**152**		**390**		**392**		**218**		**346**	

Table 5: Plan P_1 of the system IEEE-24bus considering intermediary-cost phase-shifter transformers.

Circuits	Plan P_0		Plan P_1		Plan P_2	
	TL	PS	TL	PS	TL	PS
$\mathbf{n}_{03\text{-}24}$		1		1		1
$\mathbf{n}_{06\text{-}10}$	1		1		1	
$\mathbf{n}_{07\text{-}08}$	2		2		2	
$\mathbf{n}_{08\text{-}10}$		1				
$\mathbf{n}_{09\text{-}12}$				1		
$\mathbf{n}_{10\text{-}11}$	1		1			
$\mathbf{n}_{10\text{-}12}$					1	
$\mathbf{n}_{12\text{-}23}$						1
$\mathbf{n}_{14\text{-}16}$	1		1		1	
$\mathbf{n}_{16\text{-}17}$	2		2		2	
$\mathbf{n}_{16\text{-}19}$	1		1		1	
$\mathbf{n}_{17\text{-}18}$	1		1		1	
Partial cost	**276**	**110**	**276**	**110**	**276**	**110**
Total cost	**386**		**386**		**386**	

A very interesting fact in the simulations with low-cost PS refers to transmission lines. For the five plans illustrated in Table 3, it is noticed that the lines added by the proposed specialized genetic algorithm were the same of the optimal solution for the transportation model. This fact was confirmed by utilizing a branch-and-bound algorithm presented in [13].

Results also confirmed that the optimal solution for the transportation model is not feasible for the DC model since KVL constraints are violated. Nonetheless, during the simulation, this problem was overcome by adding low-cost PS in strategic branches.

5.2. High-Cost Phase Shifters. Here there is considered $d_{ij} = 120\times10^6$ (US\$) for high-cost PS. For the same five generation plans, obtained results are illustrated in Table 4.

Again, allocation of lines deserves importance. Simulations carried out with high-cost PS indicate that there was no addition of PS in none of the five plans of expansion of the system. The justification for the absence of PS, in all the topologies, is that they are too expensive. Thus, they did not take part of the optimal solutions. Consequently, there is a tendency of solely adding transmission lines.

Another interesting fact that deserves emphasis is that the results are the same found to the conventional DC model.

5.3. Intermediary-Cost Phase Shifters. PSs with arbitrary intermediary costs were employed in order to produce expansion proposals with intermediary values when compared to extreme solutions obtained in previous simulations. The PS was considered with cost of $d_{ij} = 55 \times 10^6$ (US$) for every branch in plan P_1. Obtained results are shown in Table 5.

The proposed algorithm found alternative optimal solutions for the plan P_1. Observe that circuit 10-11, which is not present in the previous cases (PS with low and high costs), appears now. Notice that in the three topologies found for the plan P_1 were added two phase-shifter transformers in the network.

It is important to mention that all tests have been carried out for PS with nonrealistic cost values in order to test, from the theoretical point of view, the feasibility of modeling such devices as expansion components for electrical systems. Additional network transmission planning bibliography can be found in [14]. It should be observed that this novel model could be solved by other metaheuristics as presented in [9, 15, 16] after small adaptations.

6. Conclusions

Nowadays, modern elements, such as FACTS devices, are playing an important role in transmission systems. In this way, inclusion of such devices jointly with classical components is of importance for the transmission expansion planning problem. Thus, this work was aimed at presenting the technical feasibility of considering phase-shifter transformers as components for the long-term transmission expansion planning, jointly with conventional transformers and transmission lines.

A novel methodology was proposed for the inclusion of phase-shifter transformers in the mathematical model that represents the transmission planning problem. The proposed model is more complex than the model DC. However, the mathematical problem was solved adequately with genetic algorithms.

Tests have shown the model consistency as well as the high performance of the algorithm.

This contribution extends the utilization of classical components during the expansion-planning problem, to modern elements, such as the FACTS devices.

Nomenclature

v: Investment costs (US$)
c_{ij}: Cost of a circuit that can be added in path i-j (US$)
n_{ij}: Number of circuits added in path i-j
S: Node-branch transposed incidence matrix of the system
f: Active power flow composed by elements f_{ij}
g: Generation composed by elements g_k
d: Demand of the buses
f_{ij}: Total active power flow through path i-j
γ_{ij}: Susceptance of one circuit in path i-j
n^o_{ij}: Base case total number of circuits
θ_i: Phase angle of bus i
$\overline{f_{ij}}$: Active power flow limit of one circuit in path i-j
g_i: Generation level of bus i
$\overline{g_i}$: Generation capacity limit of bus i
$\overline{n_{ij}}$: Number of circuits that can be added in path i-j
Ω: Set of all paths
d_{ij}: Fixed cost of a PS in path i-j
δ_{ij}: Represents the presence (1) or not (0) of a PS in path i-j
α: Penalty factor due to load shedding
r_k: Artificial generator at load bus k
Γ: Set of buses with load
φ_{ij}: Angular difference of a PS in path i-j
$n\mathrm{PS}_{ij}$: Number of PS added in path i-j
nl: Total number of paths in the network
n^s_{ij}: Number of the circuits added in path i-j, considering an investment proposal s given by the specialized genetic algorithm
δ^s_{ij}: Represents the presence (1) or not (0) of a PS in path i-j, considering an investment proposal s given by the specialized genetic algorithm
w^s: Load shedding costs of a configuration (US$)
PC_{ij}: Performance coefficient of one transmission line in path i-j
R_C: Crossover rate
R_M: Mutation rate
FC_{ij}: Flow utilization coefficient of one transmission line in path i-j
R_{Div}: Population diversification ratio (%)
NR: Total number of repeated configurations in the current population
Pop: Total number of configurations of the population.

Acknowledgments

This work was supported by CAPES, CNPq, and Fundação Araucaria.

References

[1] P. Paterni, S. Vitet, M. Bena, and A. Yokoyama, "Optimal location of phase shifters in the french network by genetic algorithm," *IEEE Transactions on Power Systems*, vol. 14, no. 1, pp. 37–42, 1999.
[2] G. N. Taranto, L. M. V. G. Pinto, and M. Veiga Ferraz Pereira, "Representation of FACTS devices in power system economic dispatch," *IEEE Transactions on Power Systems*, vol. 7, no. 2, pp. 572–576, 1992.
[3] 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, no. 3, pp. 537–544, 2001.
[4] A. H. Escobar, R. A. Gallego, and R. Romero, "Multistage and coordinated planning of the expansion of transmission systems," *IEEE Transactions on Power Systems*, vol. 19, no. 2, pp. 735–744, 2004.

[5] R. Fang and D. J. Hill, "A new strategy for transmission expansion in competitive electricity markets," *IEEE Transactions on Power Systems*, vol. 18, no. 1, pp. 374–380, 2003.

[6] A. Seifu, S. J. Salon, and G. F. List, "Optimization of transmission line planning including security constraints," *IEEE Transactions on Power Systems*, vol. 4, no. 4, pp. 1507–1513, 1989.

[7] S. Binato, M. V. F. Pereira, and S. Granville, "A new Benders decomposition approach to solve power transmission network design problems," *IEEE Transactions on Power Systems*, vol. 16, no. 2, pp. 235–240, 2001.

[8] R. A. Gallego, A. Monticelli, and R. Romero, "Transmision system expansion planning by an extended genetic algorithm," *IEE Proceedings Generation, Transmission and Distribution*, vol. 145, no. 3, pp. 329–335, 1998.

[9] E. L. D. Silva, H. A. Gil, and J. M. Areiza, "Transmission network expansion planning under an improved genetic algorithm," *IEEE Transactions on Power Systems*, vol. 15, no. 3, pp. 1168–1175, 2000.

[10] P. C. Chu and J. E. Beasley, "A genetic algorithm for the generalised assignment problem," *Computers and Operations Research*, vol. 24, no. 1, pp. 17–23, 1997.

[11] R. Villasana, L. L. Garver, and S. J. Salon, "Transmission network planning using linear programming," *IEEE transactions on power apparatus and systems*, vol. 104, no. 2, pp. 349–356, 1985.

[12] GARVER LL, "Transmission network estimation using linear programming," *IEEE Trans Power App Syst*, vol. 89, no. 7, pp. 1688–1697, 1970.

[13] S. Haffner, A. Monticelli, A. Garcia, and R. Romero, "Specialised branch-and-bound algorithm for transmission network expansion planning," *IEE Proceedings Generation, Transmission and Distribution*, vol. 148, no. 5, pp. 482–488, 2001.

[14] G. Latorre, R. D. Cruz, J. M. Areiza, and A. Villegas, "Classification of publications and models on transmission expansion planning," *IEEE Transactions on Power Systems*, vol. 18, no. 2, pp. 938–946, 2003.

[15] E. L. da Silva, J. M. A. Ortiz, G. C. de Oliveira, and S. Binato, "Transmission network expansion planning under a Tabu Search approach," *IEEE Transactions on Power Systems*, vol. 16, no. 1, pp. 62–68, 2001.

[16] H. Faria Jr, S. Binato, M. G. C. Resende, and D. M. Falcão, "Power transmission network design by greedy randomized adaptive path relinking," *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 43–49, 2005.

Hindawi Publishing Corporation
Journal of Electrical and Computer Engineering
Volume 2012, Article ID 781041, 12 pages
doi:10.1155/2012/781041

Research Article

An Enhanced Genetic Algorithm to Solve the Static and Multistage Transmission Network Expansion Planning

Luis A. Gallego, Marcos J. Rider, Marina Lavorato, and Antonio Paldilha-Feltrin

Departamento de Engenharia Elétrica, Faculdade de Engenharia de Ilha Solteira, Universidade Estadual Paulista "Júlio de Mesquita Filho" (UNESP) Avenida Brasil 56, 15385-000 Ilha Solteira, SP, Brazil

Correspondence should be addressed to Luis A. Gallego, gallegopareja@gmail.com

Received 10 October 2011; Accepted 18 November 2011

Academic Editor: Edgar Carreno

An enhanced genetic algorithm (EGA) is applied to solve the long-term transmission expansion planning (LTTEP) problem. The following characteristics of the proposed EGA to solve the static and multistage LTTEP problem are presented, (1) generation of an initial population using fast, efficient heuristic algorithms, (2) better implementation of the local improvement phase and (3) efficient solution of linear programming problems (LPs). Critical comparative analysis is made between the proposed genetic algorithm and traditional genetic algorithms. Results using some known systems show that the proposed EGA presented higher efficiency in solving the static and multistage LTTEP problem, solving a smaller number of linear programming problems to find the optimal solutions and thus finding a better solution to the multistage LTTEP problem.

1. Introduction

1.1. Metaheuristics. Metaheuristics present a common basic strategy in the search process for an optimal solution to a complex problem. The metaheuristic search process takes place through the use of transitions in the search space. This search process can be carried out from one single point or from a group of points from the search space [1]. The transition process throughout the search space is carried out according to the particular strategy of each metaheuristic. In this context, the neighborhood concept is fundamental. The transition in the search space is carried out from the present point (solution) to the neighbor that is considered more interesting by the given metaheuristic strategy. However, in the outcome of a metaheuristic, the definition of the size and shape of the present solution is fundamental.

To solve a problem using metaheuristics, a group of necessary decisions must be taken in order to adequately characterize a problem. The main choices are the following: (1) a codification proposal, (2) a form of evaluating the quality of the solution proposed (objective function, fitness, etc.), (3) the decision of whether to carry out transitions through only feasible solutions or also through the unfeasible solutions, and (4) the choice of the neighborhood. In this context, each metaheuristic adds only the search strategy that should be adopted and the stop criterion.

The codification is a way to unambiguously specify a solution proposal or, in other words, to identify an element of the search space of the problem. The elements of the codification vector are not always related to the decision variables of the problem, and it must also be observed that many problems do not have mathematical modeling. Therefore, there are many ways of coding a problem: the chosen codification can be fundamental in the outcome of the metaheuristic. Each coding solution proposal must allow the objective function of the problem or an equivalent one to be found in a simple and clear manner.

The transitions in the search space are usually carried out only through feasible solutions (neighborhoods with many feasible elements). This kind of case occurs in most of the optimization problems in the operation of electric power systems. On the other hand, there are problems for which feasible solutions can be difficult to find (all of the chosen neighborhoods involve only unfeasible solutions) and, in this case, the best proposal consists of carrying out transitions through feasible and unfeasible solutions. This type of case occurs in some electric power system operation problems

and in practically all power system expansion planning problems.

1.2. The Transmission Network Expansion Planning Problem. The objective of the transmission network expansion planning (TNEP) is to find the transmission network that must be built in order to meet the demand growth considered in a long-term scenario, minimizing investment costs and providing electric energy to all system consumers. Then, a solution to a planning problem specifies *where*, *how many*, and *when* new equipment must be installed in an electric system, so that it operates adequately within a specified planning horizon. The TNEP problem can be approached from either static or multistage point of view. In the first case, only the quantity and location of the new elements of the network are determined. In the second case, besides the quantity and location, the timing for building the new reinforcements in the network is taken into account.

The mathematical model of the TNEP corresponds to a mixed integer nonlinear programming problem. This is due to the fact that such model includes nonlinear functions, as well as integer and real variables. Furthermore, the TNEP problem presents a high combinatorial explosion, generated by the number of alternatives that can be explored. Transmission systems are usually of great size; consequently, we are dealing with a problem of difficult solution and great mathematical complexity. There are several methodologies proposed in the specialized literature to solve the TNEP problem. Initially, in [2] Garver proposes a linear power flow estimation method to efficiently determine a preliminary network that can be used to determine the optimal network. In [3–5] constructive heuristic algorithms have been used to solve the TNEP problem. Mathematical models based on classical optimization techniques, such the Benders' decomposition [6–8] and branch and bound methods [9, 10], have also been used to solve the TNEP problem. Intelligent metaheuristic algorithms such as (1) simulated annealing, (2) tabu search, (3) genetic algorithms, and (4) harmony search algorithm have been proposed in [11–14], respectively, to solve the TNEP problem. The metaheuristics are methodology that solves combinatorial optimization problems with excellent solutions and low computational cost, especially for medium and large problems. Also, the metaheuristics are more robust in terms of processing time and find better solutions than the other classical optimization methods, such as the Benders decomposition and branch and bound methods. Thus, for example, while analyzing a huge and complex problem for the relaxed model called transportation, in [9], it was verified that the Benders decomposition algorithm presents great difficulty in convergence and the branch and bound algorithm finds quality solutions but does not converge due to the prohibitive processing time. However, the metaheuristics present the best solution for the dc model with acceptable processing time [13].

Several methodologies have been developed to include concepts of security and reliability in the TNEP problem. In [15] a mathematical model and a methodology are presented to solve the TNEP problem considering the $(n-1)$ security criterion. In [5, 14] a probabilistic reliability criterion is used to solve the same problem. The TNEP problem has been incorporated in an electricity market environment in [16–18]. The AC load flow model has been used in [19, 20] to consider the active and reactive power planning at the same time. The TNEP using AC model can be solved using a metaheuristic as shown in [19]. In this case, to determine the unfeasibility of the investment proposal, a nonlinear programming problem (instead of a linear programming problem one) is solved. In this way, the nonlinear programming problem (NLP) problem consumes most of the processing time of the metaheuristic. To solve the NLP problem, an efficient and robust algorithm necessary.

A robust metaheuristic is presented in this paper to solve the TEP problem. The metaheuristic proposed is a modification of the proposal presented by Chu and Beasley [21] for the generalized assignment problem, a multiconstrained problem that presents very similar characteristics to the TEP problem. The Chu-Beasley algorithm can be considered a modified genetic algorithm but is significantly different from the traditional genetic algorithm and other modified versions that can be found in the specialized literature. Therefore, our proposal is compared to the original Chu-Beasley proposal and to a traditional genetic algorithm.

1.3. Contributions. The main contributions of this paper are threefold.

(1) An enhanced genetic algorithm to efficiently solve the static and multistage TNEP problem. The proposed algorithm found, in some test systems, better solutions than the ones reported in the specialized literature.

(2) A critical comparative analysis between the proposed genetic algorithm and traditional genetic algorithms.

(3) An efficient solution of the operative problems in the TEP problem (linear programming problems).

This paper is a natural extension of the work presented in [22]. In this case, the authors have implemented the TNEP problem using faster and more efficient software. The proposed genetic algorithm considers an initial population, in which all individuals are feasible. Also, the search for the best solution is performed only over feasible regions of the TEP problem, and, finally, efficient tools for solving the operative problems in the TEP problem are used. The proposed methodology finds better solutions, with lower computational burden, as compared with the results reported in [22].

2. Traditional Genetic Algorithm and the Chu-Beasley Proposal

The main characteristics of the traditional and the Chu-Beasley genetic algorithms will be analyzed with a focus on the differences in operators and strategies.

2.1. Traditional Genetic Algorithm. The fundamental theory on genetic algorithms can be found in [23–27]. The

traditional genetic algorithm can be summarized in the following steps.

(1) Specify the control parameters (population size, recombination rate, mutation rate, etc.).

(2) Specify genetic algorithm characteristics such as codification type, form of setting up an initial population, unfeasibility manipulation, selection type, need and form of standardization, and so forth.

(3) Find an initial population which becomes the current population.

(4) Find the fitness of the current population and update the best solution found in the process, if possible.

(5) If the stop criteria are satisfied, stop. Otherwise, continue the process.

(6) Implement selection.

(7) Implement recombination.

(8) Implement mutation, replacement of the current population and return to step 4.

The basic theory of genetic algorithms suggests randomly setting up an initial population because the quality of the final solution must be independent of how the initial population was set up. However, some studies show that a randomly generated initial population generally takes a very long time to find quality solutions and, in addition, these solutions are of poorer quality than those of an initial population set up using efficient strategies that consider specific characteristics of the problem. Therefore, a good-quality initial population generated using a fast and robust heuristic algorithm is considered more promising.

The manipulation of unfeasibilities is another relevant topic. Most genetic algorithms applied in the optimization of power systems incorporate the unfeasibilities into the fitness through penalization or eliminate the unfeasible proposal altogether [28–31]. Usually unfeasible solutions can be eliminated in the optimization of power systems operation problems because they rarely appear. However, in electric power systems planning, the penalization strategy is used because the unfeasible proposals are numerous and usually dominant and because proposals with "small unfeasibilities" can produce excellent feasible solutions after applying the genetic operators. The great difficulty is to correctly adjust the penalty parameter. In [32] there is a detailed analysis of this form of manipulating unfeasibilities as well as of other alternative proposals.

The selection type and the necessity for standardization are analyzed separately from the other genetic operators. The basic theory of genetic algorithms considers that a problem is standardized when there is a maximization problem and the fitness values are all nonnegatives. The first genetic algorithms also suggest using the so-called proportional selection, in which a standardized problem creates a number of offspring that is proportional to the fitness value. Due to this, all fitness values must be nonnegative. As the number of offspring generally is not integer, the selection process is finished using a roulette wheel. Proportional selection thus requires standardization of the problem and has two clearly differentiated parts: (1) determination of the number of offspring using the proportional relation creating a number of non-integer offspring, (2) found integer values of the number of offspring using the roulette wheel.

Proportional selection, however, presents various problems: (1) when it is a minimization problem, it must be transformed into an equivalent maximization problem; (2) when negative fitness values appear, a strategy must be used to make all the fitness values of the current population nonnegative; (3) when the so-called superconfigurations appear, that is, excellent-quality solution proposals with the high probability of generating many offspring, there is a loss of diversity and a premature convergence; (4) when all elements of the population present very close fitness values, there is also a loss of diversity, transforming the selection into a random process. The two last problems are solved by proportional selection using modifications in the selection process such as limiting the number of offspring and/or using linear scaling mechanism selection, which modifies the fitness values by approximating them when they are far apart (in the case of superconfiguration) or separating them when they are too close. In this manner, scaling mechanism selection is the same proportional selection with an additional step: the modification of the fitness values in the current population.

Selection by tournament does not present any of the problems of proportional selection and is very simple to implement. In this proposal, the number of offspring is generated in n_{pop} games for an n_{pop} size population. In each step, a game is carried out that consists of choosing random k elements of the population, with the element of the population with the best-quality fitness considered a winner and given the right to generate one offspring. After n_{pop} games, the selection process ends. This case involves only the calibration and choosing of the k, the number of elements that participate in each game, which is easily calibrated and usually presents small values such as $k = 2, 3, 4$. Logically, selection by tournament does not require a roulette wheel because it generates an integer value for the number of offspring. In this way, selection by tournament does not require standardization; thus if this decision is made, standardization issues like maximization or minimization become irrelevant.

Recombination and mutation are operators that are highly dependent on the type of codification used. When the codification is binary, both operators are implemented in a trivial way. However, if another type of codification is used, the operators must be redefined.

The traditional genetic algorithm has a generational substitution; that is, the elements of the current population are substituted by offspring generated through genetic operators. This strategy can eliminate the best solutions still found from the current population. The use of the elitism strategy is a form of dealing with this problem. In this proposal, the best solutions (elite solutions) are passed on to the next generation, preserving the best solutions. Therefore, the current population inherits the best solutions from the previous population.

Finally, the most critical problem for the traditional genetic algorithm is the loss of diversity. Generally, a genetic algorithm does not verify if some elements of the population are repeated. If a control of diversity is not implemented, the best solutions become dominant in the new populations, leading to a loss of diversity. This problem is partially solved using two strategies: (1) using more and more elevated mutation rates and (2) verifying and eliminating the repeated solutions and carrying out a recomposition of the population, which normally involves randomly generating new solutions. This last proposal is rarely used because it is computationally expensive and the substitution process is not efficient. Therefore, the loss of genetic diversity is one of the biggest problems of traditional genetic algorithms. An interesting analysis on this topic can be found in [32].

2.2. Chu-Beasley Genetic Algorithm. Chu and Beasley [21] presented a genetic algorithm to solve the generalized assignment problem. It can be summarized in the following steps.

(1) Specify the control parameters (population size, recombination rate, mutation rate, etc.).

(2) Specify genetic characteristics of the algorithm: codification type, initial population assembly, manipulation of unfeasibilities, selection type, and so forth.

(3) Randomly find an initial population to become the current population. Find the fitness and unfitness of the current population.

(4) Implement a selection to choose only two generating solutions.

(5) Implement the recombination and preserve an offspring.

(6) Implement the mutation of the preserved offspring.

(7) Implement a phase of local improvement.

(8) Decide if the improved offspring can enter the population, substituting an element from the population.

(9) If the stop criterion is not satisfied, return to step 4. Otherwise, end the process.

Chu and Beasley presented a modified genetic algorithm with very special particularities. Here we present a summary of the most relevant aspects of the Chu-Beasley genetic algorithm with special attention to those proposals that are significantly different from a traditional genetic algorithm.

The Chu-Beasley genetic algorithm (CBGA) suggests the random generation of a population just as in the basic genetic algorithms. However, it can be observed that this proposal produces an initial population with all the unfeasible elements that is very distant from the feasibility for the case of complex problems.

The CBGA presents an innovative proposal for the manipulation of unfeasibilities. This approach presents a proposal for storing the objective function (fitness vector) and the unfeasibilities (unfitness vector) in separate form and using each for different purposes. The proposal eliminates the necessity of choosing the penalization parameter when both pieces of information are gathered into one fitness alone. The fitness is used in the selection process, and the unfitness is used along with the fitness in the substitution process to decide whether the generated offspring should be incorporated into the population by substituting it for an element of the population. The CBGA uses tournament selection, considered one of the most efficient and simple-to-implement methods for selection.

The Chu-Beasley proposal is significantly different from the traditional genetic algorithms in its process of substitution of the population elements. The traditional genetic algorithm carries out a generational substitution, substituting all (or almost all) the elements of the population, and generally diversity verification is not performed. The CBGA suggests substituting only one element from the current population in each step. This facilitates two strategies that are crucial for the development of the algorithm: (1) allowing the production of improved offspring using a local optimization; (2) allowing absolute control of the diversity of the elements in the current population. These two proposals cannot be implemented efficiently in a traditional genetic algorithm with generational substitution.

The CBGA suggests the implementation of a local improvement phase of the generated offspring. This local improvement phase can be a very simple local search or a sophisticated strategy that takes the specific characteristics of the problem into consideration. However, the local improvement phase has two phases for the multiconstrained problems: (1) an unfeasibility improvement phase (2) a quality improvement phase. This way, if the generated offspring is unfeasible, there must be an attempt to make this offspring feasible, which is not always possible. Next, the quality of the offspring must be improved by searching its neighborhood.

The CBGA suggests substituting an element of the current population for a generated offspring, preserving the complete diversity; that is, all population elements must be different. Therefore, if the generated offspring is equal to an element from the population, then this offspring is discarded. Otherwise, the process follows this strategy: (1) if the generated offspring is unfeasible, then it is verified whether the unfeasibility is smaller than the unfeasibility of the element from the population with the largest unfeasibility; if this is the case, then the substitution is carried out, and if this is not the case, the generated offspring is discarded. (2) If the generated offspring is feasible, it must substitute for the element with the largest unfeasibility. Logically, if all elements of the population are feasible, for the exchange to be possible, it must be verified that the generated offspring presents better quality than the lowest-quality element of the population.

In summary, the generated offspring can enter the population if it is different from the rest of the elements of the population and if it is more promising than any of the elements, verifying first the unfeasibility and next the quality of the objective function of the feasible solution proposals. In this context, the unfitness is used to arrange the elements of the population that are unfeasible and as an "unfeasibility measurement," and the fitness represents only the original objective function of the problem and is used to arrange feasible solution proposals, as in the selection process. This logic

of initially prioritizing the search for unfeasible solutions, neglecting the quality and later preserving the feasibility of population, has been widely analyzed by researchers in recent studies [32, 33].

The proposal for the substitution in the CBGA has many relevant aspects: (1) all elements of the population are different; (2) the substitution logic increases the number of feasible elements; (3) due to the previous observation, the process finds a current population only with feasible solutions, and this stage can be reached in a period that depends on the type of problem and the local improvement strategy; (4) the best solutions are always preserved because in each substitution process a solution of inferior quality is eliminated. The last observation means that the strategy works better than the elitism of the traditional genetic algorithms. Nevertheless, the great advantage of the CBGA is the absolute control of diversity. Thus, in complex problems with great difficulty finding feasible solutions, it might be interesting to increase the size of the population to allow the storage of feasible solutions of diverse genetic compositions.

3. Enhanced Genetic Algorithm (EGA)

A metaheuristic that represents a modified version of the Chu-Beasley proposal is presented in this section. The proposal is directed towards its application in the optimization of power systems complex problems, where there is a great application and diversity of proposals related to heuristic algorithms to solve these complex problems, especially constructive heuristic algorithms. The proposal suggests modifying the Chu-Beasley algorithm in three areas: (1) the generation of the initial population, (2) the local improvement phase of the generated offspring and (3) the control of diversity can be extended.

This proposal consists of how an initial population of good quality can be generated and diversified using heuristic algorithms and very simple additional strategies. Thus, in most applications, the initial population can be made up of only feasible solution proposals, making the function of the unfitness vector from the Chu-Beasley proposal not very active or relevant. In the local improvement phase, fast and efficient heuristic algorithms can also be used, which in most cases can totally eliminate the unfeasibility of the generated offspring, which can in turn improve the quality of the objective function. The Chu-Beasley proposal for local improvement in the generalized assignment problem, in most cases, does not eliminate the unfeasibility, and the improvement in quality is also primitive. Thus in this step, efficient heuristic algorithms from the specialized literature for each type of electric power systems problem can also be used.

The control of diversity can be easily extended. In the Chu-Beasley proposal, control is limited to verifying that all the elements of the population are different. Nevertheless, practice indicates that this diversity proposal is not sufficient in multimodal and complex problems. Frequently, the individuals of a population can be different, but this can be constrained to small differences; as a consequence, the current population may represent a reduced number of regions from the search space. A simple way to deal with this problem consists of extending the diversity. In this way, an offspring can enter the current population if it meets the following parameters: (1) it presents better quality than the lowest-quality stored solution, (2) it is different from each of the elements of the population in a minimum number of elements of the coded vector.

The proposed metaheuristic can be summarized in the following steps.

(1) Specify the control parameters (population size, recombination rate, mutation rate, etc.).

(2) Specify EGA characteristics: codification type, setting up the initial population, manipulation of the infeasibilities, choice of selection by tournament, and so forth.

(3) Find an initial population with efficient, fast, and robust heuristic algorithms. The proposal is to prioritize the use of algorithms that generate only feasible solutions. Set up the fitness of the initial population.

(4) Implement a selection by tournament to choose only two generating solutions.

(5) Implement a recombination and preserve only one offspring.

(6) Implement mutation in the preserved offspring.

(7) Implement a local improvement in the preserved offspring using efficient heuristic algorithms.

(8) Decide whether the improved offspring can enter the population, substituting an element after verifying the substitution test.

(9) If the stop criterion is not satisfied, return to step 4. Otherwise, end the process.

4. Application in the Transmission Network Expansion Planning Problem

The presented metaheuristic is especially useful in complex problems with multimodal and multiconstrained characteristics. Most of the complex problems in electric power systems fall into this category. Thus, an application for the static and multistage planning problem in the electric power transmission network expansion is presented.

The static transmission network expansion planning problem is also considered a relevant and complex problem in power systems. In this case, static means that the planning is carried out in one stage. Thus, given the network configuration for a certain year and the peak generation/demand for the next stage, along with other data such as network operation limits, costs, and investment constraints, determining an expansion plan with minimum cost is desirable, to optimize where and what type of new equipment should be installed. This is a special case of a more general problem called multistage expansion planning in which it is also desirable to know when to install new pieces of equipment. In this type of problem, the initial stages of the expansion planning studies are focused on when the basic topology

of the future network is determined. Network topologies synthesized by the proposed approach will then be further analyzed and improved by testing their performance with other analytical tools such as power flow, short circuit, transient and dynamic stability analysis [34, 35]. The static and multistage transmission network expansion planning problems are mixed-integer nonlinear programming problems with many optimal solutions. In this case, optimization techniques also only find optimal local solutions for real large-scale and complex problems. The mathematical model for the transmission network expansion planning problem can take on its most complex forms when more detailed operation models are considered, such as security and operation planning in competitive markets. Metaheuristics applied to the transmission network expansion planning problem can be found in [29, 30, 36, 37].

4.1. Static Planning Modeling. The mathematical model for the static transmission network expansion planning problem, using the DC model, presents the following format [34]:

$$\text{Min} \quad v = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} \tag{1}$$

$$\text{s.t.} \quad \mathbf{S} f + g = d, \tag{2}$$

$$f_{ij} - \gamma_{ij}\left(n_{ij}^0 + n_{ij}\right)(\theta_i - \theta_i) = 0, \tag{3}$$

$$\left|f_{ij}\right| - \left(n_{ij}^0 + n_{ij}\right)\overline{f_{ij}} \le 0, \tag{4}$$

$$0 \le g \le \overline{g}, \tag{5}$$

$$0 \le n_{ij} \le \overline{n_{ij}}, \tag{6}$$

$$n_{ij} \text{ integer}, \ f_{ij} \text{ and } \theta_j \text{ unbounded}, \tag{7}$$

$$\forall (i,j) \in \Omega, \tag{8}$$

where c_{ij}, γ_{ij}, n_{ij}, n_{ij}^o, f_{ij}, and $\overline{f_{ij}}$ represent, respectively, the cost of a circuit that can be added to the i-j right-of-way, the susceptance of that circuit, the number of circuits added to the i-j right-of-way, the number of circuits in the base case, the total power flow, and the corresponding maximum power flow to the circuit in the i-j right-of-way. v is the investment, $\mathbf{S}$ is the branch-node incidence matrix of the power system, f is a vector with f_{ij} elements, θ_j is the phase angle in j bus, g is a vector with g_k elements (generation in k bus) whose maximum value is $\overline{g}$, d is the demand vector, $\overline{n_{ij}}$ is the maximum number of circuits that can be added to the i-j right-of-way, and Ω is the set of all right-of-ways.

Constraint (2) represents the conservation of power in each node. This constraint models Kirchhoff's Current Law (KCL) in the equivalent DC network. Constraint (3) is an expression of Ohm's Law for the equivalent DC network, so Kirchhoff's Voltage Law (KVL) is implicitly taken into account and these constraints are nonlinear.

4.2. Multistage Planning Modeling. In multistage planning, the planning horizon is divided into several stages, for example in five-year-long stages, and in that context the equipment that should be installed in every planning stage needs to be determined. Considering an annual discount rate I, the present values of the investment costs, for the reference year t_0, with an initial year t_1, with a horizon of $t_T - t_1$ years, and with T stages, are the following [22, 29, 38]:

$$c(x) = (1-I)^{t_1-t_0} c_1(x) + (1-I)^{t_2-t_0} c_2(x) + \cdots + (1-I)^{t_T-t_0} c_T(x), \tag{9}$$

$$c(x) = \delta_{\text{inv}}^1 c_1(x) + \delta_{\text{inv}}^2 c_2(x) + \ldots + \delta_{\text{inv}}^T c_T(x)$$

$$\delta_{\text{inv}}^T = (1-I)^{t_t-t_0}, \quad t = 1, \ldots, T, \tag{10}$$

where, x represents the investment variables (lines to be constructed) and $c_t(x)$ represents the investment in the t stage. The DC model for the multistage planning problem assumes the following form [22, 29, 38]:

$$\text{Min} \quad v = \sum_{t=1}^{T}\left[\delta_{\text{inv}}^t \sum_{(i,j)\in\Omega} c_{ij} n_{ij}^t\right] \tag{11}$$

$$\text{s.t.} \quad \mathbf{S}^t f^t + g^t = d^t, \tag{12}$$

$$f_{ij}^t - \gamma_{ij}\left(n_{ij}^0 + \sum_{m=1}^{t} n_{ij}^m\right)\left(\theta_i^t - \theta_j^t\right) = 0, \tag{13}$$

$$\left|f_{ij}^t\right| \le \left(n_{ij}^0 + \sum_{m=1}^{t} n_{ij}^m\right)\overline{f_{ij}}, \tag{14}$$

$$\underline{g}_j^t \le g_j^t \le \overline{g}_j^t, \tag{15}$$

$$\underline{n}_{ij}^t \le n_{ij}^t \le \overline{n}_{ij}^t, \tag{16}$$

$$\sum_{m=1}^{T} n_{ij}^t \le \overline{n}_{ij}, \tag{17}$$

$$n_{ij}^t \text{ integer}, \ \theta_j^t \text{ unbounded}, \tag{18}$$

$$t = 1, 2, \ldots, T. \tag{19}$$

The variables are the same from the static planning except t that represents the stages.

4.3. Efficient Solution of Linear Programming Problems (LPs). In this work the methodology presented in [39] is applied to efficiently solve the LP problems (operative problems of the expansion planning problem) during the execution of the EGA. The methodology is divided in two steps: (1) reduction of the number of variables and constraints of the problem and (2) solution of the LP problem by means of a bounded dual simplex algorithm with a constraint relaxation strategy. The resulting linear programming problem only features a single equality constraint and a set of inequality constraints equal to the number of circuits of the electrical system. An important characteristic of this problem is that only a reduced number of inequality constraints are active in the

optimal solution. Due to this particular feature, an efficient strategy can then be formulated to solve the LP problems. This strategy consists of relaxing and solving the LP problem considering only the equality constraint plus the limits of the generation variables in the buses. After that, a ranking of the inequality constraints is performed in order to identify the one with the highest degree of infeasibility. Subsequently, this constraint is incorporated into the problem and it is solved again. This procedure is repeated until all the constraints of the problem are satisfied. A more detailed description of this procedure can be consulted in [39].

The results presented in [39], for various transmission systems, show that the computational time to solve the planning problem is lower than the time using a MINOS routine of Fortran. In this work, the methodology proposed in [39] was implemented in C++ and tested in a computer with a Core Duo processor of 3 GHz and 4 GB of RAM memory. Different tests were performed for various transmission systems to verify the efficiency of the proposed algorithm. For example, the Colombian system with 93 buses and 155 lines was implemented executing 1000 LPs (every LP obtains the optimal solution of the problem) with an execution time of approximately 3 seconds.

4.4. Codification in the Static Planning. The individual is a solution proposal for the planning problem or, better, is the topology made up of all the lines added to the system corresponding to an investment proposal. In this paper, a decimal codification to the number of circuits added (a solution proposal) is used.

In the transmission network expansion problem (TNEP), the individual of the EGA is represented by a vector size *nl*, that is, the number of right-of-ways. Each member of this vector corresponds to a right-of-way of the system that is being analyzed, and where new lines can be constructed. Each member can vary its value from 0 to the maximum number of lines that can be added to the respective branch. Thus, in the codification shown in Figure 1, branch 1-2 has 2 new lines, branch 3-4 has 1 new line, and so forth.

The method proposed in this paper does not demand that the characteristics of the lines between two buses be equal, they can work with various types of circuits between two buses. In this case the only change occurs in the form of the LP problem to be solved. The number of individuals in the EGA population, for the transmission network expansion problem, depends on the dimension of the system.

4.5. Codification in the Multistage Planning. In multistage planning, a solution proposal, that is, an individual of the EGA, is represented by a matrix with dimension ($n_{\text{est}} \times n_l$), n_{est} represents the number of stages and n_l the number of candidate branches of the system. In each stage, the lines that will be constructed in that stage are presented. For example, in the codification shown in Figure 2, the branch 3–5 has 2 lines added in the first stage and 1 line added in the *n* stage. In reality, the coding separates the operation problems for each stage and therefore smaller n_{est} LP problems are solved. In summary, to identify the quality of an investment proposal,

1-2	1–3	1–4	1–5	2-3	2–4	2–5	3-4	3–5	4-5	
2	0	1	0	3	0	0	1	2	0	Stage 1

Figure 1: Static planning codification.

1-2	1–3	1–4	1–5	2-3	2–4	2–5	3-4	3–5	4-5	
2	0	1	0	3	0	0	1	2	0	Stage 1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0	1	0	1	2	0	3	0	1	0	Stage *n*

Figure 2: Multistage planning codification.

n_{est} LP problems must be solved, representing the longest part of the process.

4.6. Knowledge Incorporation in the Initialization. Considering a population randomly generated to solve the transmission network expansion planning using GA, the algorithm may need a higher computational effort, especially in medium and large systems. A way to simplify the GA is to create the initial population efficiently [13].

The initial population is set up using the Villasana-Garver-Salon (VGS) [4] constructive heuristic algorithm (CHA), which presents excellent-quality feasible solutions using additional strategies like those presented in Section 2. In the VGS algorithm, two basic concepts are observed: (1) when the integrality constraints of investment variables in the CHA are relaxed, the VGS model is transformed into an LP problem used to identify the most adequate circuit to be added to the system during the CHA interactive process; (2) each added circuit obeys the two Kirchhoff laws, so the final solution is feasible for the DC model.

4.7. Objective Function. For each individual in a population, the objective function (*fitness*) can be easily calculated. The *fitness* represents the total costs of planned lines to be constructed. The objective function is used to implement the selection and the substitution of an individual in the population.

4.8. Selection. The proposed selection of parents uses a competition based on tournaments: in each game there are *k* individuals from the current population that compete to be one of the parents. The procedure is as follows: *k* individuals are randomly chosen from the current population; the individual that has better fitness will be parent number 1. After this, the procedure is repeated and parent number 2 is then determined. Parents 1 and 2 must be different from each other. Then the parents go on to the recombination phase.

To solve large problems, it is usually more efficient to use a larger population. In this case, this means great topological diversity. However, this enlargement of population should be followed by an increase in the number of individuals in the tournament selection.

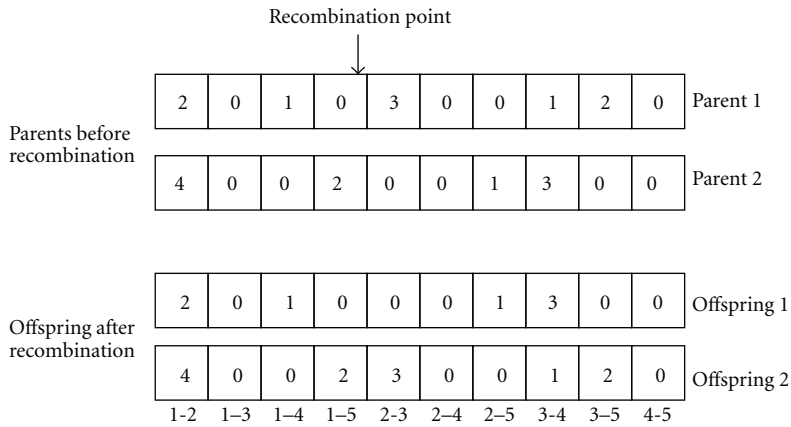

Figure 3: Single-point recombination (static codification).

4.9. Recombination. A single-point recombination is used in which a recombination point is randomly chosen and two offsprings are created. Each offspring has a piece of each parent topology, separated by the recombination point.

In the traditional GA, the two offsprings can be part of the population in the next generation. In the EGA proposal, only one offspring can do so. Thus, with the same probability, only one offspring is chosen, while the other one is eliminated. In Figure 3, we have an example of recombination where the second offspring is eliminated for static planning problems.

In Figure 4 is shown a recombination between multistage codifications when the second offspring is eliminated. The recombination must be done between stages with the same order, but the recombination point can be chosen random for different stages.

4.10. Mutation. The mutation is made in accordance with [29]. In this kind of mutation, just one point (branch) is chosen aleatorily for each stage, and one circuit of this point (branch) is added or retired aleatorily. Figures 5 and 6 show examples of mutation to the static and multistage codifications, respectively.

4.11. Local Improvement of an Offspring. The local improvement of an offspring is one of the main EGA contributions. It is made up of two types of improvement: unfeasibility and objective function improvements.

4.11.1. Improving the Unfeasibility. If the created offspring is unfeasible, that is, if it has load shedding, then the unfeasibility should be eliminated using the CHA proposed by [4].

Considering that the main objective of this phase is to completely eliminate offspring unfeasibility, the CHA proposed by VGS will add lines to the individuals to eliminate the unfeasibility, thus solving only the LP problems in each CHA step.

The Figure 7 presents the procedures for selection, recombination, mutation and elimination of the infeasibility of the offspring. Note that the proposed EGA generates only feasible solutions.

4.11.2. Improving the Objective Function. After the execution of the CHA, some lines are added to the individual in the local improvement phase. Some of the individual lines are unnecessary and should be discarded so that the individual (solution proposal) is not too expensive. Thus, all the solution proposal lines are listed in decreasing order of costs and all the lines are removed one by one. The lines that do not present load shedding when the removal of the individual is simulated are unnecessary and therefore discarded.

The lines that remain are those whose resulting solution proposal presents load shedding when their removal is simulated.

In this case, the strategy is different from that of the original Chu-Beasley proposal. In the proposal presented here, the generated offspring is made feasible, eliminating the work of the unfitness function

4.12. Convergence. The simulation process of the proposed genetic algorithm (EGA) is stopped when the incumbent (best found investment proposal) does not change after a certain predefined number of iterations.

5. Tests and Results: Static Planning

The proposed EGA to solve the transmission expansion planning problem is tested using two electrical power systems familiar to the specialized literature. The first system is the South Brazilian system, which has 46 buses and 79 branches; the second is the Colombian system of 93 buses and 155 branches.

5.1. South Brazilian System. This system has 46 buses, 79 branches, and a total demand equal to 6,880 MW. The electrical data can be found in [34]. The necessary investment to solve the planning problem for the south Brazilian system is v = 72,870,000 US$, and the following lines are added: n_{02-05} = 1, n_{05-06} = 2, n_{13-20} = 1, $n_{20\text{-}21}$ = 2, n_{20-23} = 1, $n_{42\text{-}43}$ = 1, and n_{46-6} = 1. The EGA found the solution after solving 600 LPs with a run time of 1.6 seconds on average. The initial population had 50 individuals, and the parents were selected by tournament with k = 3.

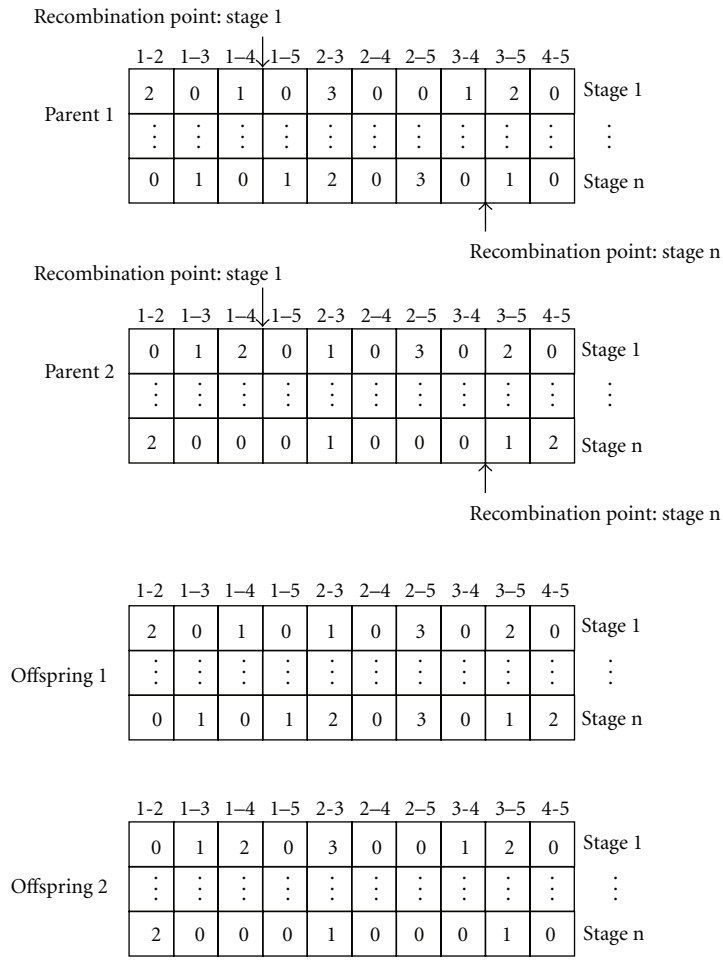

Figure 4: Single-point recombination (multistage codification).

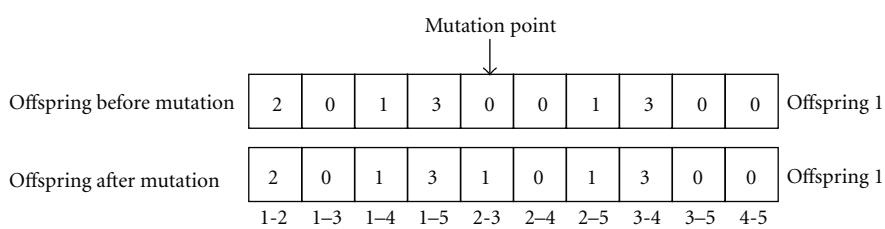

Figure 5: Mutation (static codification).

5.2. Colombian System. This system has 93 buses, 155 branches, a total demand equal to 14,559 MW, and the capacity for 5 lines to be added to each branch. This system represents a good test of the proposed methodology because it is a real system.

The proposed EGA was executed twenty times in order to determine effectiveness of this algorithm. In all tests carried out the EGA found its best solution with an investment equal to $v = 560{,}002{,}000$ US\$, with a shedding load of 0.38 MW; the following lines are added: $n_{43-88} = 2$, $n_{15-18} = 1$, $n_{30-65} = 1$, $n_{30-72} = 1$, $n_{55-57} = 1$, $n_{55-84} = 1$, $n_{56-57} = 1$, $n_{55-62} = 1$, $n_{27-29} = 1$, $n_{29-64} = 1$, $n_{50-54} = 1$, $n_{62-73} = 1$, $n_{54-56} = 1$, $n_{72\text{-}73} = 1$, $n_{19-82} = 2$, $n_{82-85} = 1$, and $n_{68-86} = 1$. The EGA found the solution after solving 4,302 LPs with a run time of 16 seconds, on average. The initial population had 100 individuals, and the parents were selected by tournament with $k = 3$.

5.3. Results Analysis: Multistage Planning. The EGA was tested to solve the multistage transmission network expansion planning as well. The algorithm was tested in the Colombian system [29]. The available data allows a three-stage planning, namely P_1, P_2, and P_3. The P_1 stage is between the years 2002 and 2005, the P_2 stage is between the years 2005 and 2009, and the P_3 stage is between the years 2009 and 2012. The annual discount rate I is equal to 10%. Obviously, the circuits added to P_1 appear in the objective function

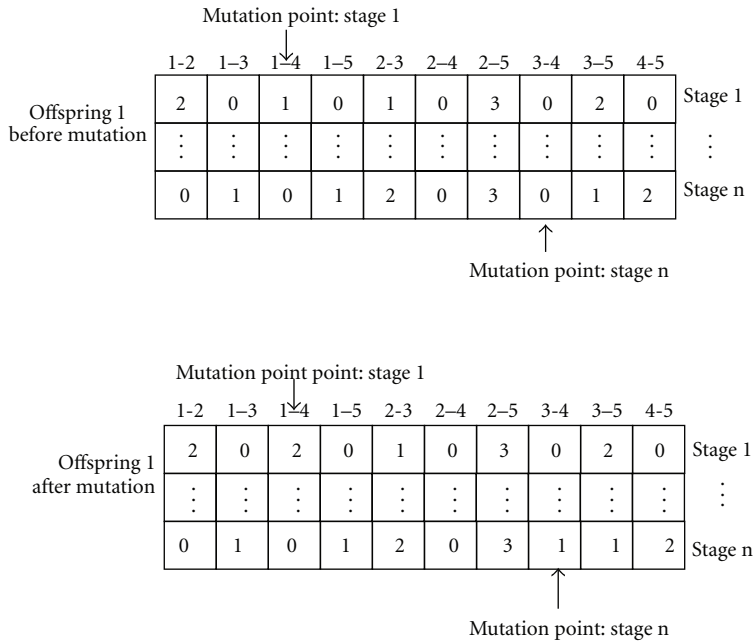

Figure 6: Mutation (multistage codification).

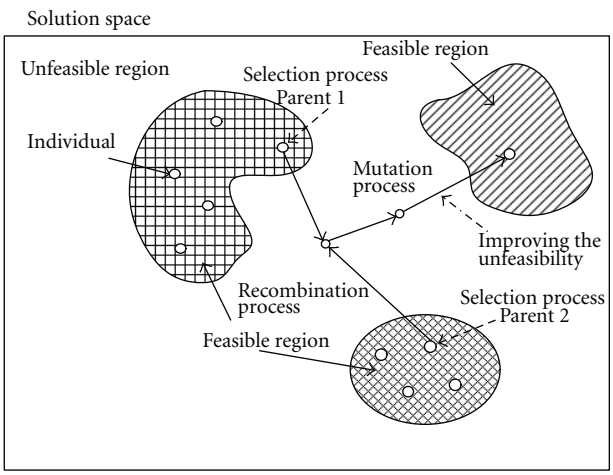

Figure 7: Local improvement process of the offspring.

with their nominal costs and those added to P_2 and P_3 are multiplied by 0.729 and 0.478, respectively. The proposed EGA was implemented with an initial population of 130 individuals, generated randomly, with feasibility generated through the CHA. A value of $k = 3$ was chosen for the tournament selection process.

As in TNEP static, the EGA was executed twenty times and the best proposal found by the proposed EGA has a capital cost equal to v = 491,012,200 US$ and shedding load of 0.4123 MW. Table 1 presents the best and worst investment proposals found by the EGA (stored in the matrix of codification) for an execution, as well as the proposals reported in the literature [22, 29, 38]. Note that all investment proposals stored in the EGA, at the end of the iterative process, have lower investment costs than those previously reported in the literature. The best solution found by the EGA was found after solving 47,520 LPs with a run time of 160 seconds on average. Of the twenty executions, in fourteen executions the EGA found the above proposal, while in the other six executions the EGA found different proposal with a higher investment cost, the proposal with worst investment being v = 500,423,000 US$.

6. Comparative Analysis between the Chu-Beasley and the Proposed EGA

In order to test the robustness and efficiency of the proposed algorithm and compare it with the performance of the Chu-Beasley genetic algorithm, a real-size power system (Colombian system) is used. Tests were carried out with both static and multistage TNEP problems. In the first case, the Chu-Beasley genetic algorithm found the same solution as the proposed EGA; however, the number of PLs executed was 68,441, with a computational time of 4.12 minutes. Comparing these results with the ones found using the proposed EGA (see Section 5.2) it can be noted that, for this particular system, the EGA is nearly 16 times faster than the traditional Chu-Beasley genetic algorithm.

On the other hand, the best solution found by the Chu-Beasley genetic algorithm for the multistage TNEP problem presents an investment cost of v = 500,423,000 US$. This solution was found in 856 iterations after solving 101,166 PLs in 4.71 minutes. In an attempt to find better solutions, the same algorithm was set to run up to 20,000 iterations; however, after solving 564,393 PLs no better solutions were found. For this same problem the proposed EGA found better solutions in less computational time as presented in Section 5.3.

Table 1: Investment proposals for the multistage expansion planning.

	Proposal of [29]	Proposal of [22]	Proposal of [38]	Better proposal by the EGA	Worst proposal by the EGA
Total investment cost	514,356,716 US$	503,717,434 US$	505,802,470 US$	491,012,200 US$	498,511,200 US$
Total load of shedding	0.0000 MW	0.0000 MW	0.0000 MW	0.4123 MW	0.000 MW
Investment cost stage 1	316,440,000 US$	338,744,000 US$	338,744,000 US$	338,744,000 US$	352,014,000 US$
Load of shedding stage 1	0.000 MW	0.000 MW	0.000 MW	0.000 MW	0.000 MW
Circuits proposal stage 1	$n_{56-81} = 1$, $n_{55-57} = 1$ $n_{56\text{-}57} = 1$, $n_{55-62} = 1$ $n_{45-81} = 1$, $n_{82-85} = 1$	$n_{57-81} = 2$, $n_{55-57} = 1$, $n_{55-62} = 1$, $n_{45-81} = 1$, $n_{82-85} = 1$	$n_{57-81} = 2$, $n_{55-57} = 1$, $n_{55-62} = 1$, $n_{45-81} = 1$, $n_{82-85} = 1$	$n_{57-81} = 2$, $n_{55-57} = 1$, $n_{55-62} = 1$, $n_{45-81} = 1$, $n_{82-85} = 1$	$n_{57-81} = 2$, $n_{55-57} = 1$, $n_{55-62} = 1$, $n_{19-82} = 1$, $n_{82-85} = 1$
Investment cost stage 2	122,011,272 US$	76,362,750 US$	76,362,750 US$	76,362,750 US$	66,688,920 US$
Load of shedding stage 2	0.0000 MW	0.0000 MW	0.0000 MW	0.0000 MW	0.0000 MW
Circuits proposal stage 2	$n_{56\text{-}57} = 1$, $n_{27-29} = 1$, $n_{62-73} = 1$, $n_{72\text{-}73} = 1$, $n_{19-82} = 1$	$n_{27-29} = 1$, $n_{62-73} = 1$, $n_{72\text{-}73} = 1$, $n_{19-82} = 1$	$n_{27-29} = 1$, $n_{62-73} = 1$ $n_{72\text{-}73} = 1$, $n_{19-82} = 1$	$n_{27-29} = 1$, $n_{62-73} = 1$ $n_{72\text{-}73} = 1$, $n_{19-82} = 1$	$n_{27-29} = 1$, $n_{62-73} = 1$, $n_{72\text{-}73} = 1$
Investment cost stage 3	75,905,444 US$	88,610,684 US$	90,695,720 US$	75,905,444 US$	79,808,140 US$
Load of shedding stage 3	0.0000 MW	0.0000 MW	0.0000 MW	0.4123 MW	0.0000 MW
Circuit proposal stage 3	$n_{43-88} = 2$, $n_{15-18} = 1$, $n_{30-65} = 1$, $n_{30-72} = 1$, $n_{55-84} = 1$, $n_{29-64} = 1$, $n_{19-82} = 1$, $n_{68-86} = 1$	$n_{52-88} = 1$, $n_{15-18} = 1$, $n_{55-84} = 1$, $n_{55-62} = 1$ $n_{29-31} = 1$, $n_{29-64} = 1$ $n_{68-86} = 1$	$n_{52-88} = 1$, $n_{15-18} = 1$, $n_{55-84} = 1$, $n_{55-62} = 1$, $n_{29-31} = 1$, $n_{29-64} = 2$ $n_{68-86} = 1$	$n_{43-88} = 2$, $n_{15-18} = 1$, $n_{30-65} = 1$, $n_{30-72} = 1$, $n_{55-84} = 1$, $n_{29-64} = 1$, $n_{19-82} = 1$, $n_{68-86} = 1$	$n_{43-88} = 2$, $n_{15-18} = 1$, $n_{30-65} = 2$, $n_{55-84} = 1$, $n_{29-64} = 1$, $n_{19-82} = 1$, $n_{68-86} = 1$

7. Conclusions

An enhanced genetic algorithm was applied to static and multistage long-term transmission network expansion planning. The achieved results for medium and large systems show excellent performance. The parameters for each simulation were determined after exhaustive tests.

The Chu and Beasley proposal can be considered a special type of genetic algorithm, but it represents a different form of recomposition of the population that allows a local improvement phase and control of diversity. The proposal in this work is to additionally generate an initial population using fast, efficient heuristic algorithms; promote better implementation of the local improvement phase; have more efficient control of genetic diversity.

The enhanced genetic algorithm showed itself to be more efficient than the other metaheuristics in solving the static planning problem in that it required solving fewer LP problems to find the optimal solutions. It was also more efficient in solving the multistage planning problem, finding a better solution after solving fewer LP problems than those reported in the literature.

An efficient metaheuristic is important when the mathematical model of expansion planning considers other requirements because these requirements make it necessary to solve more LP problems. Some examples of more complex transmission expansion planning models are planning with security constraints, planning in a fully open market, and planning with uncertainty.

The proposed metaheuristic can be used in other power system problems, especially when there is difficulty in finding feasible proposals, multimodal problems, or problems with very complex constraints and varied decision variables.

References

[1] F. Glover and G. A. Kochenberger, *Handbook of Metaheuristics*, Springer, 2003.

[2] L. L. Garver, "Transmission network estimation using linear programming," *IEEE Transactions on Power Systems*, vol. 89, no. 7, pp. 1688–1697, 1970.

[3] A. Monticelli, A. Santos, M. V. F. Pereira, S. H. Cunha, B. J. Parker, and J. C. G. Praca, "Interactive transmission network planning using a least-effort criterion," *IEEE Transactions on Power Apparatus and Systems*, vol. 101, no. 10, pp. 3919–3925, 1982.

[4] R. Villasana, L. L. Garver, and S. J. Salon, "Transmission network planning ussing linear programming," *IEEE Transactions on Power Apparatus and Systems*, vol. 104, no. 2, pp. 349–356, 1985.

[5] M. V. F. Pereira and L. M. V. G. Pinto, "Application of sensitivity analysis of load supplying capability to interactive transmission expansion planning," *IEEE Transactions on Power Apparatus and Systems*, vol. 104, no. 2, pp. 381–389, 1985.

[6] R. Romero and A. Monticelli, "Hierarchical decomposition approach for transmission network expansion planning," *IEEE Transactions on Power Systems*, vol. 9, no. 1, pp. 373–380, 1994.

[7] R. Romero and A. Monticelli, "Zero-one implicit enumeration method for optimizing investments in transmission expansion planning," *IEEE Transactions on Power Systems*, vol. 9, no. 3, pp. 1385–1391, 1994.

[8] S. Binato, M. V. F. Pereira, and S. Granville, "A new Benders decomposition approach to solve power transmission network

design problems," *IEEE Transactions on Power Systems*, vol. 16, no. 2, pp. 235–240, 2001.

[9] S. Haffner, A. Monticelli, A. Garcia, and R. Romero, "Specialised branch-and-bound algorithm for transmission network expansion planning," *IEE Proceedings: Generation, Transmission and Distribution*, vol. 148, no. 5, pp. 482–488, 2001.

[10] M. J. Rider, A. V. Garcia, and R. Romero, "Transmission system expansion planning by a branch-and-bound algorithm," *IET Generation, Transmission and Distribution*, vol. 2, no. 1, pp. 90–99, 2008.

[11] R. Romero, R. A. Gallego, and A. Monticelli, "Transmission system expansion planning by simulated annealing," *IEEE Transactions on Power Systems*, vol. 11, no. 1, pp. 364–369, 1996.

[12] R. A. Gallego, R. Romero, and A. J. Monticelli, "Tabu search algorithm for network synthesis," *IEEE Transactions on Power Systems*, vol. 15, no. 2, pp. 490–495, 2000.

[13] R. A. Gallego, A. Monticelli, and R. Romero, "Transmission systems expansion planning by an extended genetic algorithms," *IEE Proceedings Generation, Transmission and Distribution*, vol. 145, no. 3, pp. 329–335, 1998.

[14] A. Verma, B. K. Panigrahi, and P. R. Bijwe, "Harmony search algorithm for transmission network expansion planning," *IET Generation, Transmission and Distribution*, vol. 4, no. 6, pp. 663–673, 2010.

[15] I. D. J. Silva, M. J. Rider, R. Romero, A. V. Garcia, and C. A. Murari, "Transmission network expansion planning with security constraints," *IEE Proceedings: Generation, Transmission and Distribution*, vol. 152, no. 6, pp. 828–836, 2005.

[16] S. de la Torre, A. J. Conejo, and J. Contreras, "Transmission expansion planning in electricity markets," *IEEE Transactions on Power Systems*, vol. 23, no. 1, pp. 238–248, 2008.

[17] L. P. Garcés, A. J. Conejo, R. García-Bertrand, and R. Romero, "A bilevel approach to transmission expansion planning within a market environment," *IEEE Transactions on Power Systems*, vol. 24, no. 3, pp. 1513–1522, 2009.

[18] P. S. Georgilakis, "Market-based transmission expansion planning by improved differential evolution," *International Journal of Electrical Power and Energy Systems*, vol. 32, no. 5, pp. 450–456, 2010.

[19] L. A. Gallego, M. J. Rider, R. Romero, and A. V. Garcia, "A specialized genetic algorithm to solve the short term transmission network expansion planning," in *Proceedings of the IEEE Bucharest PowerTech*, pp. 1–7, Bucharest, Romania, July 2009.

[20] M. J. Rider, L. A. Gallego, R. Romero, and A. V. García, "Heuristic algorithm to solve the short term transmission network expansion planning," in *Proceedings of the IEEE Power Engineering Society General Meeting (PES '07)*, pp. 1–7, June 2007.

[21] P. C. Chu and J. E. Beasley, "A genetic algorithm for the generalised assignment problem," *Computers and Operations Research*, vol. 24, no. 1, pp. 17–23, 1997.

[22] I. J. De Silva, M. J. Rider, R. Romero, and C. A. Murari, "Genetic algorithm of chu and beasley for static and multistage transmission expansion planning," in *Proceedings of the IEEE Power Engineering Society General Meeting (PES '06)*, Montreal, Canada, June 2006.

[23] D. E. Goldberg, *Genetics Algorithms in Search, Optimization and Machine Learning*, Addison Wesley, Reading, Mass, USA, 1989.

[24] C. R. Reeves, *Modern Heuristics Techniques for Combinatorial Problems*, McGraw Hill, 1995.

[25] M. Mitchell, *An Introduction to Genetic Algorithms*, MIT Press, 1996.

[26] S. M. Sait and H. Youssef, *Iterative Computer Algorithms with Applications in Engineering*, Wiley-IEEE Computer Society Press, 1996.

[27] Z. Michalewicz, *Genetic Algorithms + Data Structures = Evolution Programs*, Artificial Intelligence, Springer, Berlin, Germany, 1996.

[28] K. N. Mïu, H. D. Chiang, and G. Darling, "Capacitor placement, replacement and control in large-scale distribution systems by a ga-based two-stage algorithm," *IEEE Transactions on Power Systems*, vol. 12, no. 3, pp. 1160–1166, 1997.

[29] A. H. Escobar, R. A. Gallego, and R. Romero, "Multistage and coordinated planning of the expansion of transmission systems," *IEEE Transactions on Power Systems*, vol. 19, no. 2, pp. 735–744, 2004.

[30] E. L. D. Silva, H. A. Gil, and J. M. Areiza, "Transmission network expansion planning under an improved genetic algorithm," *IEEE Transactions on Power Systems*, vol. 15, no. 3, pp. 1168–1175, 2000.

[31] W. M. Lin, F. S. Cheng, and M. T. Tsay, "Distribution feeder reconfiguration with refined genetic algorithm," *IEE Proceedings: Generation, Transmission and Distribution*, vol. 147, no. 6, pp. 349–354, 2000.

[32] S. Venkatraman and G. G. Yen, "A generic framework for constrained optimization using genetic algorithms," *IEEE Transactions on Evolutionary Computation*, vol. 9, no. 4, pp. 424–435, 2005.

[33] K. Deb, "An efficient constraint handling method for genetic algorithms," *Computer Methods in Applied Mechanics and Engineering*, vol. 186, no. 2–4, pp. 311–338, 2000.

[34] R. Romero, A. Monticelli, A. Garcia, and S. Haffner, "Test systems and mathematical models for transmission network expansion planning," *IEE Proceedings: Generation, Transmission and Distribution*, vol. 149, no. 1, pp. 482–488, 2002.

[35] G. Latorre, R. Darío Cruz, J. M. Areiza, and A. Villegas, "Classification of publications and models on transmission expansion planning," *IEEE Transactions on Power Systems*, vol. 18, no. 2, pp. 938–946, 2003.

[36] R. A. Gallego, A. Monticelli, and R. Romero, "Comparative studies on non-convex optimization methods for transmission network expansion planning," *IEEE Transactions on Power Systems*, vol. 13, no. 3, pp. 822–828, 1998.

[37] E. L. Da Silva, J. M. Areiza Ortiz, G. C. De Oliveira, and S. Binato, "Transmission network expansion planning under a Tabu Search approach," *IEEE Transactions on Power Systems*, vol. 16, no. 1, pp. 62–68, 2001.

[38] T. Sum-Im, G. A. Taylor, M. R. Irving, and Y. H. Song, "Differential evolution algorithm for static and multistage transmission expansion planning," *IET Generation, Transmission and Distribution*, vol. 3, no. 4, pp. 365–384, 2009.

[39] S. H. M. Hashimoto, R. Romero, and J. R. S. Mantovani, "Efficient linear programming algorithm for the transmission network expansion planning problem," *IEE Proceedings: Generation, Transmission and Distribution*, vol. 150, no. 5, pp. 536–542, 2003.

Hindawi Publishing Corporation
Journal of Electrical and Computer Engineering
Volume 2012, Article ID 738409, 5 pages
doi:10.1155/2012/738409

Research Article

Evolutionary Optimization of Electric Power Distribution Using the Dandelion Code

Jorge Sabattin,[1] Carlos Contreras Bolton,[2] Miguel Arias,[1] and Víctor Parada[2]

[1] *Departamento de Ingeniería Eléctrica, Universidad de Santiago de Chile, Avenida Ecuador 3659, Santiago, Chile*
[2] *Departamento de Ingeniería Informática, Universidad de Santiago de Chile, Avenida Ecuador 3659, Santiago, Chile*

Correspondence should be addressed to Jorge Sabattin, jorge.sabattin@usach.cl

Received 16 August 2011; Revised 12 November 2011; Accepted 12 November 2011

Academic Editor: Edgar Carreno

Planning primary electric power distribution involves solving an optimization problem using nonlinear components, which makes it difficult to obtain the optimum solution when the problem has dimensions that are found in reality, in terms of both the installation cost and the power loss cost. To tackle this problem, heuristic methods have been used, but even when sacrificing quality, finding the optimum solution still represents a computational challenge. In this paper, we study this problem using genetic algorithms. With the help of a coding scheme based on the dandelion code, these genetic algorithms allow larger instances of the problem to be solved. With the stated approach, we have solved instances of up to 40,000 consumer nodes when considering 20 substations; the total cost deviates 3.1% with respect to a lower bound that considers only the construction costs of the network.

1. Introduction

Electric power distribution must satisfy user needs within a given geographic area, and for this purpose, an electric network that can identify a primary and a secondary distribution network is used. In the primary network, electric power is distributed in a tree topology, an activity in which electric companies invest approximately 50% of the transport network's capital [1] and which gives rise to the requirement of efficient planning of the distribution network, taking into account the minimization of power loss. One way of approaching the planning is through mathematical programming models, which, although useful to solve various real situations [2, 3], have limitations when dealing with problems of large size.

The feeders allow power to be transferred from the substations to places close to the final consumers, using a voltage level that can satisfy the requirements of each consumer. The power flows radially along conductors, which, because of their nature, offer resistance to the flow, causing part of this power to be dissipated as heat. These conductors have different costs depending on their cross sections and types of materials, and, therefore, the flow must be adjusted to minimize the loss. This paper considers the design problem that also involves minimizing the amount of materials and installation costs.

Energy distribution from a substation to the consumption points can be represented by a tree in which the substation corresponds to the root and the trees nodes represent the consumers. This tree can be coded as an array of integer numbers that represent the labels of the nodes. If we consider the bijection between a Cayley tree [4] and a string of n characters, the number of possible trees given by the Prüfer number [5] is n^{n-2}. Furthermore, because each connection can be established with different types of conductors, the combinatorial degree of the problem can reach dimensions that make it computationally unmanageable.

The optimum generation of electric power distribution trees is a problem that has been studied in the literature and is known as the distribution tree problem (DTP) [6]. One way of facing this challenge is through heuristic and metaheuristic methods. Under this approach, a comparative analysis of computational performance between simulated annealing and tabu search has shown that it is possible to obtain good quality solutions for a group of instances that, although larger than previously reported in the literature, are still far from the sizes that are actually handled [7].

Various authors have studied the DTP by considering genetic algorithms (GAs), which are stochastic search methods based on principles of evolution and natural selection [8]. Typically, they use coding based on integer numbers (binary in some cases) to represent a tree, but this type of representation involves the problem of having to define adequate genetic operators to visit only feasible solutions. In this respect, Najafi et al. [9] use a binary coding scheme that allows solving a large distribution network that, in practice, is reduced to 90 nodes. Considering a similar representation, Li and Chang [10] propose a new GA supported by a minimal spanning tree algorithm and illustrate the method with a small network. The computational performance of a GA appears to become worse when the networks are larger, requiring even longer computing time to solve problem instances of approximately 500 nodes [11]. Real networks can have hundreds of thousands of nodes [12], and thus, the algorithms described above may require extremely long computing times, making it difficult to construct a computational system to support decision making in this field. The greatest computational expense in the GA is associated with the calculation of the power flow at each new solution visited and with the handling of the operators that control the feasibility of the solution. One way of reducing this expense involves using a coding based on trees, which has been explored in the literature by considering other optimization problems in graphs [13].

There are several ways of representing trees within a GA, but there is little consensus as to which of these representations is "the best" [14]. Several researchers have proposed that the representation of a tree must have certain properties for the implemented algorithm to operate efficiently [13, 15, 16]. One way of generating this representation involves using the dandelion code [17], which belongs to the Cayley family of codes [5]. The results show that the dandelion code satisfies the properties identified by Palmer and Kershenbaum [16] and therefore constitutes an interesting representation for an evolutionary search. When using the dandelion code for the DTP, each distribution tree can be evaluated without concern for the feasibility when applying the cross-over and mutation operators. In this way, the computational effort is reduced exclusively to the evaluation of the power flow. This paper tackles the problem of the optimal generation of large electric power distribution trees through a GA, using the dandelion code to represent trees.

The second section of the paper describes the main components of the model, and the third section presents the results. The last section presents the conclusion of the study.

2. Problem Modeling and Representation

Let $\Gamma = \{\tau_1, \tau_1, \ldots..\tau_m\}$ be defined as the set of all possible trees with n nodes, and let S be the set of all the integer strings of length $n-2$. The dandelion code establishes a relationship between a code $D \in S$ and a tree $\tau \in \Gamma$ such that to decode a tree $\tau \in \Gamma$ associated with D, a function $\varphi_D : [2, n-1] \to [1, n]$ is defined such that $\varphi_D(i) = d_i$ for each $i \in [2, n-1]$ [14].

2.1. Representation of the Problem. To represent a distribution tree, all of the substations are labeled with natural numbers from 1 to N, and the consumer nodes are labeled with natural numbers from $N+1$ to M; an artificial node "0" is created to represent the source of supply for all of the substations. In turn, each substation feeds the consumer points following a tree structure. Thus, a dandelion code associated with a set of distribution trees can be identified with an array of $n-2$ elements. Moreover, to ensure that each substation be the root of each tree, the positions corresponding to the substations have the value "0," which represents the artificial node.

As an example, consider an electric distribution system with $N = 3$ substations and 9 consumer points. Every set of distribution trees can be represented by a string of 10 natural numbers in {1, 2, 3,. . .,10}. To decode a given string, such as $C = (4, 6, 2, 2, 4, 8, 7, 6, 11, 12)$, we first define a string A_c with consecutive numbers from 2 to $M-1$ (in this case, $A_c = (2, 3, 4, 5, 6, 7, 8, 9, 10, 11)$) such that the first $N-1$ positions correspond to the labels of the substations. The first two positions of C have the value 0, so matrix R is constructed with the elements of A_c in the first row and the elements of C in the second row:

$$R = \begin{bmatrix} 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 \\ 0 & 0 & 2 & 2 & 4 & 8 & 7 & 6 & 11 & 12 \end{bmatrix}. \quad (1)$$

Function $\varphi(\cdot)$, corresponding to the dandelion code function, is applied where, for each element of the first row, there is a corresponding element directly below it in the second row. In this example, $\varphi(2) \to 0$; $\varphi(3) \to 0$; $\varphi(4) \to 2$; $\varphi(5) \to 2$; $\varphi(6) \to 4$; $\varphi(7) \to 8$; $\varphi(8) \to 7$. A cycle is detected and separated from $\varphi(\cdot)$, storing it in an ordered list from smallest to largest, such as in the regular dandelion decoding algorithm. Then, we continue with the following element of the first row—$\varphi(9) \to 6$, $\varphi(10) \to 11$, $\varphi(11) \to 12$—until the elements of A_c are finished. The tree is built as follows: all the nodes that represent the substations are connected with the artificial substation. In this example, nodes 1, 2, and 3 are connected with node 0. The cycles and the last node are added to one of these substations; in this case, 7, 8, and 12 are added to substation 1. A substation node is chosen on which to hang the cycles. In this case, the substation is labeled 1. To select substation 1, the criterion of choosing the substation with the lowest label that appears fewer times in C is applied. In the case of a tie, the one with the smallest label is chosen. The nodes are then added to the tree, as indicated by function $\varphi(\cdot)$. In this way, the code's bijection is retained, and a good locality is insured. Figure 1 shows the electric distribution tree corresponding to code C.

Any set of electric distribution trees that solves the DTP can be represented by the proposed model, with M substations and N consumer points. We call this representation D-DTP. For the GA code C representing a chromosome, each chromosome represents a set of electric distribution trees, and each set of trees represents a solution to the DTP.

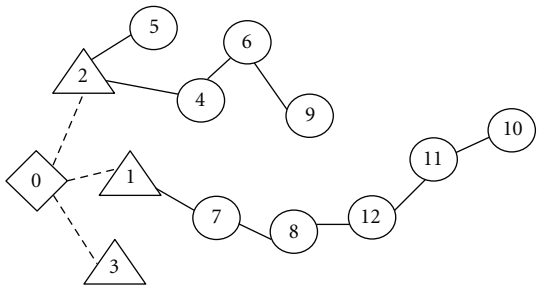

Figure 1: Electric distribution tree corresponding to code $C = (4, 6, 2, 2, 4, 8, 7, 6, 11, 12)$.

2.2. Initial Population and Objective Function. The initial population is generated using a modified Prim algorithm [18]. Each of the solutions of the initial population is represented by the D-DTP, which, in the GA, is equivalent to an individual. To evaluate the fitness of each individual, (2) is used, which allows the minimum construction cost and the minimum power loss cost to be determined:

$$\text{Min } f(y,x) = f_1(y) + f_2(y,\ x), \tag{2}$$

where $f_1(y)$ is the investment cost in equipment and $f_2(y,x)$ is the power loss cost.

The construction cost between the f_1 nodes is proportional to the Euclidean distance of the arc between the nodes that form the tree, multiplied by the cost of the conductor used in each section. Furthermore, the cost of the losses f_2 is proportional to the square of the current that flows along each section and is determined using a power flow algorithm [19].

2.3. Experimental Design. To perform the experiment, the test instances are generated first, which have the following input data: active power P, reactive power Q, and (X_1, X_2), which contains the position of the nodes in geographic space. The instances that must be created are 35,000, 40,000, and 45,000 points, which correspond to the consumption nodes. Additionally, for each instance, 20 points equivalent to the substations are considered. P is generated randomly for each node, with values between 0 and 1. In contrast, Q is generated such that it fulfills the electric power relations that satisfy the condition $Q = P\ \tan(\theta)$, where θ is generated by satisfying $\cos(\theta) > 0.8$. Similarly, the active power and the reactive power of the substations are generated. Additionally, the total power of the substations must be greater than the sum of the powers at the consumption nodes, including the losses. The geographic locations of the nodes are generated randomly with nominal values between 0 and 1. A conductor table (Table 1) must also be considered that contains the resistance, the impedance, the current capacity, and the price of each conductor.

2.4. Parameter Calibration. The main parameters of a GA are: population size, the cross-over probability, and the mutation probability. In this paper, we will use the parameters proposed by Grefenstette [20], which are 30 to 50 individuals for the population size, 0.90 to 0.95 for the cross-over probability, and 0.01 to 0.05 for the mutation probability. For the termination criterion parameter, we used the number of generations, which is 1000 in this case.

Although it is recommended to use a low mutation probability [21], experiments prior to our work have shown that when the probability increases, the results improve. For this reason, a calibration of this parameter is made. The set of values studied for the mutation probability is the following: 0.005, 0.01, 0.02, 0.04, 0.08, 0.10, 0.12, 0.14, 0.16, 0.18, 0.20, and 0.22.

The calibration process was executed 5 times with an instance of 500 nodes and 20 substations. The network's data are shown in Table 2. As an example, for a given node $P = 1$, considering a base power of 1000 kVA, the P value for this node becomes 1000 kW. The results of the calibration show that the probability of 0.16 achieves the best results, as shown in bold numbers in Table 3.

2.5. Hardware and Software. The equipment used had a 2-Quad-Core CPU 2.00 GHz Intel Xeon with 16 Gbytes of RAM, and the operating system was Ubuntu 10.04.2 LTS Kernel 2.6.32-28-generic, compiler GNU C (4.4.3).

Table 1: Conductor data.

Conductor	Impedance (Ohm/Km)	Resistance (Ohm/Km)	Current Capacity (A)	Cost (dollars)
1	0.00010	0.0016	0.08429	8000
2	0.00010	0.0008	0.12644	9000
3	0.00009	0.0005	0.14232	10000
4	0.00008	0.0004	0.18071	12000
5	0.00008	0.0008	0.21073	13000
6	0.00007	0.0004	0.24624	17000

Table 2: Network data.

Base power (kVA)	1000
Available power (kVA)	21000
Required power (kVA)	17000
Operating time (years)	10
Base voltage (kV)	12
Number of consumers	500
Number of substations	20

3. Results

For each instance, the following input data were considered: 20 substations, base power 1000 kVA, base voltage 12 kV, and an operating time of 10 years.

Figure 2 shows that the algorithm starts with good initial solutions, then moves away from the initial solution, and finally converges to a good-quality solution. The good initial solutions are explained because the initial population is generated with Prim's algorithm.

Table 3: Study of the mutation.

Mutation (%)	0.01	0.01	0.02	0.04	0.08	0.10
Av. installation cost (US$)	167895	169552	187395	170235	171649	161885
Av. loss cost (US$)	39757425	18641845	6069982	189316	519619	1462243
Av. total cost (US$)	39925320	18811398	6257377	359551	691268	1624,128
Mutation (%)	0.12	0.14	**0.16**	0.18	0.20	0.22
Av. installation cost (US$)	160996	166901	**157098**	166722	157471	156557
Av. loss cost (US$)	1570343	157148	**121282**	2839201	215340	1684931
Av. total cost (US$)	1731339	324050	**278381**	3005924	372810	1841488

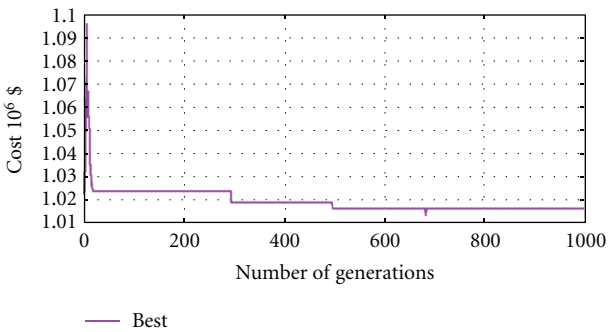

Figure 2: Cost versus number of generations.

Table 4: Results.

Number of nodes	35000	40000	45000
Total cost (average) (US$)	1021351	1069387	1132179
Minimum cost (US$)	1013664	1068609	1123047
Minimum bound (US$)	970082	1036867	1102479
Average time (HH:MM: SS)	87:17:00	110:54:46	127:00:18
Minimum time (HH:MM:SS)	84:58:47	105:3330	118:59:16
Available power (kVA)	20000	21000	22000
Required power (kVA)	16000	17000	18000

To validate the results obtained with the GA, the results are compared with a lower bound. To find such bound, use is made of a Prim algorithm with which the minimum construction cost of the network is sought. In this way, comparisons of the results are established that validate the results obtained with the GA. This can be observed in all of the test instances (Table 4).

4. Conclusions

This paper proposes a solution for the DTP that has a real application in the optimization of electric distribution networks. The problem is approached using GAs, proposing a model that considers construction and power loss costs. To perform the search in the distribution tree space, the dandelion code is used. The proposed approach shows that the code used is efficient in the representation of trees, and its use allows real problems to be solved using GAs.

The approach used also allows one to find solutions to problems with extremely large instances, e.g., for the instance of 45,000 nodes, which requires a computing time of 118:59:16.

References

[1] G. Kjolle, L. Rolfseng, and E. Dahl, "Economic aspect of reliability in distribution system planning," *IEEE Transactions on Power Delivery*, vol. 5, no. 2, pp. 1153–1157, 1990.

[2] U. G. Knight, "The logical design of electrical networks using linear programming methods," *Proceedings of the IEE A*, vol. 107, no. 33, pp. 306–314, 1960.

[3] M. A. El-Kady, "Computer-aided planning of distribution substation and primary feeders," *IEEE transactions on power apparatus and systems*, vol. 103, no. 6, pp. 1183–1189, 1984.

[4] A. Cayley, "A theorem on trees," *Quarterly Journal of Mathematics*, vol. 23, pp. 376–378, 1984.

[5] H. Prüfer, "Neuer beweis eines satzes über permutationen," *Archiv fur Mathematik und Physik*, vol. 27, pp. 742–744, 1918.

[6] V. Parada, J. A. Ferland, M. Arias, P. Schwarzenberg, and L. S. Vargas, "Heuristic determination of distribution trees," *IEEE Transactions on Power Delivery*, vol. 25, no. 2, pp. 861–869, 2010.

[7] V. Parada, J. A. Ferland, M. Arias, and K. Daniels, "Optimization of electrical distribution feeders using simulated annealing," *IEEE Transactions on Power Delivery*, vol. 19, no. 3, pp. 1135–1141, 2004.

[8] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley, 1st edition, 1989.

[9] S. Najafi, S. H. Hosseinian, M. Abedi, A. Vahidnia, and S. Abachezadeh, "A framework for optimal planning in large distribution networks," *IEEE Transactions on Power Systems*, vol. 24, no. 2, pp. 1019–1028, 2009.

[10] Y. Li and X. Chang, "A MST-based and new GA supported distribution network planning," in *Proceedings of the International Conference on Mechatronic Science, Electric Engineering and Computer (MEC '11)*, pp. 2534–2538, 2011.

[11] I. J. Ramirez-Rosado and J. L. Bernai-Agustin, "Genetic algorithms applied to the design of large power distribution systems," *IEEE Transactions on Power Systems*, vol. 13, no. 2, pp. 696–703, 1998.

[12] A. S. Pabla, *Electric Power Distribution*, Tata McGraw-Hill, New York, NY, USA, 2004.

[13] F. Rothlauf, *Representations for Genetic and Evolutionary Algorithms*, Springer, 2nd edition, 2006.

[14] T. Paulden and D. K. Smith, "From the Dandelion Code to the rainbow code: a class of bijective spanning tree representations with linear complexity and bounded locality," *IEEE Transactions on Evolutionary Computation*, vol. 10, no. 2, pp. 108–123, 2006.

[15] F. Rothlauf, "Towards a theory of representations for genetic and evolutionary algorithms," University of Bayreuth, Alemania, 2001.

[16] C. C. Palmer and A. Kershenbaum, "Representing trees in genetic algorithms," in *Proceedings of IEEE Conference on Evolutionary Computation*, vol. 1, pp. 379–384, 1994.

[17] S. Picciotto, "How to encode a tree," Univ. California, California, 1999.

[18] R. C. Prim, "Shortest connection networks and some generalizations," *Bell System Technical Journal*, vol. 36, pp. 1389–1401, 1957.

[19] M. Arias, H. Sanhueza, and V. H. Quintana, "Nuevo algoritmo para cálculo de flujo de potencia en alimentadores de distribución," in *the 6th Congreso Chileno de Ingeniería Electrica*, Punta Arenas, Chile, 1995.

[20] J. J. Grefenstette, "Optimization of control parameters for genetic algorithms," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 16, no. 1, pp. 122–128, 1986.

[21] K. A. De Jong, "An analysis of the behavior of a class of genetic adaptive systems," University of Michigan, USA, 1975.

Hindawi Publishing Corporation
Journal of Electrical and Computer Engineering
Volume 2012, Article ID 317315, 8 pages
doi:10.1155/2012/317315

Research Article

Multicriteria Reconfiguration of Distribution Network with Distributed Generation

N. I. Voropai[1] and B. Bat-Undraal[2]

[1] *Electric Power Systems Department, Energy Systems Institute, Russian Academy of Sciences, Siberian Branch, 130 Lermontov Street, Irkutsk 664033, Russia*
[2] *Power Engineering School, Mongolian University of Science and Technology, Baga Toiruu, VIII khoroo, Sukhbaatar, Ulaanbaatar 210646, Mongolia*

Correspondence should be addressed to N. I. Voropai, voropai@isem.sei.irk.ru

Received 2 August 2011; Revised 3 November 2011; Accepted 7 November 2011

Academic Editor: Edgar Carreno

The paper addresses the problem of multicriteria reconfiguration of distribution network with distributed generation according to the criterion of minimum power loss under normal conditions and the criterion of power supply reliability under postemergency conditions. Efficient heuristic and multicriteria methods are used to solve the problem including advanced ant colony algorithm for minimum loss reconfiguration of distribution network, the sorting-out algorithm of cell formation for island performing in postemergency network, and the successive concessions method for multicriteria decision making. Demonstration studies have been carried out for the Central Power System of Mongolia.

1. Introduction

Distribution networks are normally operated according to radial schemes. The problem of distribution network reconfiguration aimed at determining the most rational reconfiguration is as a rule solved by the criteria of minimum active power losses in the network, minimum undersupplied power, and minimum time for power supply restoration [1]. A review of reconfiguration methods that include classical methods of mathematical programming and modern heuristic methods based on artificial intelligence (genetic algorithms, simulated annealing, tabu search, ant colony methods, etc.) is given in [2]. In many cases the problem is considered as a multicriteria one with reliability criterion formulated through damages to consumers [3, 4] and so forth.

In the last decade much attention has been paid to disatributed generation connected to distribution network [5, 6] and so forth. The main factors stimulating the development of distributed generation are as follows:

(i) adaptation of consumers to market uncertainty in electricity industry development and electricity prices which fosters a decrease in risks of power shortage and increase of energy security;

(ii) enhancement of adaptability of electric power systems to the uncertainty of market conditions and, hence, decrease of investment risks;

(iii) emergence of new highly efficient energy technologies (gas turbines and combined-cycle units);

(iv) a growing share of gas in the fuel mix of power plants;

(v) tightening the environmental requirements to encourage the use of renewable energy sources (hydro, wind, biomass, etc.) with government support.

Distributed generation offers the possibility of maintaining voltage levels at nodes of distribution network, decreasing active and reactive power losses in the network, providing higher level of power supply reliability by maintaining power supply from distributed generation to some consumers in the case of emergency disconnection of the main supply point in the power supply system (islanding) [5, 7, 8].

Thus the coordination problem arises in controlling normal conditions of distribution network with distributed

generation through the network reconfiguration, to provide minimum power losses and to meet the required voltage and current limits, as well as in controlling postemergency conditions through islanding, to provide minimum power shortage due to the loss of supply substation of main power grid (main supply point). Such multicriteria problems cannot always be reduced to a one-criterion statement by introducing weighted coefficients for individual criteria. In this paper this problem is solved by the method of successive concessions [9]. The method of ant colony is used for distribution network reconfiguration. Islanding is performed by forming cells [10] and load flow is calculated by the backward/forward sweep algorithm [7].

2. Technology of Study

2.1. General Approach. A general approach to control coordination of normal and postemergency conditions of distribution network including distributed generation is as follows.

Under normal conditions the control aims to reconfigure the distribution network by opening loops. The minimum of active power losses in the network is given by the following criterion:

$$\sum_{l\in L} R_{lk} I_{lk}^2 \longrightarrow \min, \qquad k \in K, \tag{1}$$

where K is a set of considered normal conditions according to the load curves of consumers and loading of distributed generation plants; L is the number of branches in the network; R_{lk} and I_{lk} are active resistance and current in branch l for operation conditions k.

Under postemergency conditions, if the main supply point is lost, the problem of islanding arises with the islands including distributed generation plants that operate for a balanced load. The criterion of islanding is the minimum power shortage in the postemergency conditions:

$$\left(\sum_{n\in N} P_{nk} - \sum_{n^*\in N^*} P_{n^* j}\right) \longrightarrow \min, \qquad k \in K, j \in J, \tag{2}$$

where J is a set of considered postemergency conditions with the main supply point lost; P_{nk} is the load at node n in the network under normal condition k; $P_{n^* j}$ is the load at node n^* in the postemergency condition j of the network part including N^* nodes, that belong to all islands; N is the number of network nodes.

In control coordination of normal and postemergency conditions of distribution network, an important problem is to check whether the constraints on voltage levels at nodes and currents in network branches are met under both normal and postemergency conditions:

$$V_{nk\,\min} \le V_{nk} \le V_{nk\,\max}, \tag{3}$$

$$V_{nj\,\min} \le V_{nj} \le V_{nj\,\max}, \tag{4}$$

$$I_{lk} \le I_{lk\,\max}, \tag{5}$$

$$I_{lj} \le I_{lj\,\max}. \tag{6}$$

Instead of (5) and (6), the values of power transmitted by the network branches can be controlled using similar inequalities.

Constraints (3)–(6) in the optimization of criteria (1) and (2) are checked on the basis of radial network power flow calculations. The calculations employ backward/forward sweep algorithm with respect to distributed generation plants connected to the distribution network [7]. In order to minimize the number of such calculations, the interval implementation of backward/forward sweep algorithm [11] is applied which allows the ranges of voltage and current values to be obtained for groups of conditions.

There are two specific features of the problem related to islanding and determining postemergency conditions. The first one concerns the presence of constraints (4) and (6), which means different requirements for voltage levels at nodes and maximum load of network branches in the postemergency conditions as compared to the normal conditions. The second one related to islanding is implementation of the principle of maintaining power supply, first of all, to the most important consumers at the distribution network nodes.

One of the important control coordination problems of normal and postemergency conditions of distribution networks is minimization of switchings while passing from normal to postemergency conditions. This is important in terms of minimizing the number of switching devices, their possible failures, and personnel's errors. Therefore, the optimization problem (1)–(6) is a complex two-criterion problem. Let us consider an expedient approach to its solution.

A widely used approach is the consideration for power supply reliability through the damages due to power undersupply which allows the multicriteria problem to be reduced to a one-criterion one [3, 4] and so forth. To this end it is necessary to have reliable estimates of specific damages due to power supply interruption for different consumers. In reality these estimates cannot be obtained for all types of consumers; particularly it concerns the consumers with production processes where power supply interruptions may pose a threat to the life of people or to the environment. Therefore in a general case criteria (1) and (2) should be considered as independent and irreducible to one complex criterion. In the paper the method of successive concessions is used as a method for solving the two-criterion problem (1)–(6). The minimization by criterion (1) with regard to constraints (3) and (5) is carried out by the ant colony method, islanding (subproblems (2), (4), and (6)) by the combinatorial algorithm through formation of cells.

2.2. Minimum Loss Reconfiguration. Ant colony algorithm is a multiagent system in which the behavior of each single agent, called artificial ant, is inspired by the behavior of real ants [12]. Ant colony algorithm is one of the most successful examples of swarm intelligent systems and has been applied to many combinatorial optimization problems. Ant colony algorithm has been used lately to solve minimum loss reconfiguration problem [13–17].

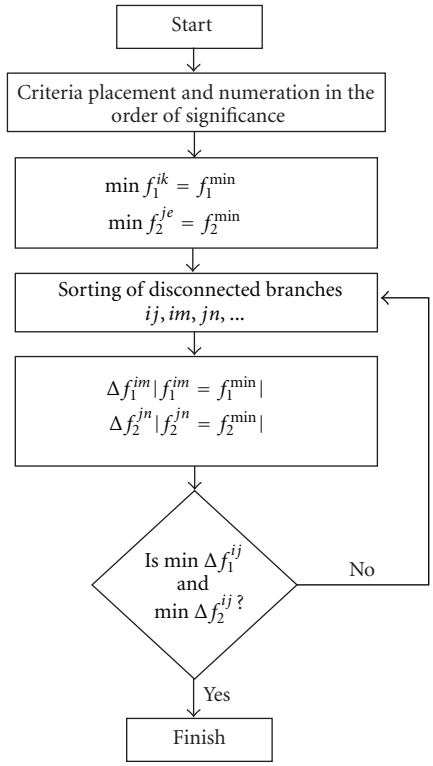

Figure 1: Flowchart of modified method of successive concessions.

The idea of the ant colony algorithm is rather thoroughly presented in [12] and given in [13–17]; therefore we will not describe it here.

The type of the ant colony algorithm implementation is determined by what is understood by the track passed by ants. In [13, 14] active power losses in the entire network are taken as a track length. In [15, 17] the track length is determined by the resistance of one branch and the algorithm consequently goes along the network graph starting from the main supply point of the power supply system.

In the first case the point of network disconnection is chosen by the roulette rule, with the disconnection point probability determined by [13]

$$P_{m(t)} = \begin{cases} \dfrac{\eta(t)^{\beta}/\tau(t)}{\sum_{s\in I_m(l)}\left(\eta(s)^{\beta}/\tau(s)\right)}, & \text{if } s \in J_m(l), \\ 0, & \text{otherwise}, \end{cases} \tag{7}$$

where $t(s)$ is a pheromone level; $h(s)$ is the so-called visibility, a value inverse to the length of track passed by ants; m is the number of ants; $J_m(l)$ is the list of branches in loop l; β is a parameter determining relative priority of pheromone; t determines a currently considered branch or a current iteration of the algorithm.

In [14], another, more complex, algorithm is used. It is related to the hypercube ant colony optimization framework.

In the second case (in [15–17]), the roulette rule is used to choose the next branch in the network graph to be considered. There are different forms of realization of roulette rule.

This paper employs the approach suggested in [13], but unlike [13] here load flow is calculated in each iteration of the ant colony algorithm by the backward/forward sweep method, and constraints (3) and (5) are checked. In the event that the constraints are not met, the branch considered as a candidate for disconnection is excluded from consideration.

2.3. Islanding. In the problem of distributed generation islanding for an equivalent load in the event that power supply from supply substation of the main network is lost, it is necessary to take into account a number of requirements.

(1) The distributed generation and load should be balanced in order to fully use and not to overload distributed generation. The condition of power balance in the island is found by the sorting-out algorithm through formation of cells [10]. For each cell meeting the condition

$$\sum P_{Sn} - \sum P_{Ln} \geq 0 \tag{8}$$

is checked, where S and L are the indices of sources and loads at cell, and n is a cell index.

(2) Cells are formed by connecting, first of all, the nearest loads, and the remoteness of load nodes is estimated by the total resistance of branches connecting source to consumer.

(3) While forming the cells first of all power is supplied to the most important consumers.

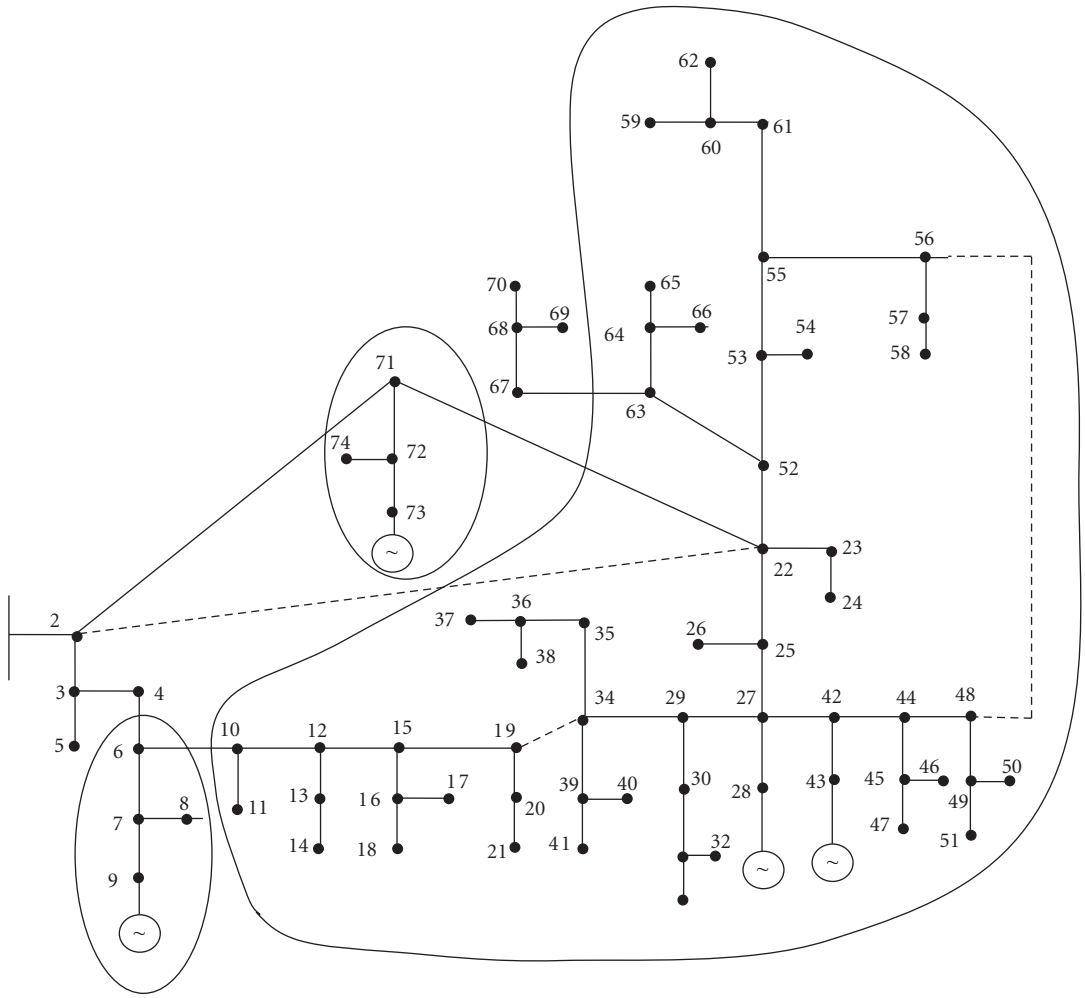

Figure 2: Points of electric network tripping in normal conditions (dashed lines) and composition of islands in the postemergency conditions (encircled).

(4) At each step of the sorting-out algorithm, the load flow in the island is calculated and constraints (4) and (6) are met. In the event that these constraints are not met, formation of an island is stopped at the previous step.

In order to eliminate the inconsistency between the second and third requirements, the third requirement is considered a priority one.

2.4. Method of Successive Concessions. The general procedure of solving a multicriteria problem by the method of successive concessions is as follows [9].

(i) All partial criteria are placed and numbered in the order of their relative significance.

(ii) The first most important criterion is optimized.

(iii) The value of the admissible deviation from the optimum of the first criterion (concession) is set.

(iv) The second important partial criterion is optimized provided that the value of the first criterion should not differ from the optimal value by more than a value of the concession set.

(v) Similarly the value of concession for the second criterion is set and the third important criterion is optimized and so on.

In a general case the presented procedure can include, when necessary, several iterations converging to a satisfactory trade-off solution.

In the paper the general method of successive concessions was modified by taking into account the specificity of the studied problem. The modified procedure includes the following four steps.

(1) All partial criteria are placed and numbered in the order of their relative significance. On our case the order of criteria is as follows:

$$f_1 = \sum_{l \in L} R_{lk} I_{lk}^2 \longrightarrow \min, \quad k \in K, \tag{9}$$

$$f_2 = \left(\sum_{n \in N} P_{nk} - \sum_{n^* \in N^*} P_{n^* j} \right) \longrightarrow \min, \quad k \in K, j \in J. \tag{10}$$

Table 1

Nodes	U, kV	P_L, MW	Q_L, MVA	P_g, MW	P_g, MVA
1	242	—	—	—	—
2	220	—	—	—	—
3	110	—	—	—	—
4	110	16.8	7.5	—	—
5	35	—		—	—
6	110	24.8	8.8	—	—
7	35	—	—	—	—
8	110	1.3	2.4	—	—
9	6	6.0	7.3	33.6	11.1
10	6	—	—	—	—
11	6	2.1	0.8	—	—
12	6	—	—	—	—
13	6	—	—	—	—
14	6	2.9	1.1	—	—
15	6	—	—	—	—
16	6	—	—	—	—
17	110	0.6	0.1	—	—
18	6	2.9	1.1	—	—
19	6	—	—	—	—
20	6	—	—	—	—
21	6	0.2	0.1	—	—
22	10	—	—	—	—
23	10	—	—	—	—
24	10	—	—	—	—
25	10	—	—	—	—
26	35	—	—	—	—
27	110	95.7	50.8		—
28	10	—	—	47.9	18.2
29	10	—	—	79.7	89.1
30	10	—	—	—	—
31	10	—	—	—	—
32	35	0.7	0.3	—	—
33	10	2.2	1.2	—	—
34	10	—	—	—	—
35	10	—	—	—	—
36	10	—	—	—	—
37	10	0.1	0.1		—
38	110	6.2	3.0	—	—
39	6	—	—	—	—
40	110	0.2	0.1	—	—
41	6	0.1	0.1	—	—
42	6	—	—	73.9	29.0
43	6	—	—	—	—
44	6	—	—	—	—
45	6	—	—	—	—
46	6	1.6	0.7	—	—
47	10	5.9	2.4	—	—
48	10	—	—	—	—
49	10	—	—	—	—
50	35	21.1	8.5	—	—
51	10	7.9	2.7	—	—
52	10	—	—	—	—
54	10	—	—	—	—
55	10	—	—	—	—
56	10	—	—	—	—
57	10	—	—	—	—
58	10	4.9	2.3	—	—
59	10	—	—	—	—
60	6	—	—	—	—
61	6	—	—	—	—
62	35	—	—	—	—
63	10	—	—	—	—
64	10	—	—	—	—
65	110	16.9	7.5	—	—
66	35	—	—	—	—
67	10	—	—	—	—
68	10	—	—	—	—
69	110	—	—	—	—
70	35	—	—	—	—
71	10	—	—	—	—
72	10	—	—	—	—
73	35	26.8	8.8	—	—
74	110	108.4	58.6	—	—

(2) The first most important criterion f_1 is minimized by the ant colony algorithm as it is described in Section 2.2. The disconnected branches are determined as a result of minimization of criterion f_1.

(3) The second criterion f_2 is minimized by the algorithm through formation of cells as it is described in Section 2.3. The other disconnected branches are determined which differ from the disconnected branches determined by minimization of criterion f_1.

(4) The combinatorial sorting algorithm is used to search for the disconnected branches which are acceptable from the point of view of both criteria f_1 and f_2 with the minimal concessions of both criteria.

The flowchart of modified method of successive concessions is shown in Figure 1.

3. Case Study

The studied network is a simplified network of the Central Power System of Mongolia (Figure 2). The data of network are presented in Tables 1 and 2. The Gusinoozyersk thermal power plant (TPP) (node 1) that is included in the Unified Power System of Russia and supplies electricity to the Central Power System of Mongolia transmission line (branch 1-2) is conditionally taken as the main supply point. In the Central Power System of Mongolia there are 4 small operating thermal power plants of similar capacity which are really distributed generation units.

Network reconfiguration by using the criterion of minimum active power losses (1) on the basis of constraints (3)

Table 2

Branches i	j	R, Om	X, Om
1	2	27.0	107.0
2	3	1.4	100.0
2	22	29.1	115.3
2	71	16.1	63.6
3	4	1.4	0
3	5	2.9	193.0
4	6	1.1	3.2
6	7	0.7	27.0
6	10	12.1	19.0
7	8	0.7	0
7	9	0.7	16.5
10	11	7.9	138.9
10	12	11.4	17.9
12	13	1.1	1.65
13	14	42.6	508.2
12	15	6.9	10.9
15	16	10.0	225.0
15	19	5.5	8.7
16	17	10.0	0
16	18	10.0	131.0
19	20	1.8	2.9
19	34	9.3	14.6
20	21	42.6	508.2
22	23	0.7	2/1
22	25	0.5	48.6
22	52	1.5	6.1
23	24	5.7	12.9
25	26	1.0	82.5
25	27	0.5	0
27	28	0.4	12.3
27	29	17.2	27.0
27	42	0.3	0.8
29	30	1.5	2.4
29	34	8.1	12.7
30	31	5.3	142.0
31	32	5.3	0
31	33	5.3	82.0
34	35	8.9	13.9
34	39	5.3	142.0
35	36	5.3	142.0
36	37	5.3	82.0
36	38	5.3	0
39	40	5.3	82
39	41	5.3	82.0
42	43	1.4	34.7
42	44	0.3	0.9
44	45	1.5	54.0
44	48	0.4	1.1

Table 2: Continued.

Branches i	j	R, Om	X, Om
45	46	1.5	0
45	47	1.5	33.0
48	49	0.7	27.0
48	56	0.3	0.8
52	53	0.2	24.3
52	63	11.3	44.9
53	54	1.0	82.5
53	55	0.5	0
55	56	0.1	0.1
55	61	3.3	5.1
56	57	0.5	0.7
57	58	7.9	138.9
59	60	0.7	16.5
60	62	0.7	0
63	64	1.4	100.0
63	67	24.1	78.6
64	65	1.4	0
67	68	0.7	50.0
68	69	0.7	0
68	70	1.4	96.5
71	72	0.2	24.3
72	73	0.5	41.2
72	74	0.2	0

and (5) allows the points of network loop disconnection to be revealed. These are branches 2–22, 19–34, and 48–56 shown in Figure 2 by dashed lines.

Then the postemergency conditions in the Central Power System of Mongolia are studied for the case of power supply loss from the Gusinoozyersk TPP. Here the generators of the Central Power System of Mongolia cover part of the load and as a result three independent islands are formed by criterion (2) (see Figure 2). For all the islands constraints (4) and (6) are met.

Comparison of the disconnection points in the normal and postemergency conditions shows that the disconnection of branch 2–22 coincides in both cases. The disconnection of branch 48–56 is of no concern for the postemergency conditions, since it does not influence on island formation.

Consider branch 19–34. In normal conditions this branch has to be tripped from the standpoint of minimum active power losses. Their value in this case is 14.34 MW. In the postemergency conditions the other branch 6–10 is tripped. When the loop is open on this branch, in the normal conditions the power losses are 11% higher than the optimal ones. Such an increase in losses is not allowed.

Find an acceptable concession from the criterion of minimum active power losses (1) in the normal conditions by the island adjustment. Consider the variant of disconnection of branch 15–19 with the corresponding reduction of the island by excluding nodes 10, 11, 12, 13, 14, 16, 17, and 18 from it. The disconnection of branch 15–19 causes an

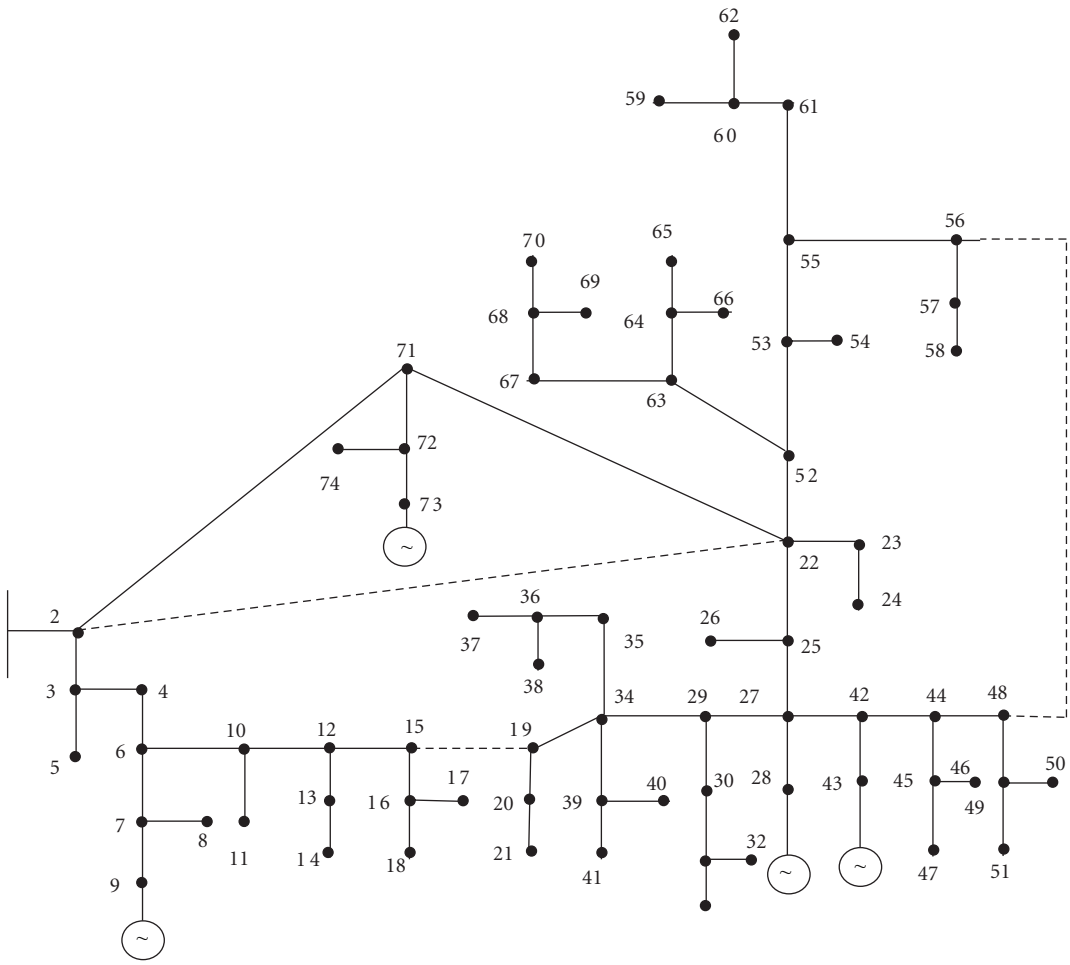

Figure 3: Optimal points of electric network tripping in the context of requirements of the normal and postemergency conditions.

increase in losses in the normal conditions by somewhat less than 5% in comparison with the optimal value that is acceptable.

We try to expand the island by an additional concession on the basis of criterion (1). To do this, we open branch 12–15 instead of branch 15–19. In this case in the normal conditions the losses rise by the value above 7% as compared to the optimal value, but such an increase is unacceptable.

Thus, in accordance with criteria (1) and (2) the opening of branches 2–22, 48–56, and 15–19 (Figure 3) is a trade-off solution and here the concession value by criterion (1) is acceptable.

4. Conclusion

In electricity supply systems with distributed generation that is connected to the distribution electric network, a complex problem arises which provide efficient operation of electricity supply systems in the normal conditions and reliable power supply to consumers in the postemergency conditions at a loss of the main supply point. This multicriteria problem is solved in the paper by applying the modified method of successive concessions. The efficiency of power system operation is studied based on the criterion of minimum active power losses by network reconfiguration that is performed by the developed ant colony method. In the postemergency conditions the islanding problem is solved by using the cell formation method. The studies carried out for the Central Power System of Mongolia have shown the efficiency of the approach described in the paper.

A general technology to control coordination of normal and postemergency conditions of distribution network with distributed generation takes into account a set of considered normal conditions according to the load curves of consumers and loading of distributed generation plants and a set of considered postemergency conditions with the main supply point lost. One of the important control coordination problems considering the above mentioned two sets of conditions is minimization of switchings while passing from normal to postemergency conditions. Proposed technology and algorithms dive the possibility of solving this problem.

Possible future work could be dealt with more detailed consideration of customer load uncertainty, variety of power output from distributed generation units based on wind or/and solar energy, minimization of both active power losses

and fuel usage at thermal distributed power plants, and other related problems. The authors hope for the success in these areas of research.

Acknowledgments

This paper was supported by the Grants of Leading Scientific School of RF no.1857.2008.8 and Russian Foundation for Basic Researches no.90-08-91330.

References

[1] A. Cárcamo-Gallardo, L. García-Santander, and J. E. Pezoa, "Greedy reconfiguration algorithms for medium-voltage distribution networks," *IEEE Transactions on Power Delivery*, vol. 24, no. 1, pp. 328–337, 2009.

[2] M. A. Tavakoli, M. R. Hanhifam, H. Lesani, S. Sanakhan, and E. Javan, "Review on reconfiguration methods of electric distribution networks," in *Proceeding of the Technical and Physical Problems in Power Engineering Conference*, Ankara, Turkey, May 2006.

[3] Y. T. Hsiao, "Multiobjective evolution programming method for feeder reconfiguration," *IEEE Transactions on Power Systems*, vol. 19, no. 1, pp. 594–599, 2004.

[4] Y. Y. Hong and S. Y. Ho, "Determination of network configuration considering multiobjective in distribution systems using genetic algorithms," *IEEE Transactions on Power Systems*, vol. 20, no. 2, pp. 1062–1069, 2005.

[5] N. Jenkins, R. Allan, P. Crossley, D. Kirschen, and G. Strbac, *Embedded Generation*, IEE Press, London, UK, 2000.

[6] T. Ackermann, G. Andersson, and L. Söder, "Distributed generation: a definition," *Electric Power Systems Research*, vol. 57, no. 3, pp. 195–204, 2001.

[7] M. Eremia, *Electric Power Systems*, vol. 1, Editura Academiei Romane, Bucuresti, Romania, 2006.

[8] T. Funabashi, K. Koyanagi, and R. Yokoyama, "A review of islanding detection methods for distributed resources," in *Proceeding of IEEE Bologna Power Tech Conference*, p. 6, Bologna, Italy, June 2003.

[9] C.-L. Hwang and A. S. Masud, *Multiple Objective Decision Making. Methods and Applications—State of the Art Survey*, Springer, Berlin, Germany, 1979.

[10] Y. Lu, X. Yi, J. Wu, and X. Lin, "An intelligent islanding technique considering load balance for distribution system with DGs," in *IEEE Power Engineering Society General Meeting (PES '06)*, June 2006.

[11] N. I. Voropai and B. Bat-Undral, "Load flow calculation in a radial electrical network using the interval method," *Electrichestvo*, pp. 64–66, 2008 (Russian).

[12] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents," *IEEE Transactions on Systems, Man, and Cybernetics B*, vol. 26, no. 1, pp. 29–41, 1996.

[13] Y.-J. Jeon, J.-Ch. Kim, and S.-Y. Lee, "Application of ant colony algorithm for network reconfiguration in distribution systems," in *Proceedings of IFAC Symposium on Power Plants and Power Systems Control*, Seoul, South Korea, September 2003.

[14] E. Carpaneto and G. Chicco, "Distribution system minimum loss reconfiguration on the hyper-cube ant colony optimization framework," in *Proceedings of the World Energy System Conference*, pp. 167–174, Torino, Italy, July 2006.

[15] J. Olamaei, T. Niknam, G. Gharehpetian, and E. Jamshidpour, "An approach based on ant colony optimization for distribution feeder reconfiguration considering distributed generation," in *Proceedings of the International Conference on Electricity Distribution (CIRED '07)*, Vienna, Austria, May 2007.

[16] X. Yiqin and T. Jia, "A new search approach in ant colony system algorithm for network reconfiguration of distribution systems," in *Proceedings of the International Conference on Deregulation, Restructuring, and Power Technologies (DRPT '2008)*, Nanjing, China, April 2008.

[17] C. F. Chang, "Reconfiguration and capacitor placement for loss reduction of distribution systems by ant colony search algorithm," *IEEE Transactions on Power Systems*, vol. 23, no. 4, pp. 1747–1755, 2008.

Hindawi Publishing Corporation
Journal of Electrical and Computer Engineering
Volume 2012, Article ID 962402, 8 pages
doi:10.1155/2012/962402

Research Article

Multiobjective Optimization Methods for Congestion Management in Deregulated Power Systems

K. Vijayakumar

Department of Electrical and Electronics Engineering, SRM University, Chennai 608302, India

Correspondence should be addressed to K. Vijayakumar, kvijay_srm@rediffmail.com

Received 8 August 2011; Revised 21 September 2011; Accepted 22 September 2011

Academic Editor: Edgar Carreno

Congestion management is one of the important functions performed by system operator in deregulated electricity market to ensure secure operation of transmission system. This paper proposes two effective methods for transmission congestion alleviation in deregulated power system. Congestion or overload in transmission networks is alleviated by rescheduling of generators and/or load shedding. The two objectives conflicting in nature (1) transmission line over load and (2) congestion cost are optimized in this paper. The multiobjective fuzzy evolutionary programming (FEP) and nondominated sorting genetic algorithm II methods are used to solve this problem. FEP uses the combined advantages of fuzzy and evolutionary programming (EP) techniques and gives better unique solution satisfying both objectives, whereas nondominated sorting genetic algorithm (NSGA) II gives a set of Pareto-optimal solutions. The methods propose an efficient and reliable algorithm for line overload alleviation due to critical line outages in a deregulated power markets. The quality and usefulness of the algorithm is tested on IEEE 30 bus system.

1. Introduction

In recent years, the power industry has undergone drastic changes due to privatization and worldwide deregulation process that has significantly affected energy markets. The restructuring of power system has led to the intensive usage of transmission grids. In deregulated electricity market, power system is operated near its rated capacity as each player in the market is trying to gain as much as possible by utilization of existing resources. Congestion in the transmission lines is one of the technical problems that appear in the deregulated environment. Congestion may occur due to lack of coordination between generation and transmission utilities or as a result of unexpected contingencies such as generation outages, sudden increase of load demand, or failure of equipments.

A large number of literatures have been reported in congestion management. Sensitivity-based methods to relieve congestion are reported in the work [1–3]. Auction-based methods are carried out in the literatures [4, 5]. Pricing-based methods are done in the papers [6–10]. A number of literature have been reported in evolutionary-based methods [11–18]. Multiobjective optimization method using various evolutionary methods [19, 20] are discussed. Very few papers [21] address the congestion management problem with security constraints of power systems with single objective only, because solving a multiobjective congestion problem with evolutionary methods is a very difficult task. For solving such complex, combinatorial optimization problem, classical techniques are unsuitable and the use of global search technique is needed. Further more if more than one objective is chosen in optimization, a suitable method must be developed to check the optimality of the solution. To overcome these difficulties, fuzzy models are developed and incorporated in EP algorithm.

This paper presents an efficient method for solving congestion management problem with two conflicting objectives in a pool-based electricity market. The two objectives are congestion cost minimization and transmission line overload alleviation. Generation rescheduling is done to relieve congestion; if it was not sufficient to alleviate overload, then load shedding is done. Here in this proposed method line, over load is alleviated with generation rescheduling alone and load shedding is not required.

Congestion management methods available consider only one objective and provide only one solution which

does not provide any choice to the operator. This proposed paper provides a set of alternate solutions for congestion management problem using two approaches (1) fuzzy EP approach and (2) NSGA II approach. The first method provides a best solution satisfying both objectives, and the later method provides a set of Pareto-optimal solutions to the transmission system operators for managing congestion in transmission network.

2. Problem Formulation

In this paper, day-ahead electric energy market based on a pool is considered. Several utilities join together to form a pool, with a central broker, to coordinate the operations on an hour-to-hour basis. Within this pool, GENCOs and DISCOs submit the purchase and sell decisions in the form of sell or buy bids to the market operator, who clears the market using an appropriate market-clearing procedure. Finally it results in 24 hourly energy prices to be paid by consumers and to be charged by producers. Transmission congestion may prevent the existence of new contracts and may lead to additional outages.

2.1. Congestion Relieving Procedure. In this paper, control measures to be taken to relieve the congestion in transmission lines due to critical line outages, generator outages, or sudden load disturbances are proposed. The objective function is to find the minimal shifts in generations and demands from initial market clearing values so as to alleviate line overloads completely and also to maintain load bus voltages within the permissible limits for secure operation of the system. The line limits and voltage limits can be considered as classical optimization problem with penalty function, but if violated it forces the solution to lie near its limits; to overcome this difficulty, these constraints are taken as the objective functions. It is considered that any change from the market-clearing conditions implies a payment to the agent involved. The total cost incurred is a sum of increment in revenues for the participating producers for adjusting the power productions and sum of revenues for the participating consumers for adjusting the power consumptions for congestion management purpose. This total cost is a measure of the decrement in social welfare due to congestion management.

2.2. Severity Index. The objective of power system control is to maintain a secure system state, that is, to prevent the power system from contingencies. This contingencies lead to overloading of the transmission lines. The severity of a contingency to line overload may be expressed as Severity Index (SI)

$$\mathrm{SI} = \sum_{k=1}^{\mathrm{NL}} \left(\frac{P_{ij}}{P_{ij}^{\max}} \right)^{2m}. \tag{1}$$

m is the integer exponent whose value is fixed as 1 in this paper. In this study, contingency analysis is conducted for base case generations and loadings (obtained by initial market clearing values) and the SI was computed for each contingency. The line outage which yields highest value of Severity Index is identified as worst contingency. Here line overloads are simulated by means of outage of critical lines and sudden increase in load demands.

2.3. Mathematical Problem Formulation. The objective function of the proposed method is to find an optimum value of shift in active power generation along with network constraints so as to minimize the total congestion cost and relieve transmission congestion simultaneously in the network. The problem of proposed algorithm may be stated as follows.

Objective 1. Minimize total congestion cost

$$\mathrm{CC} = \sum_{j=1}^{\mathrm{NG}} C_{Gj}^{u} \cdot \Delta P_{Gj}^{u} + C_{Gj}^{d} \cdot \Delta P_{Gj}^{d}. \tag{2}$$

Objective 2. Minimize the transmission congestion

$$\mathrm{TC} = \begin{cases} 0, & \text{if } P_{ij}^{\max} \le P_{ij}^{\max}, \\ \alpha \cdot (P_{ij} - P_{ij}^{\max})^2, & \text{if } P_{ij} \ge P_{ij}^{\max}. \end{cases} \tag{3}$$

Objective 3. Minimize the voltage deviation index

$$\mathrm{VD} = \begin{cases} 0, & \text{if } V_n^{\min} \le V_n \le V_n^{\max}, \\ \beta \cdot (V_n^{\min} - V_n)^2, & \text{if } V_n \le V_n^{\min}, \\ \beta \cdot (V_n - V_n^{\max})^2, & \text{if } V_n \ge V_n^{\max}. \end{cases} \tag{4}$$

α and β are the penalty factors for line flow violation and bus voltage limit violation. Precise setting of penalty factors are not needed, provided that it could be introduced to penalize the solutions with significant constraint violations. The values of α and β are taken as 10000.

Subjected to various constraints

$$P_{Gi} - P_{Di} = \sum_{j=1}^{\mathrm{NB}} |V_i| \left| V_j \right| \left| Y_{ij} \right| \cos\left(\delta_i - \delta_j - \theta_{ij}\right), \tag{5}$$

$$Q_{Gi} - Q_{Di} = \sum_{j=1}^{\mathrm{NB}} |V_i| \left| V_j \right| \left| Y_{ij} \right| \sin\left(\delta_i - \delta_j - \theta_{ij}\right), \tag{6}$$

where

$$P_{Gj} = P_{Gj}^{c} + \Delta P_{Gj}^{u} + \Delta P_{Gj}^{d}, \quad j = 1, 2 \ldots, \mathrm{NG}, \tag{7}$$

$$P_{Dj} = P_{Dj}^{c} + \Delta P_{Dj}^{d}, \quad j = 1, 2 \ldots, \mathrm{ND}, \tag{8}$$

$$Q_{Dj} = P_{Dj} \cdot \tan\left(\phi_{Dj}\right), \quad j = 1, 2 \ldots, \mathrm{ND}, \tag{9}$$

$$P_{Gj}^{\min} \le P_{Gj} \le P_{Gj}^{\max}, \quad j = 1, 2 \ldots, \mathrm{NG}, \tag{10}$$

$$Q_{Gj}^{\min} \le Q_{Gj} \le Q_{Gj}^{\max}, \quad j = 1, 2 \ldots, \mathrm{NG}, \tag{11}$$

$$V_n^{\min} \le V_n \le V_n^{\max}, \quad j = 1, 2 \ldots, \mathrm{ND}, \tag{12}$$

$$P_{ij} \le P_{ij}^{\max}. \tag{13}$$

Also

$$\Delta P_{Gj}^{u} \geq 0, \quad \Delta P_{Gj}^{d} \geq 0, \quad \Delta P_{Dj}^{d} \geq 0. \tag{14}$$

Constraints (5) and (6) correspond to active and reactive power balance at all buses. Final powers are expressed in terms of market clearing values and are given in (7) and (8). Active and reactive power demands are related through constraint (9) with constant power factor; even varying power factor can also be considered. Constraints (10) and (11) provide upper and lower bounds for real and reactive power of generators. Constraint (12) establishes threshold limits for load bus voltages. Constraint (13) ensures secure loading of transmission lines. Finally constraint (14) ensures that the increment and decrement in powers are positive in magnitude.

Since the proposed problem is complex, combinatorial optimization problem, application of conventional optimization technique such as gradient-based methods is not suitable because it depends on the existence of the first and second derivatives. So the use of heuristic technique is needed. Furthermore if more than one objective is chosen in optimization problem, a suitable method must be developed to check the optimality of the solution. Deciding the weightage for different objective function is difficult in multiobjective EP or any artificial intelligence (AI) techniques. These draw backs can be overcome using fuzzy models; so fuzzy models are developed and incorporated in EP algorithm.

3. Fuzzy EP Approach

In this section, the Fuzzy EP algorithm is developed for this problem. It includes the development of fuzzy models of the objective functions. These fuzzy models are incorporated into the EP algorithm forming the fuzzy EP algorithm. The objective of the solution technique is to determine the redispatch of generators such that the transmission congestion is relieved with voltage at all buses within limits.

Let the vector $X = [X_1 X_2 \cdots X_{\mathrm{NG}}]$ be the vector comprising of the combination of real power generation. Hence the control variable ΔP_{Gj}^{u} and ΔP_{Gj}^{d} are randomly generated increment or decrement of the generation dispatch satisfying their practical constraints

$$\left(P_{Gj} - P_{Gj}^{\min}\right) = \Delta P_{Gj}^{\min} \leq \Delta P_{Gj} \leq \Delta P_{Gj}^{\max} = \left(P_{Gj}^{\max} - P_{Gj}\right). \tag{15}$$

The EP initially chooses NC combinations of starting guesses. The objective functions 2–4 are evaluated considering the NC combination of solution vectors $X_1 X_2 X_3 \cdots X_{\mathrm{NC}}$. The fuzzy models are developed as follows.

3.1. Fuzzy Model for Total Congestion Cost. Let the total congestion cost be $\mathrm{CC}^i = f_{\mathrm{CC}}(X^i)$. The function $f_{\mathrm{CC}}(X^i)$ is defined in (2). A fuzzy satisfaction parameter μ_{CC}^i is then defined associating the satisfaction level with the solution vector X^i as below

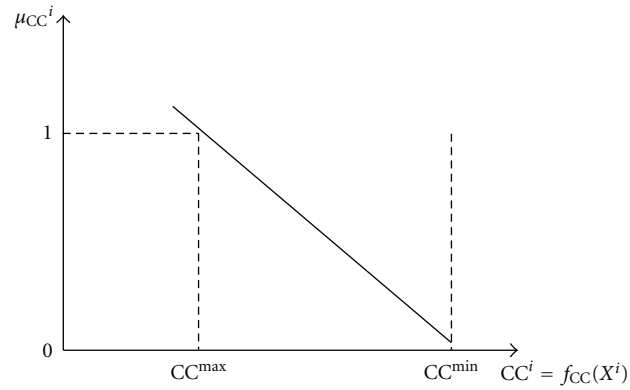

Figure 1: Fuzzy model of congestion cost.

$$\mu_{\mathrm{CC}}^i = \frac{\mathrm{CC}^{\max} - \mathrm{CC}^i}{\mathrm{CC}^{\max} - \mathrm{CC}^{\min}} = \frac{\mathrm{CC}^{\max} - f_{\mathrm{CC}}(X^i)}{\mathrm{CC}^{\max} - \mathrm{CC}^{\min}}. \tag{16}$$

$\mathrm{CC}^{\max}$ and $\mathrm{CC}^{\min}$ refer to the maximum and minimum congestion cost that would occur when the solutions X_1 to X_{NC} are considered for implementation. The diagram for the satisfaction of parameters is shown in Figure 1.

3.2. Fuzzy Model for Transmission Congestion. Let the transmission congestion index $\mathrm{TC}^i = f_{\mathrm{TC}}(X^i)$; the solution X^i is considered. The function $f_{\mathrm{TC}}(X^i)$ is defined in (3). The $f_{\mathrm{TC}}(X^i)$ is the transmission congestion calculated for X^i real power redispatch by running NR power flow. A fuzzy parameter μ_{TC}^i is the defined considering the satisfaction level with the solution X^i as below

$$\mu_{\mathrm{TC}}^i = \frac{\mathrm{TC}^{\max} - \mathrm{TC}^i}{\mathrm{TC}^{\max} - \mathrm{TC}^{\min}} = \frac{\mathrm{TC}^{\max} - f_{\mathrm{TC}}(X^i)}{\mathrm{TC}^{\max} - \mathrm{TC}^{\min}}. \tag{17}$$

$\mathrm{TC}^{\max}$ and $\mathrm{TC}^{\min}$ refer to the maximum and minimum transmission overload that would occur when the solutions X_1 to X_{NC} are considered for implementation. The diagram for the satisfaction of parameters is shown in Figure 2.

3.3. Fuzzy Model for Voltage Deviation. Let $\mathrm{VD}^i = f_{\mathrm{VD}}(X^i)$ be the the voltage deviation index for X^i real power generation redispatch considered. The function $f_{\mathrm{VD}}(X^i)$ is defined in (4). The $f_{\mathrm{VD}}(X^i)$ is evaluated after running NR power flow for a solution vector X^i considered. A fuzzy parameter μ_{VD}^i is defined, considering the satisfaction level with the solution X^i as below

$$\mu_{\mathrm{VD}}^i = \frac{\mathrm{VD}^{\max} - \mathrm{VD}^i}{\mathrm{VD}^{\max} - \mathrm{VD}^{\min}} = \frac{\mathrm{VD}^{\max} - f_{\mathrm{VD}}(X^i)}{\mathrm{VD}^{\max} - \mathrm{VD}^{\min}}. \tag{18}$$

$\mathrm{VD}^{\max}$ and $\mathrm{VD}^{\min}$ refer to the maximum and minimum transmission voltage deviation index that would occur when the solutions X_1 to X_{NC} are considered for implementation. The diagram for the satisfaction of parameters is shown in Figure 3.

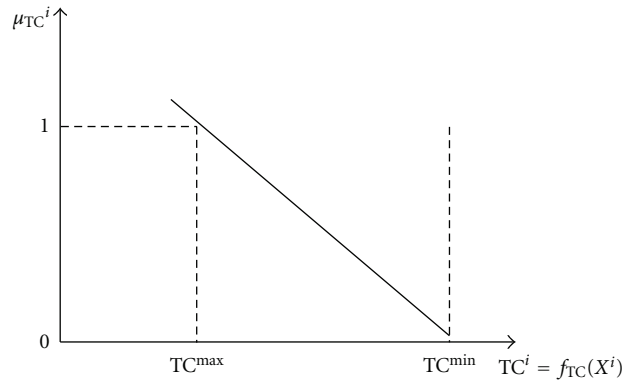

Figure 2: Fuzzy model of transmission congestion.

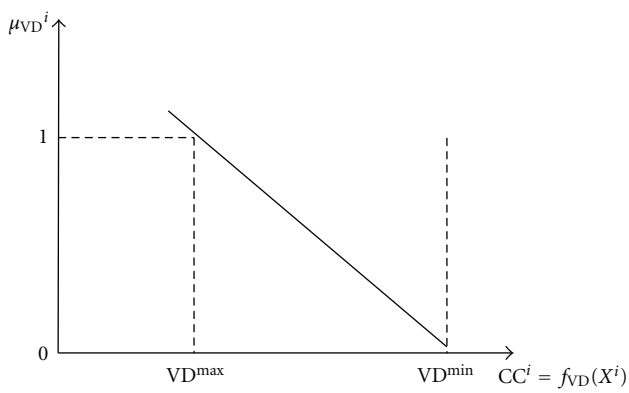

Figure 3: Fuzzy model of voltage deviation.

3.4. Development of Fuzzy Evaluation Method of Solution Vector. With the three fuzzy models for total congestion cost minimization, transmission congestion index minimization, and voltage deviation index minimization defined in the previous subsections, the overall evaluation of a solution vector $\mathbf{X^i}$ may be done by selecting any of the fuzzy operators. In this paper, one of the simplest fuzzy operator intersection is chosen. Thus the resultant satisfaction parameter associated with a solution $\mathbf{X^i}$ is determined as

$$\mu_X{}^i = \mu_{CC}{}^i * \mu_{TC}{}^i * \mu_{VD}{}^i. \tag{19}$$

In order to determine the best solution vector amongst the NC solution vectors from $\mathbf{X_1}$ to $\mathbf{X_{NC}}$, the associated satisfaction parameter values from $\mu_X{}^1$ to $\mu_X{}^{NC}$ have to be evaluated. Then the solution vector $\mathbf{X^*}$ having the highest satisfaction parameter value is chosen as the best solution vector.

3.5. Fuzzy EP Algorithm for Transmission Congestion Alleviation. The steps of the fuzzy EP technique for transmission congestion alleviation are given below.

(1) Randomly generate NC combination of solution

$$X_1\ X_2\ X_3 \cdots X_{NC}. \tag{20}$$

(2) Set iteration count $k = 1$.

(3) Evaluate fuzzy objective function μ_X^i using 19 for each of X^i, $i = 1, 2, \ldots, NC$.

(4) Generate NC more solution vectors $X_{NC+1}X_{NC+2} \cdots X_{2NC}$ through crossover

$$X^{NC+i} = \beta \frac{2(r) - r_m}{r_m}(X_{max} - X_{min})\frac{\mu_X{}^{max}}{\mu_X{}^i} + X^i, \tag{21}$$

where $\beta = 0.75$, r = random number between 0 to r_m, $r_m = 2$ to 3, and $X^{max}X^{min}$ are maximum and minimum values of X.

(5) Evaluate the newly generated solution vector $X_{NC+1}X_{NC+2} \cdots X_{2NC}$.

Choose the best NC solution vector having the highest satisfaction value of μ_X^i among 2NC solution vectors $X_1X_2X_3 \cdots X_{2NC}$ and designate the chosen set as $X_1X_2X_3 \cdots X_{2NC}$.

(6) Increment iteration count $k = k + 1$.

(7) Check maximum iteration count, if $k <$ max iteration, stop. Else go to step 4.

Choose the best among the NC solution set X_1X_2 $X_3 \cdots X_{NC}$ having highest value of μX^i.

4. NSGA II Approach

Congestion management methods available in the literature consider only one objective and provide only one solution which does not provide any choice to the operator. In this work, multiobjective nondominated sorting genetic algorithm NSGA II [22] is proposed to solve this complex nonlinear problem. Classical optimization methods (including the multicriterion decision-making methods) suggest converting the multiobjective optimization problem to a single-objective optimization problem by emphasizing one particular Pareto-optimal solution at a time. When such a method is to be used for finding multiple solutions, it has to be applied many times, hopefully finding a different solution at each simulation run. Over the past decade, a number of multi objective evolutionary algorithms (MOEAs) have been suggested to find multiple Pareto-optimal solutions in one single simulation run. The nondominated sorting genetic algorithm [23–25] is one of the Pareto-based approaches. These algorithms demonstrated the necessary additional operators for converting a simple EA to an MOEA. Two common features of MOEA are (i) assigning fitness to population members based on nondominated sorting and (ii) preserving diversity among solutions of the same nondominated front. Over the years, the main criticisms of the NSGA approach have been as follows:

(1) high computational complexity of nondominated sorting,

(2) lack of elitism,

(3) need for specifying the sharing parameter.

Table 1: Severity index of IEEE 30 bus system.

Outage of line	Severity index
1-2	3.1464
1–3	2.1743
3-4	1.1189
2–5	1.0781
2–4	0.0654
6-7	0.0564
5–7	0.0454
4–12	0.0456

So all the above issues have been solved using improved version of NSGA called NSGA II, that can find diverse set of solutions and converge near the true Pareto-optimal set. So this efficient NSGA II algorithm has been proposed to solve the congestion management problem with 2 objectives considered simultaneously that can provide set of alternative solutions to the operator instead of single solution.

4.1. NSGA II Algorithm for Congestion Management.

(1) Set up NSGA II parameters like population size, number of generations, distribution indices for crossover (mu), and mutation (mum). Here mu and mum are 20 and 20, respectively.

(2) Read line data, bus data, incremental and decrement bidding costs for each generator.

When applying evolutionary computation algorithm, the first step is to decide the control variables embedded in the individuals. In this work, control variable is generator real power redispatch. Hence the control variables are generated randomly satisfying their practical operation constraints

$$\left(P_{Gj} - P_{Gj}{}^{\min}\right) = \Delta P_{Gj}{}^{\min} \leq \Delta P_{Gj} \leq \Delta P_{Gj}{}^{\max} = \left(P_{Gj}{}^{\max} - P_{Gj}\right). \quad (22)$$

(3) For each chromosome of population, calculate objective function-1 using (2) and run Newton Raphson power flow to calculate the objective function-2 and 3 using (3) and (4).

(4) The equality and inequality constraints are handled by Newton Raphson Power Flow.

(5) Nondomination sorting of population is carried out. And then tournament selection is applied to select the best individuals based on crowding distance.

(6) Crossover and Mutation operators are carried out to generate offspring (Qt) and the new vectors obtained must satisfy the limits if not set it to the appropriate extrema.

(7) Calculate the value of each objective function of Qt and merge the parent and offspring population to preserve elites.

(8) Again perform nondominated sorting on the combined population based on crowding distance measure and obtain the best new parent population (Pt + 1) of size N out of $2N$ population, so this would be the parents for next generation and this process is carried out till a maximum number of generations are reached.

(9) Finally pareto front is achieved, that is, a set of solutions satisfying both objectives are obtained.

5. Results and Discussions

The proposed technique is tested on IEEE 30 bus system. All system data are extracted from [26]. Demand data given in [26] are taken as initial market clearing values, that is, (P_{Di}^{C}). For generators, the initial market clearing values (P_{Gj}^{c}) with their bus numbers are given in Appendix A. Price bids are submitted by GENCOs ($/MWhr) and DISCOS ($/MWhr) to alter their scheduled productions and consumptions, and the generator/load up and down costs are given in Appendix A.

For IEEE 30 bus, Three cases are considered. Case A is outage of lines 1-2 and total load raised by 40%, Case B is outage of lines 1-2 and outage of generator 2, Case C is outage of lines 1–3 and load at all buses raised by 50%. The total load increases by 40% or 50% even though not realistic in deregulated system, but it is considered to have a severe congestion in the system and to show that the proposed algorithm gives better solution without any load curtailment.

5.1. Severity Index of IEEE 30 Bus System. This system has 6 generation companies (GENCOs), 21 demand supply companies (DISCOs), and 41 transmission lines with total load of 283.4 MW and 126.2 MVAR (Load factor LF as 1.0). Contingency analysis was conducted under base case loading condition. For this system, line outages 1-2, 1–3, 3-4, and 2–5 have resulted in overloading of other lines. These lines outages are considered to be critical line outages. Outage of lines 1-2 has high severity index followed by lines 1–3, and they are given in Table 1.

5.2. Simulated Case for IEEE 30 Bus System. Table 2 shows the overloaded lines for different cases and the amount of power violated in each cases. Then the total power violation is shown with the severity index value. Case A has the highest severity index.

5.3. Final Power Adjustments for Line Overload Alleviation with Payment Particulars. Table 3 shows the new incremented or decremented power of each generator for different cases. Total congestion cost in ($/hr) found by FEP method is compared with particle swarm optimization (PSO) [17]. Even though the PSO method is found to be better than the other existing methods, the proposed method gives even better results than PSO, that is, congestion cost by the proposed method is low when compared to PSO. Moreover, congestion is relieved by generation rescheduling alone, that is, without any load curtailment.

Table 2: Simulated case for IEEE 30 bus system.

Cases	Lines overloaded	Line limit	Actual power flow	Power violation	Total power violation	Severity index
A	1–3	130	315.26	185.26	386.7	12.96
	3-4	130	268.29	138.29		
	4–6	90	153.16	63.160		
B	1–3	130	222.14	92.14	181.6	6.77
	3-4	130	199.71	69.71		
	4–6	90	109.89	19.89		
C	1-2	130	289.93	159.93	244.2	10.41
	2–4	65	104.54	39.54		
	2–6	65	109.80	44.80		

Table 3: Generation rescheduled power and congestion cost.

Case	ΔP_{g1}	ΔP_{g2}	ΔP_{g5}	ΔP_{g8}	ΔP_{g11}	ΔP_{g13}	Total cost	
							FEP	PSO
A	−9.7	82.4	2.2	9.7	20.9	17.6	3810	3916
B	−5.9	0.0	20.3	0.43	28.2	20.6	3041	3099
C	−85	0.5	3.3	21.2	40.0	16.8	5001	5355

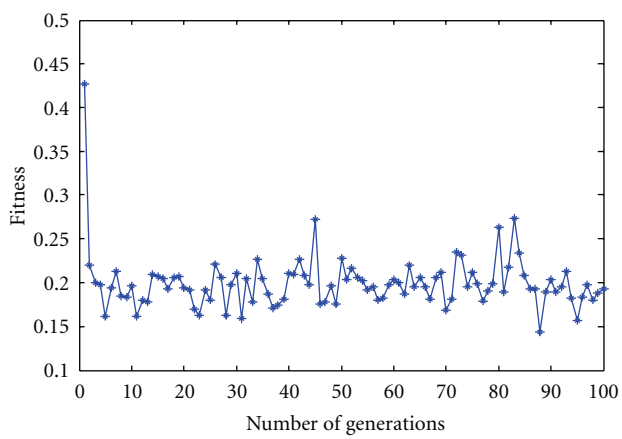

Figure 4: Convergence characteristics for Case A.

Figure 4 shows the convergence characteristic for Case A. Similarly for other cases also the fitness function becomes constant after some iteration.

The multiobjective optimization using NSGA II algorithm is developed and tested for the above-mentioned three cases. The parameters used for NSGA II are

population size: 50,

no. of generation: 100,

tournament selection,

simulated binary crossover with rate 0.9,

polynomial mutation with rate 0.1,

The Pareto-optimal solutions, for all the three cases are given in the Figures 5, 6 and 7.

Among the Pareto-optimal solutions, the three nondominated solutions from the truncated archive are presented in

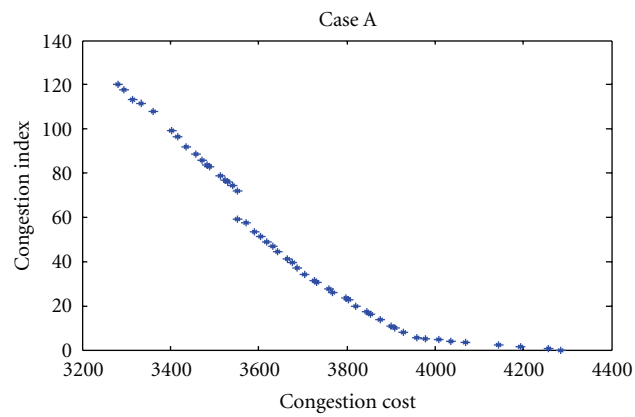

Figure 5: Pareto optimal front for Case-A.

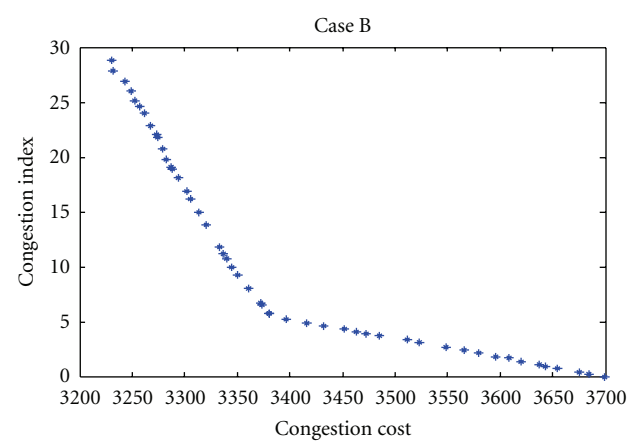

Figure 6: Pareto optimal front for Case-B.

Table 4 for all three cases. If the operator wants to alleviate congestion totally, then the generation cost increases by 4285 ($/hr) for Case A, 3699 ($/hr) for Case B, and 5197 ($/hr) for Case C. If the operator wants to minimize cost rather than congestion, solution 1 is to be selected, whereas solution 2 can be selected if some congestion is allowed with some increase in cost. The congestion can be relieved only by sacrificing the generation cost.

Table 4: Pareto optimal solution for all three cases.

Cases	Pareto-optimal solution					
	Solution 1		Solution 2		Solution 3	
	Congestion	Cost ($/hr)	Congestion	Cost ($/hr)	Congestion	Cost ($/hr)
A	120	3282	31.2	3727	0.0	4285
B	28.25	3230	5.233	3396	0.0	3699
C	170.3	3555	70.69	4285	0.0	5197

Table 5

Bus no.	Initial generation P^c_{Gj} (MW) as determined by market clearing procedure.	Price bid submitted by GENCOs ($/MWhr)	
		C^u_{Gj}	C^d_{Gj}
1	138.59	22	18
2	57.56	21	19
5	24.56	42	38
8	35.00	43	37
11	17.93	43	35
13	16.91	41	39

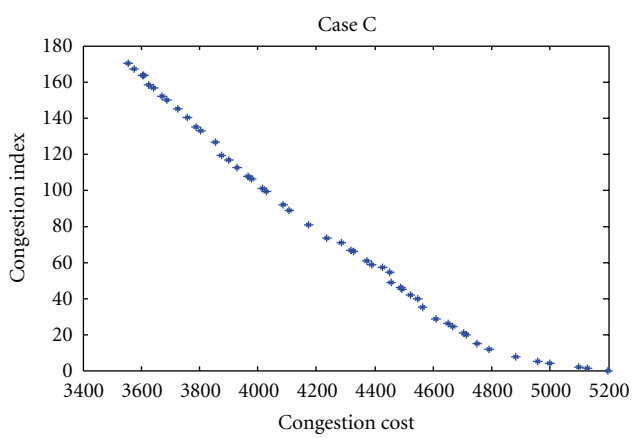

Figure 7: Pareto optimal front for Case-C.

The FEP method gives only one best solution considering both the objectives which does not provide any choice for the operator, whereas NSGA II method gives a set of non dominated solutions, the operator can use his discretion to choose the solution.

6. Conclusions

In this paper, two efficient methods are proposed for solving congestion management problem in a day ahead electricity market by generator rescheduling. The fuzzy EP approach and NSGA II approach are used. FEP gives unique solution satisfying both objectives. It has been found that the results obtained using FEP are better than PSO. That is, the congestion cost is less in FEP than PSO, also congestion is alleviated with load shedding even for the very severe congested scenario. The FEP method gives only one best solution considering both the objectives simultaneously, which may not provide any choice for the operator some times. So NSGA II algorithm is used to find a set of non dominated Pareto-optimal solutions. The system operator can use his discretion for selecting the proper solution for either for congestion alleviation or congestion cost minimization. The feasibility of the proposed method is demonstrated on IEEE 30 system for severe line outages.

Appendix

A. IEEE 30 Bus System Data

The data are taken from MATPOWER toolbox (see Table 5).

Nomenclature

ΔP^u_{Gj}: Active power increment in generator j (MW) due to congestion management

ΔP^d_{Gj}: Active power decrement in generator j (MW) due to congestion management

ΔC^u_{Gj}: Price offered by generator j to increase its pool schedule due to congestion management

ΔC^d_{Gj}: Price offered by generator j to decrease its pool schedule due to congestion management

P_{Gj}: Final active power produced by generator j (MW)

P_{Di}: Final active power consumed by demand i (MW)

Q_{Di}: Final reactive power consumed by demand i (MVAR)

P^c_{Gj}: Active power produced by generator j as determined by market clearing procedure

P^c_{Dj}: Active power consumed by demand i (MW) as determined by market clearing procedure

V_i & V_j: Bus voltage magnitude at i and j, respectively

δ_i & δ_j:	Bus voltage angle at i and j, respectively
Y_{ij}:	Mutual admittance between node i and j
Y_{ii}:	Self admittance of node i
$P_{Gj}^{\min}$:	Minimum real power output of generator j
$P_{Gj}^{\max}$:	Maximum real power output of generator j
$Q_{Gj}^{\min}$:	Minimum reactive power output of generator j
$Q_{Gj}^{\max}$:	Maximum reactive power output of generator j
P_{ij}:	Actual power flow in line i-j (MW)
$P_{ij}^{\max}$:	Loading limit of line i-j (MW)
$V_n^{\max}$ & $V_n^{\min}$:	Maximum and Minimum limit of voltage at bus—n
NB:	Number of buses
NL:	Number of lines
N_d:	No. of participating demand
L_O:	Set of overloaded lines.

References

[1] K. Y. Lee, M. Choi, and M. Shin, "Network congestion assessment for short-term transmission planning under deregulated environment," in *Proceedings of the IEEE Power Engineering Society Winter Meeting*, pp. 1266–1271, February 2001.

[2] M. Liu and G. Gross, "Role of distribution factors in congestion revenue rights applications," *IEEE Transactions on Power Systems*, vol. 19, no. 2, pp. 802–810, 2004.

[3] A. Kumar, S. C. Srivastava, and S. N. Singh, "A zonal congestion management approach using ac transmission congestion distribution factors," *Electric Power Systems Research*, vol. 72, no. 1, pp. 85–93, 2004.

[4] L. A. Tuan, K. Bhattacharya, and J. Daalder, "Transmission congestion management in bilateral markets: an interruptible load auction solution," *Electric Power Systems Research*, vol. 74, no. 3, pp. 379–389, 2005.

[5] M. I. Alomoush and S. M. Shahidehpour, "Generalized model for fixed transmission rights auction," *Electric Power Systems Research*, vol. 54, no. 3, pp. 207–220, 2000.

[6] R. S. Fang and A. K. David, "Optimal dispatch under transmission contracts," *IEEE Transactions on Power Systems*, vol. 14, no. 2, pp. 732–737, 1999.

[7] S. S. Oren, P. T. Spiller, P. Varaiya, and F. Wu, "Nodal prices and transmission rights: a critical appraisal," *The Electricity Journal*, vol. 8, no. 3, pp. 24–35, 1995.

[8] J. D. Finney, H. A. Othman, and W. L. Rutz, "Evaluating transmission congestion constraints in system planning," *IEEE Transactions on Power Systems*, vol. 12, no. 3, pp. 1143–1150, 1997.

[9] L. S. Hyman, "Transmission, congestion, pricing, and incentives," *IEEE Power Engineering Review*, vol. 19, no. 8, pp. 4–10, 1999.

[10] F. C. Schweppe, M. C. Caramanis, R. D. Tabors, and R. E. Bohn, *Spot Pricing of Electricity*, Kluwer Academic Publishers, Boston, Mass, USA, 1988.

[11] S. Dutta and S. P. Singh, "Optimal rescheduling of generators for congestion management based on particle swarm optimization," *IEEE Transactions on Power Systems*, vol. 23, no. 4, pp. 1560–1569, 2008.

[12] K. P. Wong and Z. Dong, "Differential evolution, an alternative approach to evolutionary algorithm," in *Proceedings of the 13th International Conference on Intelligent Systems Application to Power Systems (ISAP '05)*, pp. 73–83, November 2005.

[13] S. Rahnamayan, H. R. Tizhoosh, and M. M. A. Salama, "Quasi-oppositional differential evolution," in *Proceedings of the IEEE Congress on Evolutionary Computation, CEC 2007*, pp. 2229–2236, September 2007.

[14] L. dos Santos Coelho and V. C. Mariani, "Combining of chaotic differential evolution and quadratic programming for economic dispatch optimization with valve-point effect," *IEEE Transactions on Power Systems*, vol. 21, no. 2, pp. 989–996, 2006.

[15] P. Somasundaram and K. Kuppusamy, "Application of evolutionary programming to security constrained economic dispatch," *International Journal of Electrical Power and Energy Systems*, vol. 27, no. 5-6, pp. 343–351, 2005.

[16] J. S .R. Jang, C. T. Sun, and E. Mizutani, *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, Pearson Education, London, UK, 1997.

[17] M. Saravanan, S. M. R. Slochanal, P. Venkatesh, and P. S. Abraham, "Application of Particle Swarm Optimization technique for optimal location of FACTS devices considering cost of installation and system load ability," *Electrical Power System Research*, vol. 77, no. 3-4, pp. 276–283, 2007.

[18] A. J. Conejo, F. Milano, and R. García-Bertrand, "Congestion management ensuring voltage stability," *IEEE Transactions on Power Systems*, vol. 21, no. 1, pp. 357–364, 2006.

[19] M. M. Raghuwanshi and O. G. Kakde, "Survey on multiobjective evolutionary andreal coded genetic algorithms," *Complex International*, vol. 11, p. 150, 2008.

[20] J. Hazra and A. K. Sinha, "Congestion management using multiobjective particle swarm optimization," *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 1726–1734, 2007.

[21] S. N. Singh and K. David, "Congestion management in dynamic security constrained open power markets," *Computers and Electrical Engineering*, vol. 29, no. 5, pp. 575–588, 2003.

[22] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multi-objective genetic algorithm: NSGA-II," in *Proceedings of the 6th International Conference on Parallel Problem Solving from Nature*, 2000.

[23] N. Srinivas and K. Deb, "Multiobjective Optimization using non-dominated Sorting in genetic algorithms," *Evolutionary Computation*, vol. 2, no. 2, pp. 221–248, 1994.

[24] K. Deb, *Multi-Objective Optimization using Evolutionary Algorithms*, Wiley-Interscience Series in Systems and Optimization, John Wiley & Sons, New York, NY, USA, 2001.

[25] P. K. Shukla and K. Deb, "On finding multiple Pareto-optimal solutions using classical and evolutionary generating methods," *European Journal of Operational Research*, vol. 181, no. 3, pp. 1630–1652, 2007.

[26] R. D. Zimmerman and D. Gan, "MATPOWER: A Matlab Power System , Package," Ver.3.2, Power System Engineering Research Center, Cornell University, 1997, http://www.pserc.cornell.edu//Matpower/.

Hindawi Publishing Corporation
Journal of Electrical and Computer Engineering
Volume 2012, Article ID 560541, 5 pages
doi:10.1155/2012/560541

Research Article

Reliability Evaluation of Distribution Power Systems Based on Artificial Neural Network Techniques

Mohammoud M. Hadow,[1] Ahmed N. Abd Allah,[1] and Sazali P. Abdul karim[2]

[1] *Faculty of Electrical and Electronics Engineering, University of Malaysia, Pahang, Lebuhraya Tun Razak, Kuantan Pahang, 26300 Gambang, Malaysia*
[2] *National Company, Engineering, Transmission Division TNB, Kuala Lumpur, Malaysia*

Correspondence should be addressed to Mohammoud M. Hadow, hadow50@yahoo.com

Received 5 May 2011; Revised 21 July 2011; Accepted 25 August 2011

Academic Editor: Edgar Carreno

In order to assess the reliability of distribution systems, more and more researchers are directing their attention to the artificial intelligent method, and several reliability indices have been proposed, such as basic load point indices and system performance indices. Artificial neural network is recently established as a useful and much promising too, applied to variety of power systems engineering. This paper presents ANN version for evaluating the reliability of distribution power systems (DPSs), in the proposed algorithm, the ANN used to predicted (RPS) using historical data method constructed according to the backpropagation learning rule. At the same time, System indices such as SAIFI and SAIDI of real distribution system are computed and compared with results generated by network method. The result obtained by proposed method gives acceptable reliability indices and can also found that the deviation of computed values by the proposed method is less than 1% and needs running time on ASUN network environment of less than 2 s. The ANN approach demonstrates advantage over the network method.

1. Introduction

Broadly speaking, electrical power distribution systems include all parts of electrical utility systems between bulk power sources and the consumers' service-entrance equipment. The main function of distribution network is to supply electrical power generated from large sources to consumers at desired voltage level and with a degree of appropriate reliability [1]. Reliability and efficient maintenance are crucial for the continuity of electrical energy. It is customary for moderate distribution networks to have a large number of nodes, to serve a vast geographical area and to ensure a safe operation at severe ambient conditions [2]. Distribution networks operating at several voltage levels including the networks of local or municipal unities are the primary parts of view; therefore, distribution system reliability evaluation is major preoccupation of the power company, in particular, in face of emergency and necessary reconfiguration.

The techniques used in power system reliability evaluation can be divided into the two basic categories of analytical and simulation methods. The analytical techniques are highly developed and have been used in practical applications for several decades [3]. Several methods [1–5] have been presented in literature for evaluating distribution system reliability; They have been divided in two abroad groups, firstly based on solution of logic networks and secondly on the solution of state-space models. Between them, these methods can accommodate most practical systems. In addition, the network methods for determining system reliability are comparatively simple and direct.

In this paper, it is proposed to solve the problem of distribution system reliability evaluation by ANN which can learn from patterns encountered previously. Many types of network exist [1–8], but this study described here focuses on three layer feed forward network with backpropagation learning rule [4]; the developed ANN was utilized to evaluate the distribution system reliability. Three different cases are studied on a real distribution system in (north Taiwan); the output of the result from the developed ANN is satisfactory compared with that computed by network method with sufficient learning, the ANN generates result very fast and incurs only tiny deviation. The ANN also has an advantage over

the network method in computing system reliability when one or more circuit breaker opens due to a fault or overhead switching. Under such situation, the network method repeats the whole computation procedure because the system logic diagram differs. Yet in the ANN approach the related links are simply modified by resetting their weights.

The paper organized as follows: section proposed methodology includes ANN approach Section 3 test systems for the case study and Section 4 where result and discussion and Section 5 are concludes the paper.

2. The Proposed Methodology

2.1. Artificial Neural Network (ANN) Approach. Among the various kinds of ANN approaches that exit, the backpropagation (BP) learning algorithm, which has become the most popular in engineering applications, was used in this study. This network has three layers, one input layer, one hidden layer, and one output layer. To train and test the neural networks, input data patterns and corresponding targets were required. In developing a ANN model, the available data set was divided into two sets, one to be used for training of the network (70–80% of the data), and the remaining was used to verify the generalization capability of the network. The mathematical background, the procedures for training and testing the ANN, and an account of its history can be found in the text by Haykin [6]. Input-output pairs are presented to the network, and weights are adjusted to minimize the error between the network output and actual value. Once training is completed, predictions from a new set of data may be done using the already trained network.

The Neural Networks Toolbox of MATLAB 5.2 was used to form the ANN. The log-sigmoid transfer function was used in the hidden layer (first layer) and output layer (second layer). Inputs of system determine the neuron number in the input layer of the network, and its outputs determine the neuron number in the output layer of the network. Thus, input layer of network has three neurons and the output layer has two neurons. Seven neurons were used in hidden layer. Neural network requires that the range of both the input and output values should be between 0.1 and 0.9. The following formula is used:

$$\frac{\text{Actual Value} - \text{Minimum}}{\text{Maximum} - \text{Minimum}} * (\text{high} - \text{low}) + \text{low}. \quad (1)$$

This equation is a widely employed method in unification [4, 5], where minimum is minimum data value, maximum is the maximum data value, high is the maximum normalized data which equals 0.9, and low is the minimum normalized data which equals 0.1.

The backpropagation network training function updates weight and bias values according to Leven-berg-Marquardt optimization. The Levenberg-Marquardt algorithm is very well suited to neural network training, where the performance index is the mean squared error [14]. Mean squared error (MSE) that determines network performance is formulated as follows in (2). The backpropagations learning rule is an iterative gradient algorithm designed to minimize the mean square error between the actual output of multilayer feed forward network and desired output:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_k)^2, \quad (2)$$

where, y_i is the predicted value of the ith pattern, y_k is the target value of the ith pattern, and N is the number of pattern.

An essential component of the rule is the iterative method that propagates error term required to adapted weights back from nodes in the output layer to needs in the lower layer. At the beginning, all weights and node offsets are set to small random values. The input values are presented, and desired outputs are specified. Then, the network is used to calculate actual output. As recursive algorithm, starting at the output nodes and working back to hidden layer, adjusts weights until they converge and the objective function is reduced to acceptable value. The training was repeated by presenting different sets of input data to the ANN.

3. Test Systems for the Case Study

3.1. Test System. A range of reliability indices were calculated for a number of studies. The methods for evaluating these indices are described in detail in [2] and applied to practical systems in [8]. The indices include load point indices. These are failure rate (A), outage time (r), annual unavailability (U), load disconnected (L), and energy not supplied (E). These can be system indices. These are SAIFI, SAIDI, CAIDI, ASAI, ASUI, ENS, and AENS. They are fully specified and defined in [2] and can be evaluated from the load point indices for a group of load points or the whole system. The studies performed include llkV feeders. These studies consider the llkV feeders only and ignore any failures in the 33 kV system, the 33/11 kV substation, and the llkV breakers. They assume that the IlkV source breaker operates successfully when required, disconnects are opened whenever possible to isolate a fault, and the supply restored to as many load points as possible using appropriate disconnects and the alternative supply if available is 33 kV system. These studies evaluate the reliability indices at the llkV supply point busbars. They ignore any failures on the incoming 33 kV supply circuits. They include the effect of passive and active failures [2] on all components from the 33 kV busbars down to the llkV supply point busbars together with active failures on the outgoing 11 kV feeder breakers, This study system comprises one substation and feeders. As show in Figure 1, the substation is labeled X and feeders are labeled X1, X2, X3,. . ., X30 and the feeder load is show in Table 1.

3.2. The Reliability Indices. This index can then be combined with the customer composition in the distribution system to evaluate the system indices of SAIFI, SAIDI, CAIDI, ASAI, and so forth [7]. In the distribution area, the usual indices are the load point failure rate (or frequency), the average outage duration, and the average annual outage time. Normal utility practise is to measure distribution system performance in terms of SAIFI, SAIDI. This approach does not usually

Table 1: Load and customer data for each Feeder.

Feeder	Load (kVA)	No. of customers
11	48642.00	216
12	5418.7	3277
13	8470.25	6783
14	7376.5	3344
15	1222.5	86
16	3240.5	229
17	6280.5	495
18	2606.00	175
19	4247.25	384
20	4107.00	649
21	3706.5	1132
22	5418.50	3277

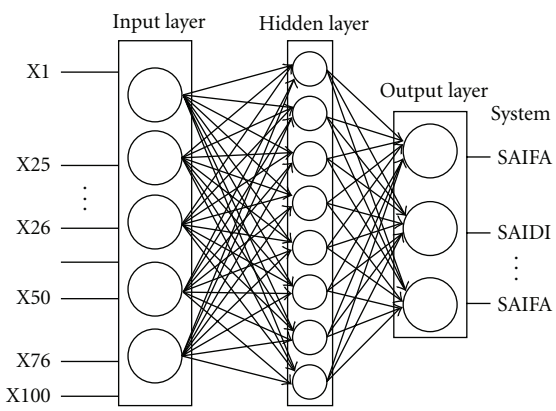

Figure 1: Structure of neural network.

encompass any discussion or appreciation that the customer-based indices can exhibit considerable natural variability on an annual basis, while still having the expected values determined by the analytical approach. In order to obtain this appreciation of the annual variability, it is necessary to include probability or frequency distribution concepts in the evaluation process to evaluate reliability of test distribution system; the following data are needed: (1) the load at each point, (2) the system configuration, (3) numbers of customer at each load point, (4) averge failure rate (λ) of all component such as lines, transformers, breakers and so forth, (6) the restoration time r of each component, and (7) the switches times s of switches and breakers. With these data available at hand, the following two reliability indices are computed [5–7]: the system average interruption frequency index (SAIFI) and system average interruption duration index as following in (3) and (4):

$$\text{SAIFI} = \frac{\text{Total number of customer interruption}}{\text{Total number of customer severed}}, \qquad \text{SAIFI} = \frac{\sum \lambda_i N_i}{\sum N_i}, \tag{3}$$

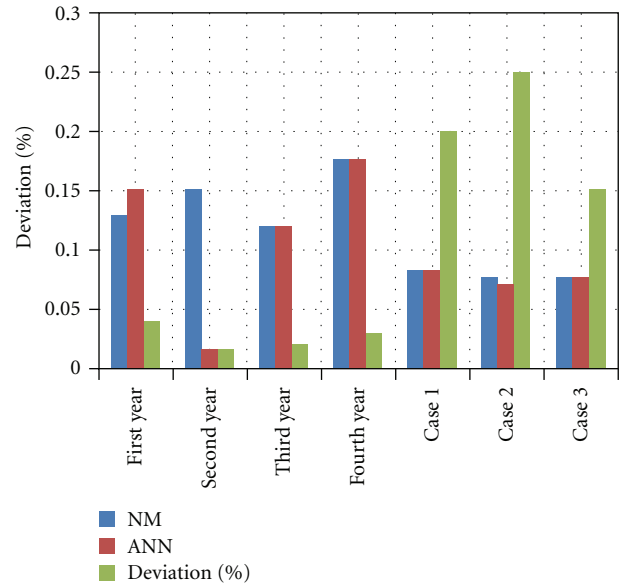

Figure 2: SAIFI values feeder X14 with deviation less than 0.25.

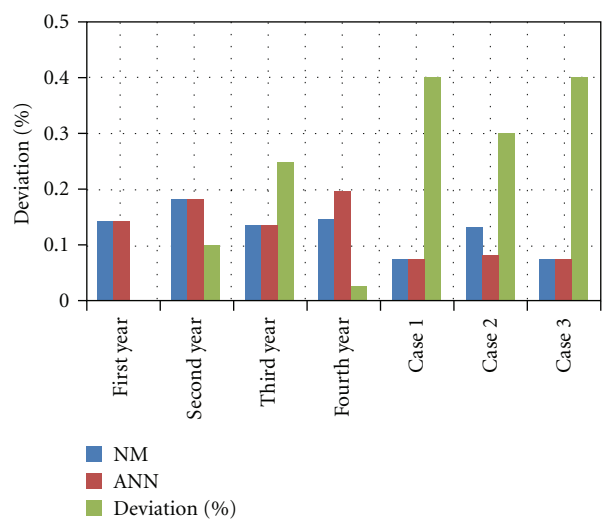

Figure 3: SAIFI values for feeder X12 with deviation less than 0.4.

where (λ_i) is average failure rate and N_i is number of customer at load point

$$\text{SAIDI} = \frac{\text{Sum of customer interruption duration}}{\text{Total number of customer severed}}, \qquad \text{SAIFI} = \left(\frac{\sum U_i N_i}{\sum N_i}\right), \tag{4}$$

where U_i is annual outage time.

4. Results and Discussion

In this work, the historical data of the test system for four years were provided by the power company. Using this data, the following cases were designed to study the applicability of the ANN approach. Case one prediction of the reliability

Table 2: System average interruption frequency index values (SAIFI).

	Feeder14			Feeder12			System		
	(NM)	(ANN)	Deviation (%)	NM	ANN	Deviations (%)	NM	ANN	Deviation (%)
Fist year	0.1292	0.1493	0.04	0.14425	0.14295	0.0.25	0.3934	0.39345	0.005
Second year	0.14935	0.01493	0.015	0.18255	0.18125	0.10	0.45255	0.4526	0
Third year	0.11915	0.1191	0.02	0.137	0.1363	0.25	0.37085	0.32085	0
Fourth year	0.17565	0.17575	0.03	0.1478	0.1977	0.025	0.52075	0.52075	0
Case 1	0.0827	0.08235	0.2	0.0733	0.0736	0.40	0.2524	0.2542	0
Case 2	0.0758	0.07045	0.25	0.1324	0.0829	0.30	0.2524	0.2541	0.02
Case 3	0.0763	0.07605	0.15	0.0733	0.0739	0.40	0.25405	0.2542	0.53

Table 3: System average interruption duration index values (SAIDI).

	X14			X12			System		
	(NM)	(ANN)	Deviation (%)	NM	ANN	Deviations (%)	NM	ANN	Deviation (%)
First year	0.1292	0.1293	0.04	0.1423	0.01429	0.30	0.3924	0.3935	0.03
Second year	0.14935	0.1493	0.02	0.1822	0.1818	0.15	0.4526	0.4526	0.00
Third year	0.1193	0.1191	0.02	0.1320	0.1363	0.25	0.3708	0.3708	0.00
Fourth year	0.1757	0.1758	0.03	0.1973	0.1977	0.03	0.1.0208	0.5206	0.00
Case 1	0.0827	0.0824	0.20	0.0733	0.0736	0.40	0.2524	0.2542	0.00
Case 2	0.0758	0.0754	0.25	0.0824	0.0826	0.30	0.2524	0.2541	0.02
Case 3	0.0713	0.0711	0.15	0.0733	0.0739	0.40	0.2542	0.2542	0.54

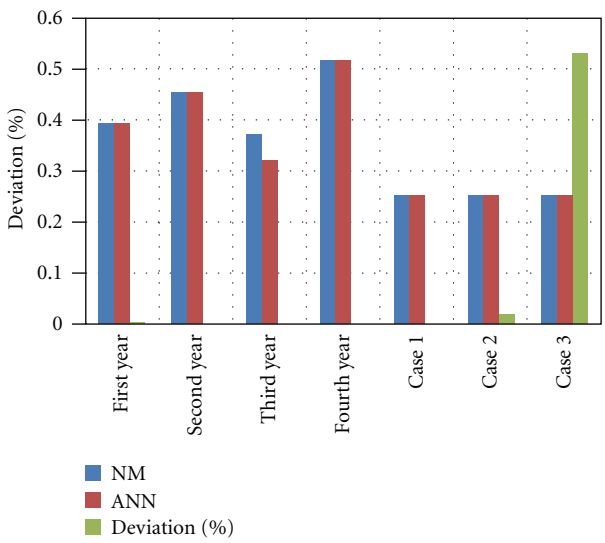

Figure 4: SAIFI values for feeder whole system with deviation less than 0.55.

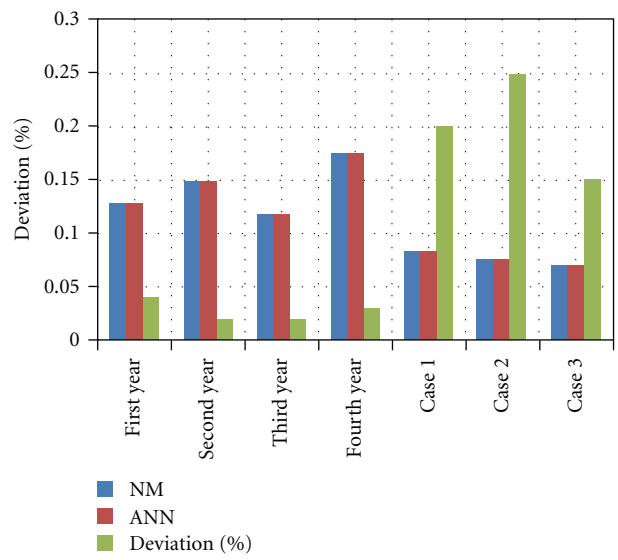

Figure 5: SAIDI values for feeder X14 with deviation less than 0.25.

indices of 1996 by feeding the ANN with system data from 1996 to 1995. Case 2. Evaluation of reliability indices when the feeder X14 is overload and part of its load is switched to X12. Case 3. Evaluation of the reliability indices when a fault occurs in feeder X14. The fault location is indicated by the arrow in Figure 1.

The developed ANN is shown in Figure 1. The data of feeder X11, X12,. . ., X22 enter the network from the input layer. The output layer result value of SAIFI, SAIDI of the whole system and each feeder. Corresponding to the number of lines, buses, circuit breaker, and transformer of each feeder, this network contains 1809 nodes in the input layer, 18 nodes in output layer, and 100 nodes in the hidden layer.

The SAIFI, SAIDI values of X14, X12, and the whole system are given in Tables 2 and 3, respectively, the values computed by ANN are compared with results from the network method. The deviations are found in the Tables 2 and 3; also the deviation is illustrated in Figures 2–7. it has found that the deviations of the values computed by the proposed approach from those network methods are less than 0.005.

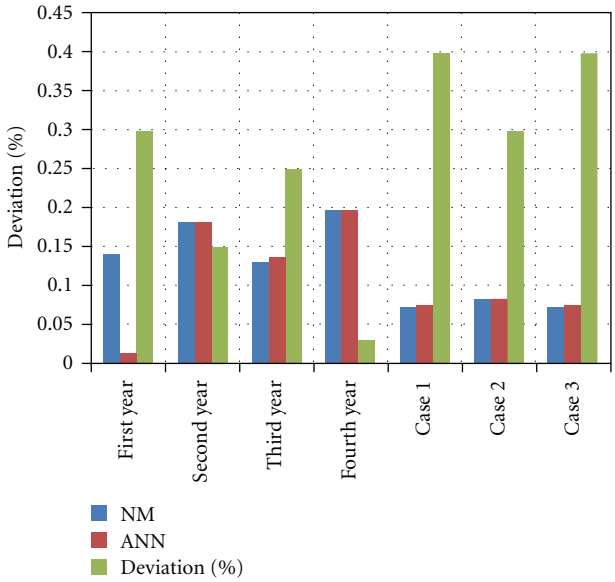

Figure 6: SAIDI values for feeder X12 with deviation less than 0.4.

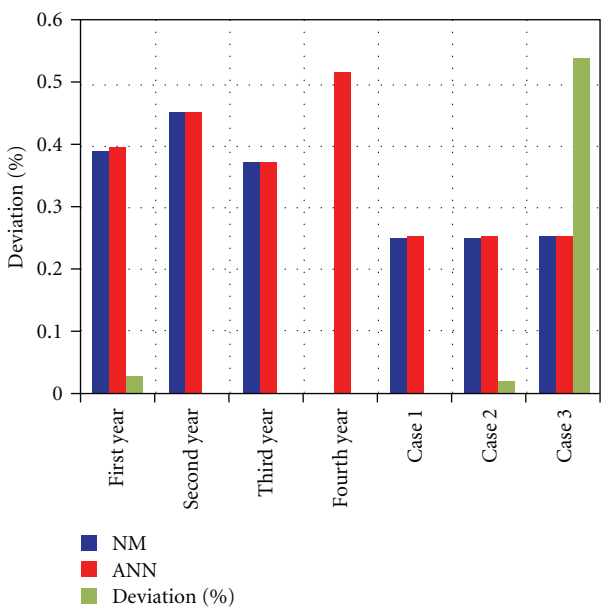

Figure 7: Total SAIDI values with deviation for whole system less than 0.54.

The required running time on ASUN network environment is less than 2 s, and the time required for the network method is 3.5 times greater than of ANN approach.

5. Conclusions

This paper has presented evaluating the reliability of distribution systems and backpropagation neural network model with a numbers of input layer—hidden layer—output layer constructed this neural network approach could be considered as alternative and practical techniqueing to evaluate distribution system indices. The cases were designed to demonstrate the capability of develop the neural network. With sufficient learning from historical data, the reliability indices of the normal, overload, and faulted conditions are computed with tiny deviations, below 0.005 from the results by the network method. The required computing times are less than 2 s. Although ANN approach is generally time consuming if one wishes to develop the best configuration for training period, it is feasible due to its ability to learn and generalize a wide range of experimental conditions. This makes ANN a powerful tool to assist distribution system for solving complicated engineering problems.

References

[1] R. Billinton and W. li, *Reliability Assessment of Power Systems Using Montecarlo Method*, Plenum Press, New York, NY, USA, 1994.

[2] R. Billinton and R. N. Alan, *Reliability Evaluation of Power Systems*, Plenum Press, New York, NY, USA, 2nd edition, 1995.

[3] D. Midence, S. Rivera, and A. Vargas, "Reliability assessment in power distribution networks by logical and matrix operations," in *Proceedings of the IEEE/PES Transmission and Distribution Conference and Exposition*, August 2008.

[4] I. A. Basheer and M. Hajmeer, "Artificial neural networks: fundamentals, computing, design, and application," *Journal of Microbiological Methods*, vol. 43, no. 1, pp. 3–31, 2000.

[5] G. E. Nasr, E. A. Badr, and C. Joun, "Backpropagation neural networks for modeling gasoline consumption," *Energy Conversion and Management*, vol. 44, no. 6, pp. 893–905, 2003.

[6] S. Haykin, *Neural Networks, A Comprehensive Foundation*, McMillian College Publishing Company, New York, NY, USA, 1994.

[7] C. L. Chen and J. L. Chen, "A neural network approach for evaluating distribution system reliability," *Electric Power Systems Research*, vol. 26, no. 3, pp. 225–229, 1993.

[8] W. M. Lin, T. S. Zhan, and C. D. Yang, "Distribution system reliability worth analysis with the customer cost model based on RBF neural network," *IEEE Transactions on Power Delivery*, vol. 18, no. 3, pp. 1015–1021, 2003.