An Efficient Simulated Annealing Algorithm for Economic Load Dispatch Problems

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Abstrak

Makalah ini menyajikan suatu algoritma simulated annealing (SA) yang efisien untuk penyelesaian masalah economic load dispatch (ELD) pada sistem tenaga listrik. Filosofi melibatkan pengenalan variabel keputusan baru melalui transformasi matematika secara bijaksana hubungan antara variabel keputusan dan pembangkitan optimal. Tujuan dari masalah ELD dalam pembangkit tenaga listrik adalah pemrograman khusus keluaran unit pembangkit sehingga dapat memenuhi kebutuhan beban dengan jumlah biaya operasional terendah yang memenuhi semua unit dan kendala persamaan dan pertidaksamaan sistem. Pendekatan optimisasi global terinspirasi oleh proses pendinginan termodinamika. Algoritma SA yang diusulkan disini diterapkan pada dua studi kasus, yang menganalisis sistem tenaga yang memiliki tiga dan enam unit pembangkit. Hasil yang diperoleh dengan pendekatan yang diusulkan dibandingkan dengan pemrograman kuadratik konvensional (QP) dan algoritma genetika (GA).

Kata kunci: *economic load dispatch, simulated annealing, pemrograman kuadratik, algoritma genetika, efisien, optimisasi global*

Abstract

This paper presents an efficient simulated annealing (SA) algorithm with a single decision variable to solve the economic load dispatch (ELD) problems. The philosophy involves the introduction of a new decision variable through a prudent mathematical transformation of the relation between the decision variable and the optimal generations. The objectives of ELD problems in electric power generation is to programmed the devoted generating unit outputs so as to meet the mandatory load demand at lowest amount operating cost while satisfying all units and system equality and inequality constraints. Global optimization approaches is inspired by annealing process of thermodynamics. The proposed SA algorithm presented here is applied to two case studies, which analyze power systems having three, and six generating units. The results determined by the proposed approach are compared to those found by conventional quadratic programming (QP) and genetic algorithm (GA).

Keywords: *economic load dispatch, simulated annealing, quadratic programming, genetic algorithm, efficient, gobal optimization*

1. Introduction

Economic load dispatch (ELD) is one of the most important problems in power system operation and planning. The main objective of ELD is to determine the optimal combination of power outputs of all generating units to meet the required load demand at minimum operating cost while satisfying system equality and inequality constraints [1]. In this problem, fuel cost of generation is represented as cost curves and overall calculation minimizes the operating cost by finding a point where total output of generators equals to total system load that must be delivered plus losses. In the traditional ELD problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based on the optimization techniques such as lambda-iteration method, gradient-based method, etc. [2].

Classical methods like Newton-based and gradient methods cannot perform very well for problems having highly nonlinear characteristics with large number of constraints and many local optimum solutions. Dynamic programming is one of the approached to solve non-linear and discontinuous ELD problem, but it suffers from problem of curse of dimensionality or local optimality [3]. Methods based on artificial intelligence techniques, such as artificial neural

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networks, are presented [4-6]. However, neural network-based approaches may suffer from excessive numerical iterations, resulting in huge calculations. Heuristic search techniques, such as evolutionary programming [7], particle swarm optimization [8], genetic algorithms [9-11], differential evolution [12], tabu search [13] and ant colony optimization [14] have also been successfully applied to ELD problems.

Simulated annealing (SA) algorithm is a promising heuristic algorithm for handling the combinatorial optimization problems. It has been theoretically proved that SA algorithm converges to the optimal solution. Another strong feature of SA algorithm is that a complicated mathematical model is not required and the problem constraints can be easily incorporated. In power systems, SA has been applied to a number of power system optimization problems with impressive successes [15, 16].

In this paper, the proposed SA is discussed to solve the ELD problem by considering the linear equality and inequality constraints for the three units and six units system and the results were compared with conventional quadratic programming and GA. The algorithm described in this paper is capable of obtaining optimal solutions efficiently.

2. Research Method

2.1. Economic Load Dispatch Formulation

The objective of an ELD problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying an equality constraint and inequality constraints. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output from the generating units. For a given power system network, the problem may be described as optimization (minimization) of total fuel cost as defined by (1) under a set of operating constraints.

$$F_T = \sum_{i=1}^{N} F(P_i) = \sum_{i=1}^{N} \left(a_i P_i^2 + b_i P_i + c_i \right) \tag{1}$$

where F_T is total fuel cost of generation in the system ($/hr), a_i, b_i, and c_i are the cost coefficient of the i th generator, P_i is the power generated by the i th unit and N is the number of generators.

The cost is minimized subjected to the following power balance and generator capacity constraints.

2.1.1. Power Balance Constraint:

$$\sum_{i=1}^{N} P_i - P_D - P_{Loss} = 0 \tag{2}$$

where P_D is the total power demand and P_{Loss} is total transmission losses.

The transmission loss P_{Loss} can be calculated by using **B** matrix technique and is defined by (3) as,

$$P_{Loss} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j \tag{3}$$

where B_{ij} 's are the elements of loss coefficient matrix **B**.

2.1.2. The Generator Capacity Constraint:

$$P_{i,\min} \le P_i \le P_{i,\max} \quad \text{for} \quad i = 1,2,\cdots,N \tag{4}$$

where $P_{i,\, min}$ and $P_{i,\, max}$ are the minimum and maximum power output of the i th unit.

The conditions for optimality can be obtained by using Lagrangian multipliers method and Kuhn Tucker conditions as follows [1]:

$$2a_i P_i + b_i = \lambda \left(1 - 2\sum_{j=1}^{N} P_i B_{ij} \right), i = 1, 2, \ldots, N \tag{5}$$

The following steps are followed to solve the economic load dispatch problem with the constraints:

Step-1: Allocate lower limit of each plant as generation, evaluate the transmission loss and incremental loss coefficients and update the demand.

$$\begin{aligned} & P_i = P_{i\,\min}\,,\; X_i = 1 - \sum_{j=1}^{N} P_i B_{ij} \\ & P_D^{new} = P_D + P_{Loss}^{old} \end{aligned} \tag{6}$$

Step-2: Apply quadratic programming to determine the allocation P_i^{new} of each plant. If the generation hits the limit, it should be fixed to that limit and the remaining plants only should be considered for next iteration.

Step-3: Check for the convergence:

$$\left| \sum_{i=1}^{N} P_i - P_D^{new} - P_{Loss} \right| \le \varepsilon \tag{7}$$

where ε is the tolerance. Repeat until the convergence criteria is meet.
A brief description about the quadratic programming method is presented in the next section.

2.2. Quadratic Programming Method

A linearly constrained optimization problem with a quadratic objective function is called a quadratic programming (QP) [17]. Due to its numerous applications; quadratic programming is often viewed as a discipline in and of itself. Quadratic programming is an efficient optimization technique to trace the global minimum if the objective function is quadratic and the constraints are linear. Quadratic programming is used recursively from the lowest incremental cost regions to highest incremental cost region to find the optimum allocation. Once the limits are obtained and the data are rearranged in such a manner that the incremental cost limits of all the plants are in ascending order.

The general quadratic programming can be written as:

Minimize $f(x) = cx + \frac{1}{2} x^T Q x$ (8)

Subject to $Ax \le b$ and $x \ge 0$ (9)

where **c** is an *n*-dimensional row vector describing the coefficients of the linear terms in the objective function, and **Q** is an (*n* × *n*) symmetric matrix describing the coefficients of the quadratic terms. If a constant term exists it is dropped from the model. As in linear programming, the decision variables are denoted by the *n*-dimensional column vector **x**, and the constraints are defined by an (*m*× *n*) **A** matrix and an *m*-dimensional column vector **b** of right-hand-side coefficients. We assume that a feasible solution exists and that the constraint region is bounded. When the objective function *f*(**x**) is strictly convex for all feasible points the problem has a unique local minimum which is also the global minimum. A sufficient condition to guarantee strictly convexity is for **Q** to be positive definite.

If there are only equality constraints, then the QP can be solved by a linear system. Otherwise, a variety of methods for solving the QP are commonly used, namely; interior point, active set, conjugate gradient, extensions of the simplex algorithm etc. The direction search algorithm is minor variation of quadratic programming for discontinuous search space. For every demand the following search mechanism is followed between lower and upper limits of those particular plants. For meeting any demand the algorithm is explained in the following steps:

(i) Assume all the plants are operating at lowest incremental cost limits.
(ii) Substitute $P_i = L_i + (U_i - L_i)X_i$,
(iii) Where $0 < X_i < 1$ and make the objective function quadratic and make the constraints linear by omitting the higher order terms.
(iv) Solve the ELD problem using quadratic programming recursively to find the allocation and incremental cost for each plant within limits of that plant.
(v) If there is no limit violation for any plant for that particular piece, then it is a local solution.
(vi) If for any allocation for a plant, it is violating the limit. It should be fixed to that limit and the remaining plants only should be considered for next iteration.
(vii) Repeat steps 2, 3, and 4 till a solution is achieved within a specified tolerance.

2.3. Simulated Annealing Algorithm
2.3.1. Overview

Simulated annealing is an optimization technique that simulates the physical annealing process in the field of combinatorial optimization. Annealing is the physical process of heating up a solid until it melts, followed by slow cooling it down by decreasing the temperature of the environment in steps. At each step, the temperature is maintained constant for a period of time sufficient for the solid to reach thermal equilibrium. At any temperature *T*, the thermal equilibrium state is characterized by the *Boltzmann distribution*. This distribution gives the probability of the solid being in a state *i* with energy E_i at temperature *T* as

$$P_i(T) = k\exp\left(-E_i / T\right) \tag{10}$$

where *k* is a constant.

Metropolis et al. [18] proposed a Monte Carlo method to simulate the process of reaching thermal equilibrium at a fixed value of the temperature *T.* In this method, a randomly generated perturbation of the current configuration of the solid is applied so that a trial configuration is obtained. Let E_c and E_t denote the energy level of the current and trial configurations, respectively. If $E_t < E_c$; then a lower energy level has been reached, and the trial configuration is accepted and becomes the current configuration. On the other hand, if $E_t \geq E_c$ the trial configuration is accepted as current configuration with probability proportional to exp($\Delta E/T$), $\Delta E = E_t - E_c$. The process continues until the thermal equilibrium is achieved after a large number of perturbations, where the probability of a configuration approaches Boltzmann distribution [19, 20].

By gradually decreasing the temperature *T* and repeating Metropolis simulation, new lower energy levels become achievable. As *T* approaches *zero* least energy configurations will have a positive probability of occurring. The flowchart of simulated annealing (SA) is shown in Figure 1. The general algorithm of SA can be described in steps as follows:

Step 1: Set the initial value of C_{p0} and randomly generate an initial solution x_{initial} and calculate its objective function. Set this solution as the current solution as well as the best solution, i.e. $x_{\text{initial}} = x_{\text{current}} = x_{\text{best}}$
Step 2: Randomly generate an n_1 of trial solutions in the neighborhood of the current solution.
Step 3: Check the acceptance criterion of these trial solutions and calculate the acceptance ratio. If acceptance ratio is close to 1 go to Step 4; else set $C_{p0} = \alpha.C_{p0}$; $\alpha > 1$; and go back to Step 2.
Step 4: Set the chain counter *k* = 0.

Step 5: Generate a trial solution x_{trial}. If x_{trial} satisfies the acceptance criterion set $x_{current} = x_{trial}$, $J(x_{current}) = J(x_{trial})$ and go to Step 6; else go to Step 6.
Step 6: Check the equilibrium condition. If it is satisfied go to Step 7; else go to Step 5.
Step 7: Check the stopping criteria. If one of them is satisfied then stop; else set $k = k + 1$ and $C_p = \mu.C_p$; $\mu < 1$; and go back to Step 5.

2.3.2. Proposed SA

In all the existing SA algorithm based approaches for solving ELD problems, the real power generation of all generating units are considered as the decision variables that makes the size of the problem vary large, slow down the speed of these algorithms and hence not suitable for systems having larger number of generating units. In the proposed approach, the penalty factor λ of the classical λ - iteration is considered as the only decision variable irrespective of the number of generating units. The real power of all the generating plants are considered as the problem dependant variables and expressed as a function of λ. The real power generations are computed using (5) for each λ value obtained during the SA iterations.

The lower and upper limits of the decision variable-λ depend on the minimum and maximum power demands that the system can supply. The first step in obtaining these values is to compute the lower and upper incremental cost values by substituting the respective to real power limits in (5) for all the plants as

$$\begin{aligned} IC_i^{\min} &= 2a_i P_i^{\min} + b_i \\ IC_i^{\max} &= 2a_i P_i^{\max} + b_i \end{aligned} \tag{11}$$

The next step is choosing the lowest and highest incremental cost value, obtained from (11), as the limits for λ.

$$\begin{aligned} \lambda^{\min} &= \min\left(IC_1^{\min}, IC_2^{\min}, \ldots, IC_N^{\min}\right) \\ \lambda^{\max} &= \max\left(IC_1^{\max}, IC_2^{\max}, \ldots, IC_N^{\max}\right) \end{aligned} \tag{12}$$

The SA searches for the optimal solution by minimizing a cost function. In the proposed formulation, the net fuel cost of all the generating plant is considered as the cost function. However, a penalty term is included in the cost function to handle the explicit power balance constraint. The penalty term increases the cost function for infeasible solutions. The cost function is therefore built as a blend of fuel cost function and the power balance constraint through the use of a penalty factor as

$$Minimize \quad F_T = \sum_{i=1}^{N} F_i(P_i) + \lambda\left[\sum_{i=1}^{N} P_i - P_D - P_{Loss}\right] \tag{13}$$

The number of decision variables in this formulation is always one, whereas the existing SA based approaches require the generation of all the plants as the variables. This reduction in decision variables will reduce the overall computational burden and improves the convergence rate. The algorithm of the proposed SA for solving the ELD problem is outlined.

1. Read the input data of the ELD problem
2. Set $k = 0$
3. Choose initial temperature T_t, cooling coefficient α, number of iterations for each temperature N_t and maximum number of iterations N_{max}.
4. Choose a random start point λ_0 within the specified range
5. Repeat the following:
    a. Select a random point λ_k from the neighbourhood of λ_0 within the specified range
    b. Solve (5) for P_i while imposing the limits given by (4)
    c. Calculate F_T^k using (13)
    d. If $F_T^k < F_T^0$ then accept the trial solution by setting $\lambda_0 = \lambda_k$

Else select a random number $\Re$ in the range [0, 1]

If $P(T) > \Re$, then $\lambda_0 = \lambda_k$, otherwise discard the trial point

e. Check convergence by comparing the number of iterations *k* with N_{max}

If converged, stop and print the ELD corresponding to the λ_0. Otherwise, set $k = k + 1$

6. Reduce the temperature by the factor *α* and go to step 5.

3. Results and Analysis

To verify the feasibility and effectiveness of the proposed SA algorithm, two different power systems were tested consisting of three and six generating units [21, 22]. Results of the proposed SA algorithm are compared with conventional quadratic programming (QP) and genetic algorithm (GA) methods. A reasonable B-loss coefficients matrix of power system network has been employed to calculate the transmission losses. The software has been written in the MATLAB-7 language.

Case 1: 3-Generating Units

In this case, a simple power system consist of three-generating units is used to demonstrate how the work of the proposed approach. Characteristics of thermal units are given in Table 1, followed by coefficient matrix B_{ij} losses.

Table 1. Generating unit capacity and coefficients

Unit	P_i^{min} (MW)	P_i^{max} (MW)	a_i (\$/MW^2)	b_i (\$/MW)	c_i (\$)
1	50	250	0.00525	8.663	328.13
2	5	150	0.00609	10.04	136.91
3	15	100	0.00592	9.76	59.16

$$B_{ij} = \begin{bmatrix} 0.000136 & 0.0000175 & 0.000184 \\ 0.000175 & 0.0001540 & 0.000283 \\ 0.000184 & 0.0002830 & 0.000161 \end{bmatrix}$$

For the system loads of 275 MW, 300 MW, 350 MW, and 400 MW, the conventional QP method is applied and results obtained are shown in Table 2.

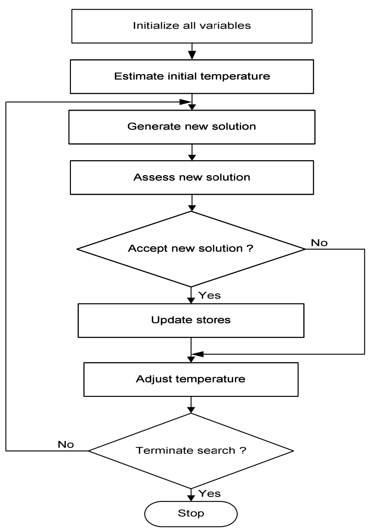

Figure 1. Flowchart of simulated annealing

The optimal scheduling of generators obtained by the proposed SA algorithm for three unit systems is shown in Table 3. The comparison of results between conventional QP method and the proposed SA method are shown in Table 4. The comparison of results shows that the proposed SA algorithm is better than conventional QP method for each loading and it is very reliable in the aspect of solution quality.

Table 2. Economic dispatch for 3-generating units using QP method

P_{Demand} (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_{Loss} (MW)	F_{cost} ($/hr)
275	193.8232	74.7838	15.0000	8.6070	3333.10
300	207.6799	87.4010	15.0000	10.0808	3621.50
350	235.5798	112.8921	15.0000	13.4720	4215.20
400	250.0000	150.0000	19.2169	19.2169	4850.80

Table 3. Economic dispatch for 3-generating units using the proposed SA

P_{Demand} (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_{Loss} (MW)	F_{cost} ($/hr)
275	193.6474	74.8906	15.0002	8.5383	3332.43
300	207.6336	87.2867	15.0000	9.9203	3619.76
350	235.7958	112.2489	15.0006	13.0452	4210.25
400	249.9998	150.0000	16.6752	16.6750	4825.49

Table 4. Comparison of results between QP and the proposed SA for 3-generating units

P_{Demand} (MW)	Methods	P_{Loss} (MW)	F_{cost} ($/hr)
275	QP	8.6070	3333.10
	SA	**8.5383**	**3332.43**
300	QP	10.0808	3621.50
	SA	**9.9203**	**3619.76**
350	QP	13.4720	4215.20
	SA	**13.0452**	**4210.25**
400	QP	19.2169	4850.80
	SA	**16.6750**	**4825.49**

Case 2: 6-Generating Units

In this case, a standard of six-generating units (IEEE 30 bus test systems) is used to demonstrate how the work of the proposed approach, as shown in Figure 2. Characteristics of thermal units are given in Table 5, followed by coefficient matrix B_{ij} losses.

The simulation results using the proposed SA algorithm are shown in Table 6 and Table 7 respectively for the load variation of 700 MW and 800 MW. The simulation results show that the generation outputs of each unit obtained were smaller than those of the genetic algorithm (GA), which is taken from [22]. Further, as a result, there was some reduction of the total generation cost and transmission losses.

Table 5. Generating unit capacity and coefficients

Unit	P_i^{min} (MW)	P_i^{max} (MW)	a_i ($/MW^2)	b_i ($/MW)	c_i ($)
1	10	125	0.0033870	0.856440	16.817750
2	10	150	0.0023500	1.025760	10.029450
3	35	225	0.0006230	0.897700	23.333280
4	35	210	0.0007880	0.851234	27.634000
5	130	325	0.0004690	0.807285	36.856880
6	125	315	0.0003998	0.850454	30.147980

$$B_{ij} = \begin{bmatrix} 0.000140 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\ 0.000026 & 0.000015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\ 0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

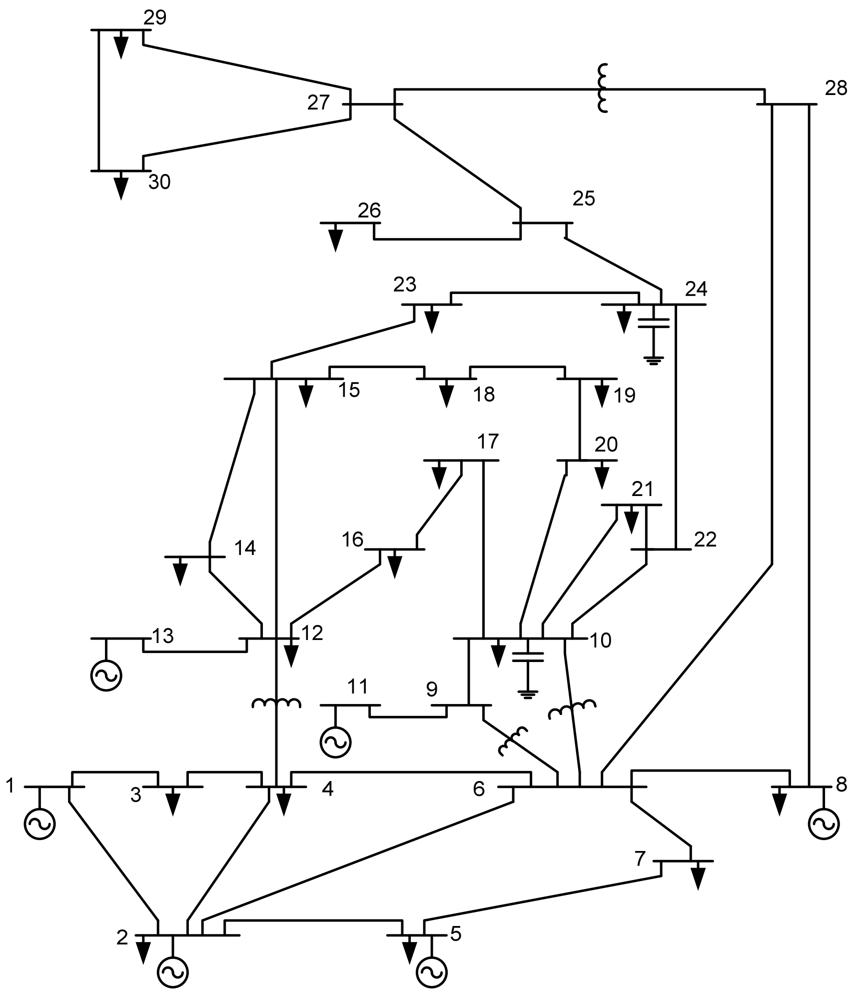

Figure 2. IEEE 30-bus 6-generator test systems

Table 6. Economic dispatch for 6-generating units (P_D = 700 MW)

Unit Output	GA [22]	SA
P1 (MW)	27.3010	26.7391
P2 (MW)	15.6124	12.2597
P3 (MW)	120.3109	126.3482
P4 (MW)	116.7756	117.6017
P5 (MW)	226.8377	230.3174
P6 (MW)	212.4050	205.9579
Total power output (MW)	719.2426	**719.2241**
Total generation cost ($/hr)	820.4200	**820.3707**
Power losses (MW)	19.2426	**19.2241**

Table 7. Economic dispatch for 6-generating units (P_D = 800 MW)

Unit Output	GA [22]	SA
P1 (MW)	32.6737	32.5980
P2 (MW)	15.8161	14.5035
P3 (MW)	141.6623	141.5182
P4 (MW)	131.3117	136.0152
P5 (MW)	252.3711	257.6949
P6 (MW)	251.5507	243.0010
Total power output (MW)	825.3855	**825.3309**
Total generation cost ($/hr)	931.1060	**931.0322**
Power losses (MW)	25.3855	**25.3309**

4. Conclusion

In this paper, an efficient simulated annealing (SA) algorithm with a single decision variable has been successfully introduced to obtain the optimum solution of economic load dispatch problem. The proposed SA method has been tested on two test cases consisting of 3-generating units and 6-generating units systems and the results are compared to those of the conventional quadratic programming method and the GA method. Test results have shown that the proposed method can provide better solution than above mentioned methods.

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