Bayesian Optimization Algorithm for Multi-Objective Solutions: Application to Electric Equipment Configuration Problems in a Power Plant

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Abstract- This paper applies Bayesian Optimization Algorithm with Tabu Search (Tabu-BOA) to electric equipments configuration problems in a power plant. Tabu-BOA is a hybrid evolutionary computation algorithm with competent GAs and meta-heuristics. The configuration problems we consider have complex combinatorial properties with multiple objectives, therefore, they are hard to solve via conventional techniques. First, we investigate the performance of the proposed algorithm using simple test functions, Next, using the method, we solve the following practical problems: both (1) minimize the cost of implementation and operation, and (2) maximize the marginal supply capacity in operation.

1 Introduction

In this paper, we improve a hybrid evolutionary algorithm with Bayesian Optimization Algorithm[1] and Tabu Search[2][3] (Tabu-BOA) in order to solve electric equipments configuration problems in a power plant. In a power plant, extremely many equipments are installed to securely and economically supply electric power in operation. The configuration of load dispatchers, the cables among them, and the decrease of the power loss must be carefully designed. The formulation of the problems results in complex combinatorial optimization problems with multiple objectives. We must have multiple solutions.

In the evolutionary algorithms literature, there are so many researches on multi-objective optimization problems. For example, Khan et al have proposed a variation of BOA for multi-objective optimization problems[4], in which they have hybridized BOA and NSGA-II and reported the results applied to typical deceptive functions. Laumanns et al. have solved knapsack problems by introducing a new selection mechanism into conventional BOA[5]. Tan et al. have proposed an evolutionary algorithm with Tabu search for multi-objective optimization[6].

Furthermore, Katsumata et al. [7]-[11] have developed Tabu-BOA, and have solved the configuration problems with multiple peaks[12][13]. This paper will extend the research to multi-objective optimization problems to solve the electric equipments configuration problems: (1) minimize the cost of implementation and operation, and (2) maximize the marginal supply capacity in operation . These problems are too complicated and never solved so far.

In the electric power domain, Abido have reported the application of multi-objective optimization problems with both the fuel cost of power generation and the amount of emission of atmospheric pollutants[14]. Although he has used NSGA for their problems, the size and complexity of the problems are very small. Therefore, we believe our approach on the problems is a very novel one.

The rest of the paper is organized as follows: In Section 2, we will briefly describe the extension to the multi-objective optimization problems of Tabu-BOA. In Section 3, we explain several experiments using basic test functions, then in Section 4, we describe the basic models of the electric equipment configuration problems in a power plant. In section 5, we apply the proposed method to the problems. Finally, in Section 6, some concluding remarks will follow.

2 Brief Description of Tabu-BOA and its Extension to Multi-Objective Optimization Problems

In this section, we briefly describe the principles of Tabu-BOA and its extension to multi-objective optimization algorithms. In the following, we call the algorithm *Multi-Objective Tabu-BOA*.

As for the multi-objective optimization using evolutionary computation, the maintenance of the diversity of the population is critical[15]. As reported earlier, Tabu-BOA has good properties to keep the diversity. It is worth while to extend Tabu-BOA to multi-objective optimization problems.

The basic idea is very simple. We introduce the Pareto ranking method to the selection phase in Tabu-BOA according to the multi-objective values. The outline of the algorithm is illustrated in Fig.1. Both a long-term and a short-term tabu list are used to keep the plural Pareto optimum solutions in each generation as shown in the Fig.2.

The basic procedure of the Pareto ranking method is: First, give the score rank 1 to the individuals not inferior to the others measured by the multiple values, them delete rank 1 individuals from the population and repeat the process to give ranks to all the individuals in the population. The condition to store one individual into the long term tabu-lists is that (1) the multi-objective fitness value is not inferior to the ones in the tabu-list and (2) the distance between the candidate and the ones in the tabu list is large compared with a given constant value d. The condition to store one individuals into the short-term tabu–list is that the distance between the candidate and the ones in the tabu list is large compared with a given constant value d. The procedure of multi-objective Tabu-BOA is summarized as follows:

STEP (1) : Set the Initial Population. set t:= 0; random generation of initial population P(0);

STEP (2) : Compare Pareto Individuals with the one in the Long-term and Short-term Tabu List. The Pareto individuals or rank 1 individuals in the population are compared with the ones in the long-and short- term tabu list. The individual satisfied the above conditions are stored into the two corresponding tabu-lists.

STEP (3) : Select a Set of Promising Strings S(t) from P(t);Candidate individuals are selected from the population based on the Pareto ranking principle.

STEP (4) : Construct the Bayesian Network ;Construct the Bayesian Network B from the selected individuals using a given metric and network complexity constraints;

STEP (5) : Generate New Individuals (Offspring). ; Generate a new set of strings O(t) according to the joint distribution encoded by B; The probability of each locus is found based on the Bayesian network. Next, new individuals (offspring) are generated based on this generating probability.

STEP (6) : Delete Tabu Strings ; Check the Individuals in O(t) that are already stored in the tabu lists within distance d, then delete them;

STEP (7) : Substitute the Population. ; Create a new population P(t+1) by replacing inferior individuals in P(t) with O(t); Set t:=t+1;

STEP (8) : Termination. ; If termination conditions do not hold; go to STEP (2).

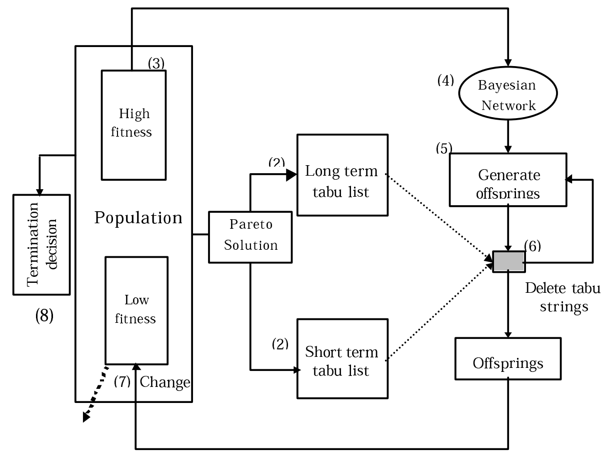

Fig.1 Outline of multi-objective Tabu-BOA.

Generation=5	S(5,1)	S(5,2)	S(5,3)	S(5,4)	S(5,5)		
Generation=4	S(4,1)	S(4,2)	S(4,3)	S(4,4)	S(4,5)	S(4,6)	
Generation=3	S(3,1)	S(3,2)	S(3,3)	S(3,4)			
Generation=2	S(2,1)	S(2,2)	S(2,3)	S(2,4)	S(2,5)	S(2,6)	
Generation=1	S(1,1)	S(1,2)	S(1,3)	S(1,4)	S(1,5)	S(1,6)	S(1,7)

Fig.2 Tabu list.

3 Experiments on Test Functions

This section explains how the proposed method works well. We represent the individuals in the binary expressions as are reported in the other literature of BOA related papers[1]. All the experiments have been carried out using a PC with Celeron CPU(500MHz), Windows 98 Operating System, and in C++ language. First we apply the method to a simple quadratic function[15]. Then we apply it to more complex functions[16]. These two types of kind test functions are often used as benchmarks of the algorithms in evolutionary computation literature.

3.1 Quadratic Function Example

The first example is to optimize the following two formulas.

$$min \quad f1(x) = x_1^{\,2} / 4 \quad \text{......................................}(1)$$

$$min \quad f2(x) = x_1(1 - x_2) + 5 \quad \text{..............................}(2)$$

The experiment conditions are: Population size =256; Long-term tabu list size =10; Long term distance threshold (measured by the Hamming distance) =4, Short-term tabu list size =2, Short term distance threshold (measured by the Hamming distance) = 1, and Generation number = 40.

The experimental results are illustrated in Fig.3. The rank 1 individuals of the 40th generation are plotted in the Figure. The X-axis and the Y-axe respectively mean values of $f_1(x)$ and $f_2(x)$. The individuals form a single curve, which means the Pareto front is obtained. Also, the individuals are uniformly distributed, which means the method keeps the diversity of the solutions.

Compared with conventional evolutionary algorithms, BOA as an estimation of distribution algorithm requires much more number of individuals in the population. This results in the 256 individuals.

3.2 KUR Function Example

The KUR problem is a much more difficult multi-objective optimization problem introduced in reference (16). Considering the complexity of our problems in Section 5, we set the dimension n equal to 10, which is rather smaller than the papers in the literature, however, our experiments will show the performance of the proposed method.

The problem is defined by the equations (3) and (4). The KUR problem has closed relation of the neighbors' variables in $f_1(x)$, and has multiple peaks in $f_2(x)$. The Pareto front of this problem becomes very complex shapes with discrete properties.

$$min \quad f_1(x)=\sum_{i=1}^{n-1}\left(-10\,exp\left(-0.2\sqrt{x_i^2+x_{i+1}^2}\right)\right) \quad \text{.......}\ (3)$$

$$min \quad f_2(x)=\sum_{i=1}^{n}\left(|x_i|^{0.8}+5sin\,x_i^3\right) \quad \text{..........................}\ (4)$$

$$x_i\ [-5,5], \quad i=1,\cdots,n, \quad n=10$$

The experiment conditions are: Population size = 512; Problem size = 60. Long-term tabu list size = 4; Long term distance threshold (measured by the Hamming distance) = 1; Short-term tabu list size = 2, Short term distance threshold (measured by the Hamming distance) = 1, and Generation number = 20.

One of the experimental results is shown in Fig.4. From the figure, we observe the Pareto optima are obtained.

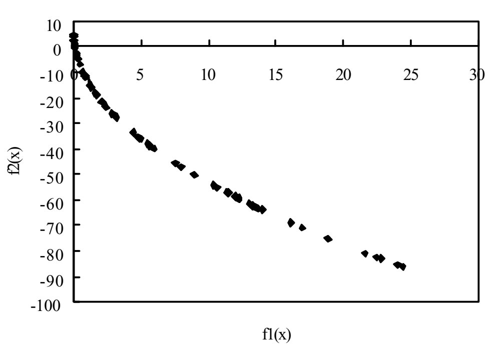

Fig.3 Experiment result (quadratic function).

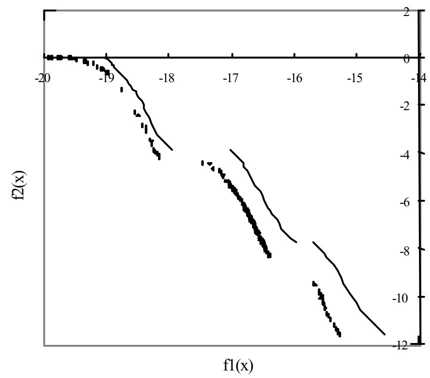

Fig.4 Experiment result (KUR : n=3).

In Fig.4, solid lines represent the Pareto fronts of KUR function (n=3) by NSGA-II and SPEA reported in Deb et al[17]. The plotted points are solutions obtained by Multi-Objective Tanu-BOA. We observe the proposed method works well.

4 Basic Model of Electric Equipment Configuration Problems in a Power Plant

The configuration problems of electric equipments in a power generation plant cover various variety of practical issues, therefore, in this section, we will cope with the one: to minimize the sum of the installation costs of electric equipments and the loss of electric energy in operation, determine the numbers of electric sources, their capacities, the installation places, and the numbers and places of load dispatchers connecting to the power sources. The load dispatchers consist of translators and switches. Each equipment connects to a load dispatcher with cables. If the distance between an equipment and a load dispatcher is so long and they use low voltage cables to connect them, the energy loss will become increasing, thus, it is desirable to use high voltage cables between power sources and load dispatchers. The situation is shown in Fig.5. In the case of Fig.5, the larger numbers of load dispatchers are desirable because the sum of the length of low voltage cables are smaller; this means the cable cost reduction. However, on the other hand, the installation costs of the load dispatchers and the cost of high voltage cables between a power source and the load dispatcher becomes larger. Thus, there are some tradeoffs among these decisions. This makes the difficulty of the problems and needs of multiple solutions. The objective function and constraints are summarized below: Objective: Minimize Sum of Cabling Costs and Loss of Energy in Operation. Constraints: Electric Supply Capacities; Decreases of the Voltage; and Capacity of the Cables. Determine: The number and capacities of Translators, Cables, and Switches; and Cabling Route among the Equipments. The loss of electric energy and the decrease of the voltage are respectively described[18] in equations (5) and (6).

Power Loss : $W_{loss} = 3 \cdot I^2 \cdot R \cdot t$ .... (5)

Voltage Drop : $\Delta V = \sqrt{3} I (R cos\theta + X sin\theta)$ .... (6)

where, ΔV : Voltage Drop, I : Current of the circuit, $cos\,\theta$: Power Factor, R : Resistance of the circuit, X : Reactance of the circuit, and t : time.

The loss of electric energy is calculated during the lifetime of the equipments, namely, 15 years in thermal power plants cases. This causes the problem much more difficult, however, more practical. We also assume that the specifications of translators are also discrete ones. We apply Tabu-BOA to a practical example, which is a simpler version of a real plant configuration.

Fig.6 shows the plant layout. Some part of the generated electric energy is supplied to the equipments from a power source 0 shown at the low left corner of Fig.6 Electric cables are connected each equipment through the cable trays. The dotted lines in Fig.6 represent their routing candidates. The 6,600V high voltage cables are used to connect the power source to the load dispatchers. The black points represent candidate places of the load dispatchers. The number of the candidates is 16 and we must determine which of them are used. Each load dispatcher translates the voltage to 600V, and then the energy is supplied to 10 corresponding equipments through the low voltage cables.

We assume that (1) the allowable number of the load dispatchers is less than or equal to 4, and that (2) the placements and load capacities of each equipment are given from the design specifications.

To apply Tabu-BOA, each individual consists of 76 bit string chromosome: 2 bits to specify the number of the load dispatchers, 16bits for the placements of the load dispatchers, 20 bits for the equipments to connect the load dispatchers, 8 bits for the high voltage cable specification, and 30bits for the low voltage cables. The experiment conditions are: Population size =1024; Long-term tabu list size =10; Long term distance threshold (measured by the Hamming distance) =3; Short-term tabu list size =4, Short term distance threshold (measured by the Hamming distance) = 1, and Generation number = 43.

The objective function is the sum of equipment costs and operating energy loss for 15 years. The procedure to get the objective function value is summarized as follows:

STEP (1) : Generate and Place the load dispatchers up to 4.

STEP (2) : Connect 10 equipments to the load dispatchers.

STEP (3) : Determine the Higher and Lower voltage cables, each of which is selected based on the information shown in Table 1.

STEP (4) : Determine the load capacities of the equipments and translator capacities of the load dispatchers, namely sum up the load capacities of the connected equipments to a load dispatcher and determine the corresponding translator capacity at 13 levels.

STEP (5) : Calculate the cost of each load dispatcher: 5*translator cost + JPN 2,000K

STEP (6) : Calculate the minimum length of the high voltage cables among the power sources and the load dispatchers using the Dijkstra algorithm.

STEP (7) : Check the maximum currency of the high voltage cables: Calculate the currency of each cable and if the result is over the capacity, then remove the individual from the population.

STEP (8) : Check the voltage loss of the high voltage cable: Set the power factor 0.8 and if the loss is larger than 4%, then remove the individual from the population.

STEP (9) : Calculate the cost of the high voltage cables: the cost is determined by 2.0*direct cable cost.

STEP (10) : Calculate the energy loss in operation for the high voltage cables: JPN 13.0/kwh and 15 years operation.

STEP (11) : Calculate the cost of the low voltage cables in the same way at STEPs 6 and 10: The power factor is set to 0.9.

STEP (12) : Calculate the total value of the objective function.

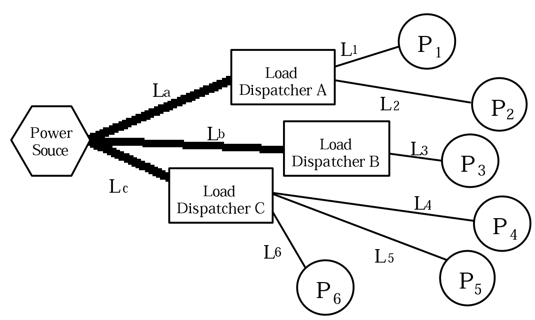

Fig.5 Connection by multi load dispatcher.

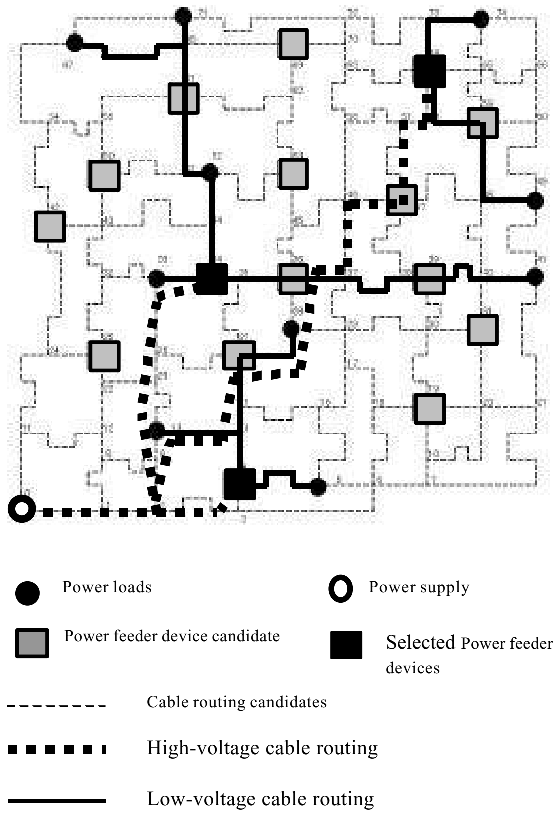

Fig.6 Experiment result (43rd generations).

5 Extending the Configuration Problems to a Multi-Objective One

The problem of the basic model of section 3 is extended to a multi-objective optimization problem in this section. In the actual design, they require to optimize more than one objective at the same time. However, for example, there exist trade-offs among such candidate objectives as “development cost”, “machine performance”, and “reliability”. Therefore, it is impossible to optimize all objectives. To overcome the issue, we must cope with multi-objective optimization problems. In the following arguments, we apply Multi-Objective Tabu-BOA to the configuration problems.

The first objective function is the sum of the initial cost of the equipments and the cost of electric power loss. The second objective function is the marginal supply capacity of load dispatchers in operation. For example, a large ventilator in a power plant has big inertia. When it starts, the bigger power must be supplied. Therefore, at the start time, the currency of the motor is several times larger than that in usual operation. The capacity of load dispatchers may be short when such large ventilators start at the same time. The larger, the marginal capacity of load dispatchers are, the more desirable for operation. Also, for future development of the plant for the equipment addition and remodeling, it is better to let the devices have the larger marginal capacity. Therefore, the second objective function should be maximized. Trade-off exists between the marginal capacity of load dispatchers and the initial and operational costs. This is a typical multi-objective optimization problem. The conditions of the problem we formulate are summarized as follows:

$$min \quad f_1 = \sum C_e + \sum C_l \qquad (7)$$

$$min \quad f_2 = \sum \left(W_i - P_{ij}\right) \qquad (8)$$

$$W_i \geq 1.1 P_{ij}$$

where, C_e : Initial Equipment Cost (kYen), C_l : Operational Power Loss (kYen), W_i : Capacity of Power feeder device i (kW), P_{ij} : Power lord of electric equipment j supplied by power supply i (kW).

Population size =512, the number of generation =40 long-term tabu list size =32 (Hamming distance threshold =30), short-term tabu list size =8 (Hamming distance threshold =30). One of the experiment results is shown in Fig.7. It takes about five minutes to get the results in the same computer environment described in the previous sections.

In Fig.7, we have plotted the individuals of rank 1 of the population of the 40h generation. The individuals form continuous line-shaped curve, this indicates the results are good enough because of the diversity of the population. The concrete solutions at Point A and point B are respectively illustrated

The computational time used to obtain the results in Fig.7 is within 5 minutes in the same PC used in the experiments in Section 2. This is reasonable time to repeatedly apply our method to practical problems with changing the model parameters.

Fig.8 and Fig.9. In these figures, we have observed that the equipment configurations, the numbers of load dispatchers, and the cable route are different from each other. The problem has totally different solutions with the same performance as for the multi-objective functions.

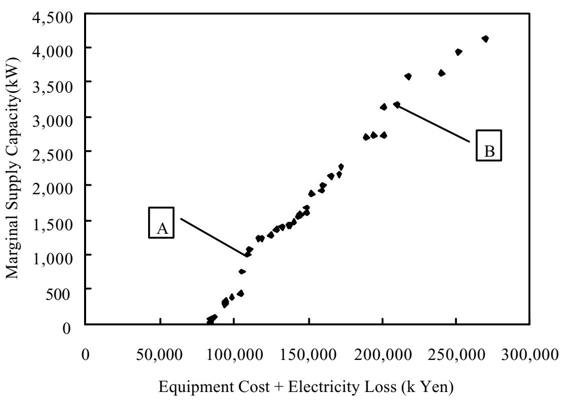

Fig.7 Experiment result (Optimal deign of the electric circuit in the power plant).

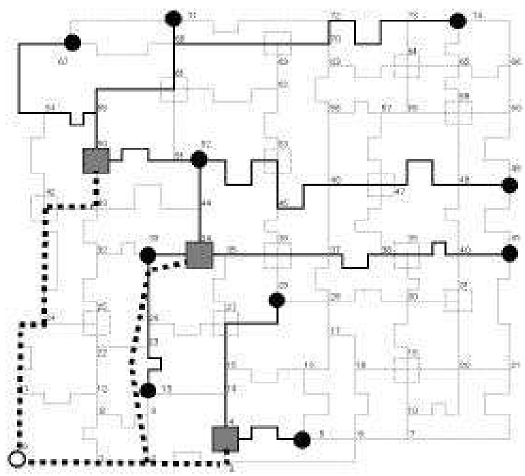

Fig.8 Experiment Result at Point A.

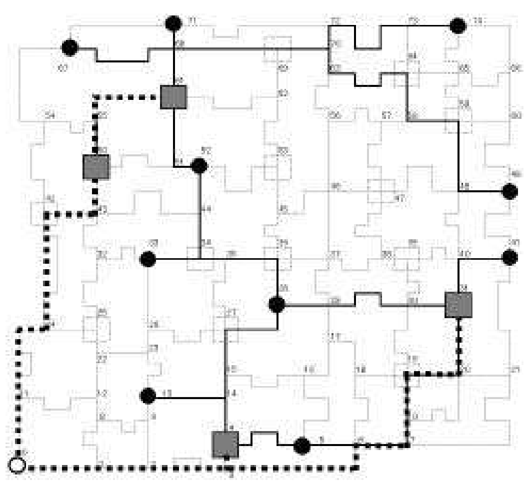

Fig.9 Experiment Result at Point B.

6 Conclusions

In this paper, we have reported the experimental and practical results of multi-objective Tabu-BOA applied to the electric equipment configuration problems in a power plant. So far, the problems have been too complicated and difficult, thus, they have never tried to solve them.

Our method is enough powerful and robust against the practical problems: (1) It takes reasonable computational time to get the solution via multi-objective Tabu-BOA. (2) Pareto optimal solutions with enough diversity are obtained. This means that the proposed method is applicable to resolve practical complex problems by changing preconditions many times.

Our future work includes (1) theoretical investigation and experimental evaluation of Multi-Objective Tabu-BOA, which will be reported elsewhere, and (2) the further development of Tabu-BOA of the real-coded type problems. As for the practical design domains, there are so many cases that a real-code should be handled.

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