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An Efficient Multi-Objective Meta-heuristic Method for Probabilistic Transmission Network Planning

Kakuta Hiroki[a], Hiroyuki Mori[b]*

[a] *Dept. of Electonics & Bioinformatics, Meiji University, Kawasaki, 214-8571, Japan*
[b]*Dept. of Network Design, Meiji University, Tokyo, 164-8525, Japan*

Abstract

In this paper, a new method is proposed for probabilistic transmission network expansion planning in Smart Grid. The proposed method makes use of Controlled Nondominated Sorting Genetic Algorithm (CNSGA-II) of multi-objective meta-heuristics (MOMH) to calculate a set of the Pareto solutions. In recent years, electric power networks increase the degree of uncertainties due to new environment of Smart Grid with renewable energy, distributed generation, Demand Response (DR), *etc*. Smart grid planners are interested in improving power supply reliability of transmission networks so that probabilistic expansion planning approaches are required. This paper focuses on a multi-objective problem in probabilistic transmission network expansion planning. The multi-objective optimization problem may be expressed as multi-metaheuristic formulation that evaluates a set of the Pareto solutions in Monte Carlo Simulation (MCS). In this paper, CNSGA-II is used to calculate a set of the Pareto Solutions. The proposed method is successfully applied to the IEEE 24-bus reliability test system.

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Keywords: meta-heuristics; multi-objective optimization; smart grid; transmission network expansion; probabilistic reliability

1. Introduction

Transmission network expansion planning (TNEP) is one of important tasks in Smart Grid planning. The objective is to evaluate the optimal network configuration by setting new transmission lines between nodes and to balance

* Corresponding author. Tel.: +81-3-5343-8292; fax: +81-3-5343-8113.
E-mail address:hmori@isc.meiji.ac.jp

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between future generation and loads under some constraints. The mathematical formulation may be represented as a combinational optimization problem that is difficult to solve. To solve the optimization problem, a lot of methods have been developed. The conventional methods on TNEP may be classified into Linear Programming [1], Dynamic Programming [2], Benders-decomposition-based methods [3,4], Heuristics [5], the combination of the above methods [6], *etc*. It is known that the conventional methods have a drawback that they calculate a locally optimal solution or that it is very time-consuming to calculate the optimal solution. In recent years, meta-heuristics is noteworthy for a practical optimization method in a sense that it repeatedly makes use of heuristics or simple rules to evaluate highly approximate solutions close to global one in given time. The following meta-heuristic methods are well-known: Simulated Annealing (SA) [7], Genetic Algorithm (GA) [8], Tabu Search (TS) [9], Ant Colony Optimization (ACO) [10], Particle Swarm Optimization (PSO) [11], Differential Evolution (DE) [12], *etc.* The combinational optimization problem of TNEP was solved by meta-heuristic methods [13-16]. Romero, *et al.,* applied to SA for solving the non-convex problem [13]. It contributed to the cost reduction of 7% in comparison with the conventional method. Wen, *et al.,* made use of TS to evaluate better solutions easily [14]. Afterward, Gallego, *et al.* made a comparison of SA, GA and TS [15]. Their results showed that the improved TS provided better results than others. Sensarma, *et al.* developed a PSO-based method for the TNEP problem and their results showed the good performance [16]. However, the conventional methods just solved the transformed formulation in a sense that the multi-objective TNEP is transformed into the scalarization formulations like the weighted sum method of the cost functions [17], the constraint transformation method [18], *etc*. Specifically, however, they have drawbacks to require *a priori* knowledge on each objective function or to select only one solution by disregarding the existence of a set of the Pareto solutions [19]. As a result, they are not desirable in dealing with the multi-objective TNEP. In recent years, MOMH (Multi-objective Metaheuristics) has been developed to focus on evaluating a set of the Pareto solutions systematically. Shahidehpour, *et al*. developed Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) to TNEP [20]. It does not necessarily imply good MOMH because of the existence of missing solutions and/or biased solutions in distribution of the Pareto solutions. In addition, the uncertain factors should be considered in TNEP. Thus, there is still room for improving the solution quality and considering the uncertainties.

This paper proposes an efficient CNSGA-II–based multi-objective meta-heuristic method for probabilistic transmission network expansion planning. CNSGA-II is different from NSGA-II in a way that the reproduction of solution candidates is employed at the next generations to maintain the diversity of the solution set in CNSGA-II. It has better performance on the solution accuracy and the diversity in the Pareto solution set. Also, MCS is used to evaluate the probabilistic reliability assessment with index EENS (Expected Energy Not Supplied). In this paper, two cost functions of probabilistic reliability index EENS and the construction cost are optimized to evaluate a set of the Pareto solutions. The proposed method is successfully applied to the IEEE-24 node reliability test system.

2. Transmission Network Expansion Problem (TNEP)

This section outlines the conventional formulation of TNEP that minimizes the installation cost of the transmission line under the constraints [15]. It determines the location and the number of transmission lines while satisfying the balance between generation and loads under the constraints on the power flows and the variables. A lot of the power flow calculations are required in the optimization process so that the DC power flow calculation is often employed due to the numerical efficiency and the rescheduling of generators is useful for optimizing the cost function. Specifically, the mathematical formulation may be written as follows:

Cost function:

$$v = \sum_{i=1}^{NL} c_i x_i + \alpha \sum_{s=1}^{NB} r_s \rightarrow \min \tag{1}$$

Constraints:

$$B\left(x + \gamma^0\right)\theta + g + r = d \tag{2}$$

$$\left|f_i\right| \le br_i C_i \tag{3}$$

$$0 \le g \le \overline{g} \tag{4}$$

$$0 \le r \le d \quad (5)$$
$$MIN(i) \le br_i \le MAX(i) \quad i = 1,\ldots,NL \quad (6)$$
$$s = 1 \quad (7)$$

where

NL : Number of transmission lines

NB : Number of nodes

c_i : Installation cost per line at line i

x_i : Number of transmission lines installed at line i

r_s : Output of dummy generator at node s

α : Penalty for dummy generator

$B(\cdot)$: Susceptance matrix of $\cdot$

x : Susceptance of installed lines

γ^0 : Initial susceptance

θ : Voltage angle

g : Generation of generator

$\overline{g}$: Upper bound of g

d : Load

f_i : Active power flow at line i

br_i : Number of lines at line i

C_i : Transmission capacity per line at line i

$MIN(i)(MAX(i))$: Lower (upper) bound of installed lines at line i

Eqn. (1) shows the sum of the installation cost of new transmission lines and the penalty on the dummy generators, where coefficient α is set to be large due to the balance between generation and loads. Eqn. (2) gives the DC power flow equation. Eqn. (3) denotes the constraints on the line flow limitation of each line. Eqn. (4) provides the upper and the lower bounds of generator output. Eqn. (5) denotes the lower and the upper bounds of the dummy generator output that contributes to the rescheduling of generators. Eqn. (6) means the lower and the upper bounds of installed lines at each line. Eqn. (7) gives the conditions that the isolated nodes or isolated islands do not exist in the network, where s=1 means the network with all the nodes connected. The formulation of (1)-(7) may be solved with two phases. Phase 1 determines the location and the number of lines while Phase 2 optimizes output of dummy generations for a given network configuration. Now, suppose that a network configuration is given by a certain method. Phase 2 may be expressed as the following linear programming (LP) problem:

Cost function:

$$w = \alpha \sum_{s=1}^{NB} r_s \rightarrow \min \quad (8)$$

Constraints:

$$B(x + \gamma^0)\theta + g + r = d \quad (9)$$
$$|f_i| \le br_i C_i \quad (10)$$
$$0 \le g \le \overline{g} \quad (11)$$
$$0 \le r \le d \quad (12)$$

3. Reliability Assessment

Reliability assessment is outlined in this paragraph. It consists of the two basic aspects: adequacy and security. The former is related to static reliability in power system planning while the latter is concerned with dynamic reliability in power system operation. In this paper, adequacy is discussed to deal with TNEP. As Smart Grid operators are faced with severe blackouts in recent years, more sophisticated methods are required to understand the probabilistic behavior of Smart Grid. The Monte Carlo Simulation (MCS) technique is one of popular methods that satisfy such requirements. It may be classified into state sampling method, state transition sampling method, and state duration sampling method [22]. In this paper, the state sampling method is used due to the advantage of reduced computational time and memory requirements. The basic sampling procedure is conducted by assuming that the behavior of each component is determined by the uniform distribution of random number [0, 1]. In case of the component representation for two states, the probability of outage may be given by the component forced outage rate. Now, suppose that a system state is expressed as vector $S = (S_1, S_2, ..., S_n)^T$, where S_i denotes the state of the i^{th} component. Vector S of n components includes the state of each element of the system (generators, transmission lines, transformers, *etc.*). Let us define the forced outage rate of the i^{th} component as FOR_i. State S_i of the i^{th} component is determined by uniformly random number x=[0, 1] as follows:

$$S_i = \begin{cases} 0(Normal \quad State) & x \geq FOR_i \\ 1(Outage \quad State) & 0 \leq x \leq FOR_i \end{cases} \tag{13}$$

Variation β is often used as the termination conditions in MCS.

$$\beta = \frac{\sqrt{V(\hat{E}(X))}}{\hat{E}(X)} \tag{14}$$

where,

β : Coefficient of variation

$V(\cdot)$: Variation of. $\cdot$

$\hat{E}(X)$: The estimate of expectation of probabilistic variable X

In the state sampling method, adequacy index *EENS* (Expected Energy Not Supplied) may be written as follows:

$$EENS = 8760 \times \frac{\sum_{s=1}^{N_s} E_s}{N_s} \tag{15}$$

where,

$EENS$: Expected energy not supplied (KWh/year)

E_s : Energy not supplied in state S

N_s : Number of samplings

The algorithm may be written as follows:

Step 1: Sample a system state by the sampling technique.

Step 2: Calculate transmission line power flows with the DC load flow calculation. Go to Step 4 if this state is normal. Otherwise, go to Step 3.

Step 3: Solve the linear programming minimization problem to reschedule generation, alleviate line overloads and minimize the total load curtailment.

Step 4: Accumulate the adequacy index. Stop if coefficient β is less than the termination conditions error. Otherwise, return to Step 1.

4. Multi-objective Metaheuristics

As multi-objective Metaheuristics (MOMH), CNSGA-II is outlined to solve a multi-objective optimization problem of TNEP [24]. NSGA-II developed by Deb, *et al.*, [23] was extended into CNSGA-II to improve a set of the Pareto solutions efficiently. It has the following strategies: Fast non-dominated sort strategy, Crowding distance strategy, and Elitism strategy. The fast non-dominated sort strategy evaluates the solution dominance and classifies the solutions into each Front. This strategy is used for evaluating, classifying, and storing the Pareto solutions efficiently. CNSGA-II is the improved NSGA-II in a way that reproduction is applied to the next generation. CNSGA-II provides better solution candidates by introducing the reproduction into solution search in NSGA-II. The number of populations stored as solution sets of the next generation is given by

$$n_i = rn_{i-1} \tag{16}$$

where

n_i: Number of population allowed as Front i

r: Decreasing rate (r<1)

Fig. 1 shows the concept of CNSGA-II, where the solutions are preserved in each Front for creating the next

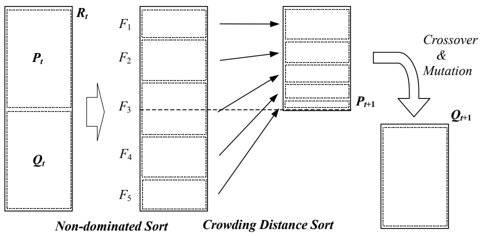


Fig. 1. Concept of CNSGA-II

generation solution set from the integrated solution set. The crowding distance determines the priority of storing the solutions in Front. Although the number of stored solutions as the low Front decreases exponentially, a few numbers of them is stored. The algorithm of CNSGA-II may be written as follows:

Step 1: Set initial conditions (t=0), and create random parent population P_0 and children population Q_0.

Step 2: Form a combined population $R_t \in P_t \cup Q_t$ and sort R_t according to fast non-dominated sort.

Step 3: Create new parent population P_{t+1} by adding solutions from the first front considering n_i till $|P_{t+1}| > N$ is satisfied.

Step 4: Calculate the crowding distances of the last accepted Front and pick high crowding ones according to N.

Step 5: Stop if t is equal to t_{max}. Otherwise, go to Step 6.

Step 6: Perform genetic operations to P_{t+1} and create Q_{t+1} and go to Step 2.

5. Proposed Method

In this section, a CNSGA-II–based method is proposed for multi-objective transmission network expansion planning problem. Most of the conventional methods do not consider uncertainties in Smart Grid since they focus on minimizing construction cost. In recent years, Smart Grid increases the degree of uncertainties under new environment of Smart Grid, the emergence of renewable energy, *etc*. Thus, it is necessary to consider the uncertainties in TNEP under new environment. To deal with the uncertainties, this paper evaluates probabilistic reliability criterion EENS in MCS. As the new stage of probabilistic transmission network expansion planning, this paper solves the TNEP problem as the multi-objective optimization. Namely, the proposed method aims at minimizing EENS as well as the construction cost. The formulation of the proposed method may be written as follows:

Objective function:

$$f_1 = \sum_{(i,j)\in\Omega} c_{ij} n_{ij} + \alpha \sum r_i \quad \rightarrow \quad \min \tag{17}$$

$$f_2 = \sum EENS_i \quad \rightarrow \quad \min \tag{18}$$

Constraints:

$$Sf + g + r = d \tag{19}$$

$$f_{ij} - \gamma_{ij}\left(n_{ij}^0 + n_{ij}\right)\left(\theta_i - \theta_j\right) = 0 \tag{20}$$

$$\left|f_{ij}\right| \le \left(n_{ij}^0 + n_{ij}\right)\bar{f}_{ij} \tag{21}$$

$$0 \le g \le \bar{g} \quad (22)$$
$$0 \le r \le d \quad (23)$$
$$0 \le n_{ij} \le \bar{n}_{ij} \quad (24)$$

where, $EENS_i$: EENS of bus i

The proposed method evaluates the Pareto optimal solutions by minimizing (17) and (18). CNSGA-II is an efficient method for calculating a set of the Pareto optimal solutions efficiently in multi-objective optimization problems. The proposed method allows system planners to determine expansion planning in consideration of tradeoff between construction cost and probabilistic reliability. The algorithm of the proposed method may be written as follows:

Step 1: Set initial conditions (t=0), and create random parent population P_0 and children population Q_0.

Step 2: Evaluate construction cost and EENS for combined population $R_t \in P_t \cup Q_t$.

Step 3: Sort R_t according to the fast non-dominated sort and create new parent population P_{t+1}.

Step 4: Stop if t is equal to t_{max}. Otherwise, go to Step 6.

Step 5: Perform genetic operations to P_{t+1}, create Q_{t+1} and go to Step 2.

6. Simulation

The proposed method is successfully applied to the IEEE 24-node reliability test system in Fig. 2. The following simulation conditions were used:

- The test system has 41 transmission line candidates and the total loads of 8550MW. It is assumed that the system has at most four lines at each transmission line. As a result, the number of combination results in 7.3×10^{24}. As a sample system, the IEEE 24-bus system was modified to have three times more generation and load amounts than the original data [25, 26].

- Table 1 shows the parameters of CNSGA-II that were determined by the preliminary simulation. To evaluate probabilistic reliability index EENS, this paper assumes that the components consists of generators and transmission

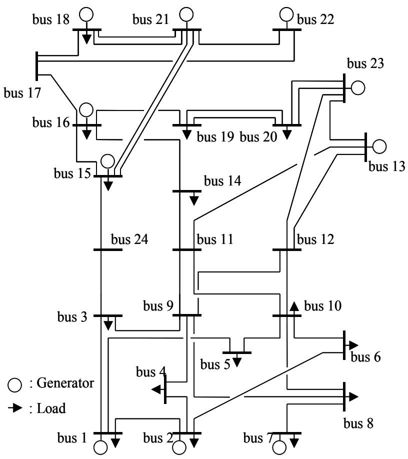
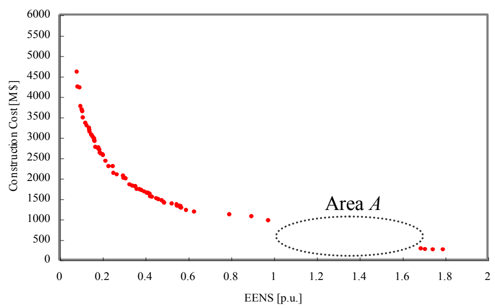


Fig. 2. IEEE 24-node reliability test system

Table 1 Parameters of NSGA-II and CNSGA-II

Parameters	Methods	
	NSGA-II	CNSGA-II
No. of parent populations	100	100
No. of child populations	100	100
No. of generations	500	500
Crossover rate	0.9	0.9
Mutation rate	0.08	0.08
Reproduction rate		0.5



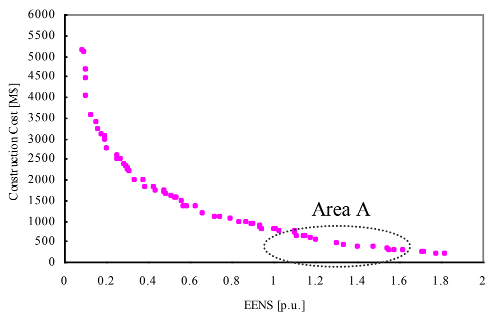
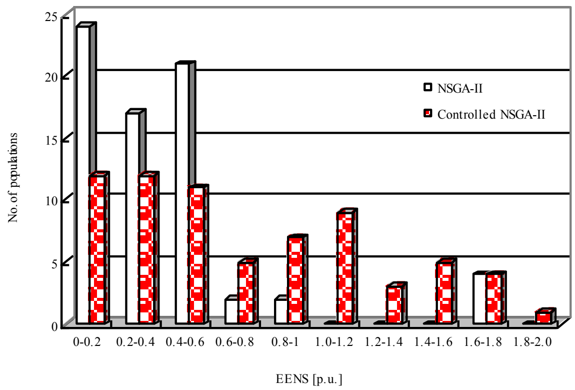


Fig. 4. Simulation results for CNSGA-II

Fig. 3. Simulation results for NSGA-II



lines in MCS. Parameter β and the maximum number of sampling are set to be 0.01 and 1,000, respectively. The outage rates of the components are determined by data of IEEE RTS [25].

- All computations were performed on UNIX Server Fujitsu PRIMEPOWER 1500 (SPARC 64V, 8CPU, 1.89GHz, SPEC int 2000: 108, SPEC fp 2000: 126).

Figs. 3 and 4 show sets of solution evaluated by NSGA-II and CNSGA-II, respectively. It can be seen that CNSGA-II found out the Pareto solutions in Area A ($1.0 \leq$ EENS [p.u.] ≤ 1.7) and NSGA-II is inferior to CNSGA-II in terms of the ability to find the Pareto solutions in Area A. This is caused by the difference of preserving the solution candidates at the next generation. NSGA-II employs the elitist strategy while CNSGA-II makes use of the strategy to accept the low Front solution candidates. As a result, CNSGA-II succeeded in maintaining the solution diversity and improving the Front. Fig. 5 gives the distribution characteristics of EENS in solutions. It can be observed that CNSGA-II obtained diverse solutions compared with NSGA-II obviously. Therefore, the proposed method allows system planners to select optimal expansion planning more flexibly. Regarding computation time, NSGA-II and CNSGA-II took 747583 [s] and 545874 [s], respectively. As a planning method, these computational times are acceptable.

The above results demonstrated that the proposed method gives more flexible transmission network expansion planning in consideration of the tradeoff relationship between the construction cost and EENS.

7. Conclusion

In this paper, an efficient method has been proposed for transmission network expansion planning with CNSGA-II of multi-objective metaheuristics. The proposed method focused on a multi-objective optimization problem of construction cost and reliability to evaluate a set of the Pareto solutions efficiently, where probabilistic reliability index EENS was used to evaluate the probabilistic reliability under Smart Grid environment with the uncertainties. The proposed method was successfully applied to the IEEE 24-bus system. The simulation results have shown that the proposed method succeeded in evaluating more accurate and diverse a set of the Pareto solutions in comparison with NSGA-II. Also, the proposed method contributed to the clarification of the trade-off relationship of a set of objective functions. Therefore, the proposed method allows the system planners to select the transmission network expansion planning flexibly.

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