Total Optimization of Smart City by Global-best Brain Storm Optimization

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ABSTRACT

This paper proposes a total optimization method of a smart city (SC) by Global-best brain storm optimization (GBSO). The SC model includes natural gas utilities, electric power utilities, drinking and waste water treatment plants, industries, buildings, residences, and railroads. The proposed method minimizes energy cost, shifts actual electric power loads, and minimizes CO2 emission using the model. Particle Swarm Optimization (PSO), Differential Evolution (DE), and Differential evolutionary particle swarm optimization (DEEPSO) have been applied to the optimization problem. However, there is room for improving solution quality. The proposed GBSO based method is applied to a model which considers a moderately-sized city in Japan, such as Toyama city. The proposed method is compared with the conventional DEEPSO and BSO based methods with promising results.

1 INTRODUCTION

Recently, global warming is one of the main issues in the world [1]. Therefore, the importance of SC increases all over the world. Since it is difficult to evaluate how much the communities can reduce CO_2 emission in actual SC, SC should be evaluated by models. Therefore, a SC model have been developed in Japan so that they can evaluate energy costs or the amount of CO_2 emission of the whole SC [2-4].

The authors have already proposed total optimization of whole SC to minimize energy costs, electric power loads at high load hours namely, peak load shifting, and CO2 emission using the developed model and PSO [5], DE [6], and DEEPSO [7]. In addition, reduction of search space considering not only facility characteristics, but also load and cost characteristics and continuity of weekday operation have been also proposed [5][6]. However, there is still room for improving solution quality.

This paper proposes total optimization of SC by GBSO. The results by the proposed method are compared with those by the conventional DEEPO and brain storm optimization (BSO) based methods. The details of the problem formulation can be found in [7].

2 TOTAL OPTIMIZATION OF A SMART CITY

GBSO is proposed to improve BSO[8] performance. The modifications which are adopting a fitness-based grouping mechanism, and using the global-best idea information for updating the population were proposed in [9]. A fitness-based grouping and updating the population considering the global-best idea are shown as follows:

A. Clustering: Fitness-based grouping (FbG) is utilized in GBSO. FbG algorithm is shown below:

Step. 1 Rank individuals using objective function values in descending order.

Step. 2 Divide M individuals into K groups using (1).

$$g(i) = (i-1)\%K + 1 \qquad (i = 1,..,M)) \tag{1}$$

where, $g(i)$ is the group number of individual i.

B. New individual generation: GBSO follows the same process as BSO's. However, GBSO consider information of $gbest$ which is the best individual so far among all individuals before new individual generation if a condition (3) is satisfied. The condition is shown below:

$$C = C_{min} + \frac{iter}{ITER} \times (C_{max} - C_{min}) \tag{2}$$

$$C < rand(1,0) \tag{3}$$

where, C is a probability utilized to determine whether the g-best information is utilized or not, $Cmax$ is the maximum value of C, $Cmin$ is the minimum value of C.

If (3) is satisfied, x_{ij}^{old} is modified using the following equation:

$$x_{ij}^{old} = x_{ij}^{old} + rand(DimSize, 1) \times C \times (x^{gbest} - x_{ij}^{old}) \tag{4}$$

where, $DimSize$ is dimension size.

Through pre-simulation, since dimension size of the problem is too big to be considered in an equation and $rand(DimSize, 1)$ is changed to $rand(1, 0)$ in this paper. In addition, considering (2), (3), and (4), the $gbest$ information tends to be considered at the

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early stages of iterations more than the final stages of iterations. However, usually, it is considered that exploration should be applied at the early stages and exploitation should be applied at the final stages, in evolutionary computation. Therefore, $C < rand(1,0)$ is changed to $C > rand(1,0)$ in this paper.
Consequently, In the proposed method, conditions (3) and (4) are changed to (5) and (6) as shown below:

$$C > rand(1,0) \tag{5}$$

$$x_{ij}^{old} = x_{ij}^{old} + rand(1,0) \times C \times (x_j^{gbest} - x_{ij}^{old}) \tag{6}$$

3 SIMULATIONS

3.1 Simulation Conditions

The proposed method is applied to a typical mid-sized smart city like Toyama city in Japan. The following are the number of models in each sector so that ratios of various sector loads using models are about the same as the ratios of various sector loads in Toyama city [10]:

Drinking water treatment plant: 1, Waste water treatment plant: 1, Industry model: 15, Building model: 50, Residential model: 45000, Railroad: 1

The proposed method is compared with the conventional DEEPSO [7] and BSO based methods.
Three cases are utilized. Case 1 is minimization of energy costs and actual electric power loads at peak load hours. Case 2 is minimization of CO_2 emission and actual electric power loads at peak load hours. Case 3 is minimization of energy costs, CO_2 emission, and actual electric power loads at peak load hours. Parameters of the objective function are set to the following values to keep the calculated values of all terms as same as possible (case 3).

Case 1: w_1 : 1, w_2 : 0, w_3: 0
Case 2: w_1 : 0, w_2 : 0, w_3: 1
Case 3: w_1 : 0.00001, w_2 : 0.99998, w_3: 0.00001

The following parameters are utilized for DEEPSO:
τ is set to 0.2, τ' is set to 0.006, p is set to 0.75, the initial weight coefficients of each term (A, B, and C) are set to 0.5, the number of clones are set to 1.
The following are parameters for BSO and MBSO:

$p_{clustering}$: 0.5 , $p_{generation}$: 0.5 , $p_{OneCluster}$: 0.2 , $p_{TwoCluster}$: 0.2, pr: 0.005, C_{min}: 0.5, C_{min}: 0.5

The maximum numbers of iteration for BSO and the proposed GBSO based methods are set to 4000. However, DEEPSO utilizes twice evaluation for both new and clone agents. Therefore, the maximum iteration number for DEEPSO is set to 2000 in order to set the same number of evaluations. The number of agents is set to 50, and the number of trials is set to 50. Initial searching points are set randomly.
The simulation software has been developed using C language (gcc version 4.92 on Cygwin) on a PC (Intel Core i7 (3.60GHz)).

3.2 Simulation Results

Table 1 shows comparison of average, the minimum, the maximum, and standard deviation of the objective function values of Case 1, 2, and 3 among DEEPSO, BSO, and the proposed GBSO based methods. All of values are rates when the average of the objective function is set to 100 % by the DEEPSO based method. It is verified that average, the maximum, and the minimum values by the proposed method can be reduced the most among DEEPSO, BSO, and the proposed GBSO at all cases.

Table 1: Comparison of average, the minimum, the maximum, and standard deviation values for case 1, 2, and 3 by DEEPSO, BSO, and the proposed based methods.

		Ave.	Min.	Max.	Std.
	DEEPSO	100.00	98.88	103.09	0.72
Case 1	BSO	98.45	97.34	99.38	0.51
	GBSO	**96.81**	**95.96**	**97.60**	**0.33**
	DEEPSO	100.00	99.61	100.40	0.21
Case 2	BSO	99.76	99.36	100.09	**0.17**
	GBSO	**99.24**	**98.71**	**99.71**	0.21
	DEEPSO	100.00	99.11	101.02	0.52
Case 3	BSO	99.52	99.23	99.66	**0.09**
	GBSO	**99.16**	**98.95**	**99.38**	0.10

*) All of values are rates when average of the objective function value by DEEPSO based method is set to 100 %.

4 CONCLUSION

This paper proposes a total optimization method of a smart city by GBSO. The proposed GBSO based method can generate better results than DEEPSO and BSO based methods. The proposed method can minimize energy costs, actual electric power at high load hours, and the amount of CO_2 emission.
As a future work, more effective methods for large-scale SC optimization problem will be investigated considering uncertainty of renewable energy.

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