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

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Abstract: This paper proposes a total optimization method of a smart city (SC) by Global-best Modified Brain Storm Optimization (GMBSO). Almost all countries have a goal to reduce CO2 emission as the countermeasures of global warming. In addition, these countries have conducted SC demonstration projects. The problem of the paper considers CO_2 emission, energy cost, and electric power load at peak load hours. In order to solve the problem, Differential Evolutionary Particle Swarm Optimization (DEEPSO), Modified Brain Storm Optimization (MBSO), and Global-best Brain Storm Optimization (GBSO) have been applied to the problem. This paper proposes a novel evolutionary computation method, called Global-best Modified Brain Storm Optimization (GMBSO), which is a combined method of GBSO and MBSO in order to obtain better results. The total optimization of SC is solved by the proposed GMBSO based method. The results by the proposed GMBSO based method is compared with those by conventional DEEPSO, BSO, only GBSO, and only MBSO based methods.

1 INTRODUCTION

Many environmental problems have been focused recently in the world and one of the main problems is global warming. Increase of the amount of CO_2 emission can be considered as the reason of the global warming (Ministry of Economy, Trade, and Industry of Japan, 2014; Xcel Energy, 2007; Jaber, 2006). Hence, it is important that we should "efficiently" utilize energy for reduction of the emission. SC can be defined that it realizes a sustainable city considering reduction of carbon dioxide emission using various IT technologies, and renewable energies such as wind power and photovoltaic generation, and storage batteries. In 2011, Great East Japan Earthquake struck Tohoku in Japan. Hence, many SC has been considered in Tohoku especially after 2011 (Tohoku Bureau of Economy, Trade and Industry, 2012).

Usually it is difficult to obtain quantitative evaluation of reduction rate of carbon dioxide emission, and purchased electric power and natural gas cost. Hence, SC model should be developed for the numerical evaluation. Various models of each sector in SC has been separately developed. (Marckle, et al., 1995; Henze, 2000; Suzuki, et al., 2012; Makino, et al., 2015). However, as far as the authors know, no research can be found for the total SC model which can numerically calculate purchased electric power and natural gas cost, and environmental loads with interaction of all sectors in SC. Hence, IEE of Japan team have developed SC model which can numerically calculate CO_2 emission and energy cost with interaction of all sectors (Yasuda, 2015; Yamaguchi, et al., 2015; Matsui, et al., 2015).

The authors have conducted researches on total optimization of SC using the SC model with interaction among all sectors. The SC optimization problem minimizes purchased electric power and natural gas cost, shifts peak load, and minimizes CO_2 emission. In addition, the authors have applied many evolutionary computation techniques (particle swarm optimization (PSO) (Sato, and Fukuyama, 2016a), differential evolution (DE) (Sato, and Fukuyama, 2016b), differential evlutionary particle swarm optimization (DEEPSO) (Sato, and Fukuyama, 2017), and global-best brain storm optimization (GBSO) (Sato, and Fukuyama, 2018)). As far as authors know, these researches are the the first trial in the world. However, it has a possibility to realize

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more reduction of CO_2 emission, more shift of actual electric power, and more reduction of the purchased electric power and natural gas cost. The optimization results can be improved when the more effectve evolutionary computation method is applied to the SC prroblem.

The paper proposes Global-best Modified Brain Storm Optimization (GMBSO), which is a new evolutionary computation method and a combined method of GBSO and MBSO considering these backgrounds. The proposed method is applied to a total optimization problem of SC. The results by the proposed method are compared with those by DEEPSO, BSO, only GBSO, and only MBSO based methods.

2 SMART CITY MODEL

2.1 Concept of the Whole Smart City

IEE of Japan had developed the SC model with interaction of all sectors. It can numerically calculate cost of electric power and natural gas which is purchased and CO_2 emission (Yasuda, 2015). The model includes various sectors which are divided into supply-side group and demand-side group (see fig.1). The supply-side group consists of drinking water and waste water treatment plants, and electric power and natural gas utilities sectors. The demand-side group consists of railroad, residences, building, and industrial sectors.

2.2 Supply-side Group Sectors

Supply-side group sectors supply natural gas, electric power, and drinking water. The models can supply the energies, and the amount of the energies is equal to the amount of the energies which are consumed by demand-side group. Details are shown in Yamaguchi, et al. (2015).

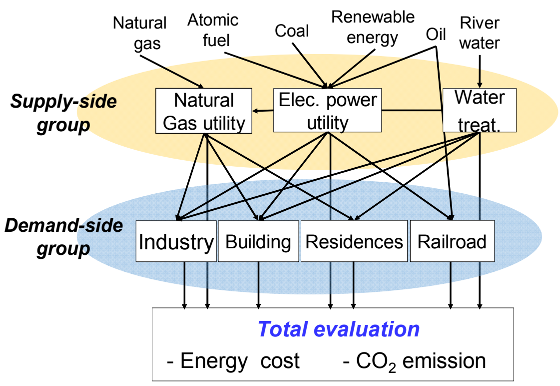

Figure 1: A Configuration of a smart city model.

2.3 Demand-side Group Sectors

The demand-side group cooperates with the supply-side group. The demand-side group can obtain natural gas, electric power, and drinking water from the supply-side group. Loads of various energies in the demand-side group, which are electric power, heat, steam, and hot water are obtained with fixed values. The demand-side group sectors generate or purchase energies in order to satisfy the energy loads. Details are shown in Matsui, et al. (2015).

3 PROBALEM FORMULATION OF TOTAL OPTIMIZATION OF WHOLE SMART CITY

3.1 Decision Variables

Decision variables are listed as follows:

- Drinking water treatment plant sector
  - (D1) Inflow from river,
  - (D2) Inflow of water into a service reservoir,
  - (D3) Output of electric power of a co-generator (CoGen),
  - (D4) Charged or discharged electric power of a storage battery (SB).
- Waste water treatment plant sector
  - (W1) Input of Pumped waste water,
  - (W2) Output of electric power of a CoGen,
  - (W3) Charged or discharged electric power of a SB.
- Industrial sector
  - (I1) Output of electric power of a gas turbine generator (GTG),
  - (I2) Heat output of turbo refrigerators (TRs),
  - (I3) Heat output of stream refrigerators (SRs),
  - (I4) Charged or discharged electric power of a SB.
- Building sector
  - (B1) Output of electric power of a GTG,
  - (B2) Heat output of TRs,
  - (B3) Heat output of SRs.
- Residential sector
  - (R1) Heat output of SRs,
  - (R2) Output of electric power of a fuel cell,
  - (R3) Heat output of a heat pump water heater.
  - (R4) Charged or discharged electric power of a SB
- Railroad sector

(RR1) The number of passengers / h,
(RR2) Average of journey distance by one passenger / h,
(RR3) The number of operated trains / h,
(RR4) The numbers of passenger cars / set,
(RR5) Average of journey distance by one train / h,
(RR6) Average of speed / h,
(RR7) The number of passengers / car

24 hour's variables should be considered for each decision variables. Totally, there are 816 decision variables. Hence, the problem is one of the large-scale optimization problems.

3.2 Objective Function

Usually various SC have each purpose for realizing SC. Three terms are dealt in order to consider each purpose. Minimization of energy cost is the first term considering SC such as industrial parks. Minimization of actual electric power loads at peak load hours is the second term, namely, peak load shifting. The actual electric power load at each hour is summation of electric power changed to the other energies, the original load of electric power, and electric power charged to the storage battery at each hour. Interval of hours, when total actual electric power loads of all sectors are higher than the average of total actual electric power loads, are defined as peak load hours. Minimization of CO_2 emission is the third term considering SC such as local governments.

$$min\left\{w_1 \sum_{s=1}^{Sec}\sum_{t=1}^{H}(PurG_{st} \times UC_{st}^{G} + PurE_{st} \times UC_{st}^{E}) + w_2 \sum_{s=1}^{Sec}\sum_{p=PST}^{PET}(AL_{sp}) + w_3 \sum_{s=1}^{Sec}\sum_{t=1}^{H}(BuyG_{st} \times C^{G} + BuyE_{st} \times C^{E})\right\} \quad (1)$$

where Sec is the number of all sectors, H is the number of hours per day (=24), $PurG_{st}$ is natural gas which is purchased of sector s at hour t, UC_{st}^{G} is a unit cost of natural gas which is purchased of sector s at hour t, $PurE_{st}$ is electric power which is purchased by sector s at hour t, UC_{st}^{E} is a unit cost of electric power which is purchased by sector s at hour t, AL_{sp} is an actual electric power load of sector s at hour p, PST is the start hour of peak load hours of actual electric power loads, PET is the final hour of peak load hours of actual electric power loads, C^{G} is a coefficient for changing from natural gas, which is purchased, to CO2 emission, C^{E} is a coefficient for changing from electric power, which is purchased, to CO2 emission, w_1, w_2, and w_3 are weighting coefficients ($w_1 + w_2 + w_3 = 1$).

3.3 Constraints

There are two constraints for treatment of energy balances and facility characteristics.

- Energy balances: In the model, there are many energies such as electric power, natural gas and so on. Energy balances are expressed with (2).

$$eb_{se}(y_i, z_i) = 0, \quad (i = 1, \ldots, DNum, s = 1, \ldots, Sec, e = 1, \ldots, En_s) \quad (2)$$

where y_i is startup or shutdown status of a facility for decision variable i, z_i is an input or output value of a facility for decision variable i, $eb_{se}(y_i, z_i)$ is an energy balance of energy e in sector s, $DNum$ is the number of decision variables, En_s is the number of energies in sector s.

- Facility characteristics: Efficiency functions of Facilities, and upper and lower bounds of various facilities can be expressed with (3):

$$fc_{sr}(y_i, z_i) \leq 0, \quad (i = 1, \ldots, DNum, s = 1, \ldots, Sec, r = 1, \ldots, R_s) \quad (3)$$

where $fc_{sr}(y_i, z_i)$ is a function for efficiency of a facility or an upper and lower bounds of facility r of sector s, R_s is the number of facilities in sector s.

The problem deals with discrete and continuous variables. Start-up / shutdown status can be expressed as discrete variables, and input and output values of facilities can be expressed as continuous variables. Some characteristics of various facilities are expressed as nonlinear functions. Hence, the problem can be categorized into a mixed integer nonlinear optimization programming problem. Hence, various evolutionary computation methods have to be applied.

4 TOTAL OPTIMIZATION OF A SMART CITY BY GMBSO

4.1 Overview of BSO

This paper proposes a new evolutionary computation method, GMBSO. The proposed GMBSO is based on BSO. BSO has been developed by Shi in 2011 (Shi, et al., 2011) inspired by brainstorming. The main algorithm of BSO is expressed in this section:

Step.1 $IndN$ individuals are randomly generated and $IndN$ individuals are evaluated.
Step.2 $IndN$ individuals are divided into NK clusters by k-means based algorithm.
Step.3 $IndN$ new individuals are generated.
Step.4 The individuals which are generated at step. 3 are compared with the current individuals with the same individual number. The better individual is set as the new current individual.
Step.5 Compare the current individuals with the best individual. The individual is recorded as the best individual if the current individual is better than the pre-best individual.
Step.6 The procedure is stopped and go to Step.7 if the number of current iteration reaches the maximum number of iteration which was pre-determined. Otherwise, go to Step.2 and repeat the procedures.
Step.7 Finally, output the results.

4.1.1 Clustering (Step. 2)

BSO deals with clustering in order to divide search space to several regions using k-means based algorithm. The clustering algorithm is explained as follows:
Step.1 $IndN$ individuals are divided into NK clusters by k-means.
Step.2 a value r_c is generated using random number in the range from 0 to 1.
Step.3 All individuals are ranked according to the objective function values of each individual in each cluster. if $r_c \geq p_c$ (pre-determined probability),set the best individual in each cluster as the cluster center in each cluster. Otherwise, one individual is randomly generated, and the generated individual is set as the cluster centre.

4.1.2 New Individual Generation (Step. 3)

Using one or two current individual(s), a new individual can be generated. The following equations are utilized for new individual generation:

$$newx_{ij} = oldx_{ij} + \xi(t) \times r(1,0) \tag{4}$$

$$\xi(t) = logsig\left(\frac{0.5 \times MaxIter - iter}{c}\right) \times r(1,0) \tag{5}$$

$$oldx_{ij} = r(1,0)_i \times s1x_{ij} + (1 - r(1,0)_i) \times s2x_{ij} \tag{6}$$
$$(i = 1, \ldots, IndN, j = 1, \ldots, DNum)$$

where $newx_{ij}$ is decision variable j of new individual i, $oldx_{ij}$ is decision variables j of the ith current individual, $\xi(t)$ is a step size function, $MaxIter$ is the maximum number of iteration, $iter$ is the current iteration number, c is a coefficient in order to change slope of log sigmoid transfer function, $s1x_{ij}$ and $s2x_{ij}$ are decision variables j of ith new generation which are centers or randomly selected other individuals of selected clusters, $r(1,0)$ is a randomly generated value in the range from 0 to 1, and $r(1,0)_i$ is a randomly generated value in the range from 0 to 1 for individual i.
Equations (4) and (5) are utilized when one individual is utilized in order to generate one new individuals. Equation (4) to (6) are utilized when two individuals are utilized in order to generate one new individual. There are four conditions for determining $oldx_{ij}$ as shown below:

If $p_{one}$is smaller than $r(1,0)$,
  Randomly select one cluster.
  If p_{OC} is bigger than $r(1,0)$,
    Set the cluster centre from the selected cluster as $oldx_{ij}$. Then, one new individual is generated using (4) and (5).
  Otherwise,
    Randomly select one cluster and randomly select one individual as $oldx_{ij}$ from the selected cluster randomly and generate one new individual using (4) and (5).
Otherwise,
  Randomly select two clusters.
  If p_{TC} is smaller than $r(1,0)$,
    the two cluster centers are set as $s1x_{ij}$ and $s2x_{ij}$ and combined using (6). Using the combined $oldx_{ij}$, one new individual is generated using (4) and (5).
  Otherwise,
    Randomly select two individuals from each selected cluster. Set these selected individuals as $s1x_{ij}$ and $s2x_{ij}$, and combine them using (6). Using the combined $oldx_{ij}$, one new individual is generated using (4) and (5).

4.2 Overview of GBSO

GBSO has been proposed by El-Abd in 2017. The method improves original BSO performance (El-Adb, 2017). Fitness-based grouping (FbG) is utilized as clustering method instead of k-means in GBSO. In addition, when a certain condition is satisfied, information of the best individual among all individuals (gbest) is applied to the current individuals.

4.2.1 Clustering for GBSO

GBSO utilizes FbG as a clustering method. Algorithm of FbG can be expressed as follows:

Step. 1 All individuals are ranked according to the objective function values.

Step. 2 All individuals are divided into K groups using (7).

$$g_i = (r_i - 1)\%K + 1 (i = 1, .., IndNum) \quad (7)$$

where g_i is the group number of individual i, and r_i is a ranking of individual i.

4.2.2 New Individual Generation for GBSO

When the following condition (9) is satisfied, $gbest$ information is added to the current individuals.

$$C = C_{min} + \frac{iter}{ITER} \times (C_{max} - C_{min}) \quad (8)$$

$$C < rand(1,0) \quad (9)$$

where C is a probability utilized to determine whether the $gbest$ information is utilized or not, C_{max} is the maximum value of C, C_{min} is the minimum value of C.

When the condition (9) is satisfied, gbest information is added to current individuals using (10).

$$\begin{aligned} oldx_{ij} = oldx_{ij} + r(DNum, 1) \times C \\ \times \left(gbestx_j - oldx_{ij}\right) \\ (i = 1, \dots, IndN, j = 1, \dots, DNum) \end{aligned} \quad (10)$$

where $gbestx_j$ is decision variable j of the best individual among all individuals ($gbest$).

The above equation has been improved in Sato, M., and Fukuyama, Y., 2018 as follows. Using above condition and equations, information of $gbest$ can be focused at the early iterations more than the final iterations. In addition, the number of decision variables of the problem is too large to be considered in (10). Hence, $r(DNum, 1)$ of the equation (10) is changed to $r(1, 0)$. In addition, it can be usually considered that exploitation should be focused at the final search iterations and exploration should be focused at the early search iterations. Hence, the condition (9) ($C < r(1,0)$) is changed to $C > r(1,0)$. In the simulation, conditions (9) and (10) are changed to (11) and (12) as shown below:

$$C > rand(1,0) \quad (11)$$

$$\begin{aligned} oldx_{ij} = oldx_{ij} + rand(1,0) \\ \times C \times (gbestx_j - oldx_{ij}) \end{aligned} \quad (12)$$

4.3 Overview of MBSO

MBSO has been proposed as one of improved BSOs. There are two points which are improved in MBSO from BSO (Zhan, et al., 2012). One is that simple grouping method (SGM) is utilized as a clustering method instead of k-means in order to reduce calculation time. Another one is that a new individual generation equation focuses more diversification.

4.3.1 Clustering for MBSO

MBSO utilizes SGM as a clustering method instead of k-means. Algorithm of the SGM is expressed as follows:

Step. 1 K different individuals are selected randomly from individuals at the current iteration as group centers.

Step. 2 Distances from the current individuals to each cluster centre are calculated and these are compared each other. Then, the individuals are divided into the group which has the nearest distance from the current individual to the cluster centers.

Step.3 a value r_c is randomly generated in the range from 0 to 1.

Step.4 All individuals are ranked according to the objective function values of each individual in each cluster.
if $r_c \geq p_c$ (pre-determined probability),
set the best individual in each cluster as the cluster center in each cluster,
Otherwise,
one individual is randomly generated in each cluster, and the generated individual is set as the cluster center.

4.3.2 New Individual Generation

New equations for new individual generation is proposed in MBSO considering diversification of individuals:

$$newx_{ij} = \begin{cases} r\left(H_j, L_j\right) & (r(1,0) < pr) \\ oldx_{ij} + r(1,0) \times \left(oldx_{aj} - oldx_{bj}\right) & \left(pr \leq r(1,0)\right) \end{cases} \quad (13)$$
$$(i = 1, \dots, IndNum, j = 1, \dots, DNum)$$

where, pr is a probability utilized to determine the utilized equation, L_j is the lower bound of decision variable i, H_j is the upper bound of decision variable i, and $oldx_{aj}$ and $oldx_{bj}$ are randomly selected individuals.

4.4 Total Optimization of SC Algorithm by GMBSO

The proposed algorithm of total optimization of SC by GMBSO is shown below:

Step.1 $IndN$ individuals are randomly generated. inside the search space which is reduced using the method proposed in Sato, M., and Fukuyama, Y., 2016a, b. The random decision variables of individuals are changed to operational variables by the cut-out transformation function (Suzuki, et al., 2012) and calculate the object function value of all individuals using equation (1).

Step.2 $IndN$ individuals are divided into NK clusters by FbG.

Step.3 Select $oldx_{ij}$ by four conditions explained in 4.1.2. When the condition (11) is satisfied, $oldx_{ij}$ is modified using (12). New individuals are generated using (13).

Step.4 Calculate the objective function values of $IndN$ individuals with operational variables which is changed by the cut-out transformation function. Compare the new individuals with the current individuals of the same individual number. Then, if the new individual is better than the current individual, the new individual is set as the new current individual.

Step.5 Calculate the objective function values of all new individuals using (1). Compare the values with the objective function value of gbest individual. The gbest is updated when the objective function value of the current individual is better than pre-$gbest$.

Step.6 Proceed to step. 7 if the current number of iteration reaches the maximum number of iteration which is pre-determined. Otherwise, proceed to Step.2 and repeat the procedures.

Step.7 Finally output the best solution with the objective function value and operational variables.

5 SIMULATIONS

5.1 Simulation Conditions

The proposed GMBSO based method is applied to a typical mid-sized smart city model in Japan. The number of each model of each sector is set considering the typical mid-sized smart city and shown below:

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

These number are set considering that a load ratio of each sector is almost the same as the load ratio of each sector in Toyama city (Kanno, et al., 2015). In the paper, DEEPSO, BSO, MBSO, and GBSO based methods are utilized as conventional methods and the results of the conventional methods are compared with the results of the proposed GMBSO based method.

Many countries have developed various SCs and the SCs have their goals. Hence, the simulation deals with three cases. Case 1 considers a SC such as industrial parks and the goal is set as minimization of energy cost. Case 2 considers a SC such as local governments and the goal is set as minimization of CO_2 emission. Case 3 considers all terms of the objective function almost equally.

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

As shown in the cases, appropriate weighting coefficients can be set and it is practical to utilize one weighted function as an objective function instead of multi-objective functions.

Parameters for DEEPSO are set as follows:

τ : 0.2, τ' : 0.006, p : 0.75, initial weight coefficients of each term of update equations: 0.5, the number of clones: 1.

Parameters for BSO, GBSO, MBSO, and the proposed GMBSO method are shown as follows:

$p_{clustering}$: 0.5, $p_{generation}$: 0.5, $p_{OneCluster}$: 0.2, $p_{TwoCluster}$: 0.2, Cr: 0.2, F: 0.2 (for MBSO, and GMBSO), c_{max}: 0.7 , c_{min}: 0.2 (for GBSO, and GMBSO).

Common parameters are set as follows:

The number of individuals: 80, the number of trials: 50, the maximum iteration numbers for BSO, GBSO, MBSO, and GMBSO based methods: 4000, the maximum iteration number for DEEPSO based method: 2000 (Two evaluations are done for one individual in DEEPSO. Hence, the number is set in order to set the same number of the objective function evaluations.), Initial searching points are set randomly.

C language (gcc version 4.92 on Cygwin) has been utilized for development of simulation software on a PC (Intel Core i7 (3.60GHz)).

5.2 Simulation Results

Table 1 shows comparison of average, the minimum, the maximum, and standard deviation values of the objective function values for three cases among conventional DEEPSO, BSO, GBSO, MBSO and the proposed GMBSO based methods. The results in the table are calculated when the average objective function value by one of the conventional methods, DEEPSO based method, is set to 100 %. It can be observed that the proposed method can reduce the most for average, the maximum, the minimum, and standard deviation values among all conventional methods, which are DEEPSO, BSO, GBSO, and MBSO, and the proposed GMBSO based method at all cases. It is considered that about one million US$ a year can be reduced for reduction of energy cost when 1 % of the objective function is reduced (case 1). It can be said that GBSO can focus on more intensification and MBSO can focus on divesification. Hence, the proposed GMBSO can effectively work in order to keep a balance between diversification and intensification. In addition, the problem is one of large-scale optimization problems. Hence, the balance between diversification and intensification is important and the proposed GMBSO can effectively work for the SC problem.

Table 1: Comparison of average, the minimum, the maximum, and standard deviation value of Case 1, 2, and 3 among DEEPSO, BSO, GBSO, MBSO, and the proposed GMBSO.

Case		Ave.	Min.	Max.	Std.
1	DEEPSO	100.00	98.75	101.63	0.57
	BSO	97.13	96.46	97.96	0.30
	GBSO	95.94	95.55	97.03	0.26
	MBSO	97.20	96.75	97.66	0.20
	GMBSO	**95.06**	**94.90**	**95.29**	**0.09**
2	DEEPSO	100.00	99.53	100.58	0.20
	BSO	99.28	98.98	99.60	0.14
	GBSO	98.29	98.22	98.42	0.04
	MBSO	99.38	99.15	99.50	0.06
	GMBSO	**98.26**	**98.17**	**98.36**	**0.04**
3	DEEPSO	100.00	99.44	100.88	0.32
	BSO	99.64	99.38	99.87	0.09
	GBSO	99.36	99.12	99.53	0.10
	MBSO	98.37	98.30	98.46	0.04
	GMBSO	**98.10**	**98.05**	**98.16**	**0.03**

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

Table 2 shows comparison of the optimal operation for reduction of energy cost (case 1) among conventional DEEPSO, BSO, GBSO, MBSO and the proposed GMBSO based methods. As an example, the table shows operation of industrial sector. In the table, column A expresses output of electric power from GTG, and column B expresses electric power which is purchased by industrial sector. In the model, output of electric power from GTG is inexpensive. Electric power which is purchased by the sector is expensive at 8 to 22 hours. Hence, output of electric power from GTG should be increased and electric power which is purchased by the sector should be reduced from 8 to 22 hours for reduction of cost of electric power and natural gas which are purchased. It is observed that output of electric power from GTG is increased and electric power which is purchased is reduced from 8 to 22 hours the most by the proposed GMBSO based method.

6 CONCLUSIONS

This paper proposes a new evolutionary computation method, called, GMBSO which is a combined method of GBSO and MBSO in order to keep a balance between diversification and intensification. In addition, it also proposes a total optimization method of a smart city by GMBSO. The better results can be obtained by the proposed method than the conventional DEEPSO and BSO, GBSO, and MBSO based methods.

Applications of novel evolutionary computation methods which work effectively for large-scale optimization problems such as the SC problem will be conducted to the problem as one of future works.

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Table 2: Comparison of the best facility operation for case 1 among DEEPSO, BSO, GBSO, MBSO, and the proposed GMBSO in an industrial model.

	DEEPSO		BSO		GBSO		MBSO		GMBSO	
	A	B	A	B	A	B	A	B	A	B
1	0.00	8.21	0.00	7.85	0.00	7.59	0.00	7.00	0.00	7.25
2	0.00	5.13	0.00	5.09	0.00	5.22	0.00	7.07	0.00	7.16
3	0.00	8.08	0.00	7.97	0.00	8.03	0.00	7.22	0.00	7.15
4	0.00	8.08	0.00	8.25	0.00	8.22	0.00	7.17	0.00	7.00
5	0.00	8.29	0.00	9.22	0.00	9.23	0.00	9.17	0.00	9.17
6	0.00	8.90	0.00	9.09	0.00	8.91	0.00	8.90	0.00	9.25
7	0.00	9.03	0.00	8.58	0.00	9.18	0.00	9.24	0.00	9.12
8	6.00	1.09	6.00	1.15	6.71	0.30	7.46	1.84	8.98	0.12
9	10.65	2.15	12.26	0.81	12.36	0.55	8.98	1.99	10.74	0.22
10	10.92	2.24	10.48	2.48	11.63	1.37	13.85	0.95	14.71	0.33
11	14.06	3.81	17.47	1.35	16.68	2.20	18.32	0.61	18.80	0.17
12	14.32	8.67	7.73	15.71	18.45	4.91	20.00	4.67	19.72	4.98
13	14.99	2.61	14.12	5.13	18.54	0.59	15.48	2.31	17.06	0.88
14	13.02	9.20	18.21	3.91	18.81	3.49	19.40	2.78	20.00	2.00
15	13.86	9.32	17.22	6.03	19.05	4.14	20.00	3.08	20.00	3.07
16	18.84	6.07	16.77	6.51	18.55	4.55	16.14	4.96	20.00	1.10
17	10.88	13.03	16.30	6.68	18.48	4.43	18.27	4.51	20.00	2.79
18	18.16	3.84	20.00	2.17	18.55	3.44	20.00	1.97	20.00	1.99
19	20.00	3.11	18.96	3.77	18.37	4.07	20.00	3.04	19.15	3.85
20	19.44	1.96	16.53	3.97	17.14	3.66	17.25	4.09	20.00	1.23
21	17.26	0.09	13.74	3.93	16.79	0.87	16.33	0.93	17.12	0.08
22	7.26	4.97	8.73	3.27	10.84	1.16	11.56	0.59	12.13	0.09
23	0.00	13.03	0.00	12.84	0.00	12.97	0.00	13.05	0.00	12.92
24	0.00	10.38	0.00	10.45	0.00	10.45	0.00	10.45	0.00	10.20
	209.65	72.15	214.50	66.88	240.97	39.72	243.02	38.32	258.43	22.90

*) A: the amount of electric power output by GTG, B: the amount of purchased electric power, Sum: summation of each column A, and B at 8 to 22 hours.

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