Overall Optimization of Smart City by Multi-population Global-best Brain Storm Optimization using Cooperative Coevolution

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Abstract— **This paper proposes a method for the overall optimization of smart city (SC). The proposed method is based on multi-population global-best brain storm optimization using cooperative coevolution (MP-CCGBSO). Using a SC model, energy cost, actual power loads during peak periods, and carbon dioxide emission can be minimized. For the SC problem, many researchers have proposed various evolutionary algorithms including CCGBSO, which applied cooperative coevolution to GBSO. However, there is still room to improve quality of the solution by CCGBSO. Taking Toyama city of Japan as the research object, the calculation results of original CCGBSO method and the proposed MP-CCGBSO method of 2, 4, 8 and 16 populations are compared.**

Keywords— ***global-best brain storm optimization, cooperative coevolution, Large scale mixed integer nonlinear optimization problem, reduction of CO_2 emission, smart city, multi-population***

I. INTRODUCTION

Global warming has caused many disasters in recent years, and climate emergency is worsening every day. The emergency includes extreme high temperature, air pollution, wildfires, intensified floods, and drought, and it is affecting lives of people all over the world. Reasons of global warming include the excessive emission of greenhouse gases [1]. Therefore, it is necessary to advance renewable energies in order to reduce carbon dioxide emissions and traditional fossil energies. Many countries are implementing and validating SC demonstration projects to reduce carbon dioxide emissions [2][3]. SC is a sustainable low carbon city using renewable energy, batteries, and the latest information technology. The climate change conference (COP25), held in Madrid, Spain, in 2019, considered ways to further reduce carbon dioxide emissions and strengthen the implementation of the Paris Agreement [4]. Since it is difficult to evaluate the actual carbon dioxide emission reduction and energy cost in the development of SC, it is necessary to establish a model to evaluate it. Industry, building, residence, and railway sectors are modeled by two models respectively. One is a dynamic model considering the transient phenomena in various sectors. Another one is a static model considering all kinds of energy balance. However, there is no SC model that can solve the calculation of carbon dioxide emissions or energy consumption in all sectors at the same time. Therefore, experts in various sectors have developed SC models to quantitatively assess the energy cost or carbon dioxide emissions of the whole SC. However, considering the interaction between various sectors, the optimization of SC energy network had not been applied to these models.

In the past, the authors have put forward overall optimization methods of SC energy network using PSO [5], DE [6], DEEPSO [7], BSO [8], MBSO [9], GBSO [10], and CCGBSO [11]. These methods including the recently developed CCGBSO can reduce the energy cost and carbon dioxide emission to the maximum extent, and transfer the peak loads to other periods. However, solution quality by the conventional methods still needs to be improved.

For large-scale optimization problems (LSOPs), to further improvement of solution quality, CC has been developed [11-13]. CC divides a LSOP with a large number of decision variables (DecVars) into several smaller sub problems. It utilizes the same algorithm to solve each sub problem in turn to make the whole problem solution converge step by step.

The solution quality of the SC problem can be improved by the evolutionary computation method based on multi-population [14-16]. Utilizing MP, a whole population is divided into several subpopulations, and the optimal solution is searched in each sub-population.

This paper proposes an improved coevolution algorithm, multi-population global-best brain storm optimization using cooperative coevolution (MP-CCGBSO), and utilizes this algorithm to optimize the SC problem, so as to improve the solution quality. The contribution of this paper are as follows:

- A new CC algorithm, called MP-CCGBSO is proposed,
- An overall optimization method of SC based on MP-CCGBSO is proposed,
- The original CCGBSO based method was compared with the proposed MP-CCGBSO based method with 2, 4, 8, and 16 subpopulations, and the effectiveness of this method is verified by taking Toyama city of Japan as an example. Using Friedman test, the solution quality of MP-CCGBSO based method with 4 subpopulations is verified to be the most improved.

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The structure of this paper is as follows. Section II explains the concept of the SC model. Section III explains the formulation of the overall optimization problem of SC. Section IV introduces the proposed MP-CCGBSO and the application of MP-CCGBSO to the overall optimization problem of SC. In section V, using the Friedman test, effectiveness of MP-CCGBSO method to SC problem is verified. Section VI shows conclusions of the whole paper.

II. SMART CITY MODEL

A. Overview of SC Model

To calculate energy costs and carbon dioxide emission in a supply chain considering an interaction between different sectors, the SC model has been established [17-19]. The sectors in the SC model can be split into demand sides and supply sides [18]. Building, industry, railway, and residence sectors is included in the demand side. Drinking water treatment plants (DWTPs), electric power (EP) utilities, wastewater treatment plants (WWTPs), and natural gas (NG) utilities sectors are included in the supply side. The SC model considers the interaction among all sectors of the whole supply chain, and can calculate energy flow, energy cost, and carbon dioxide emissions (see Fig.1).

B. Supply-Side Sectors

The supply side supplies drinking water, EP and NG to the demand side [18]. The supply side can supply various energies to the demand side.

The NG sector model is a model for NG utilities. In other words, NG required by demand side sector models can be provided to each sector through the NG sector model.

The EP sector model is a model for EP utilities. EP can be produced in nuclear power, thermal power, renewable power such as hydropower, photovoltaics power, and wind power plants. The carbon dioxide emission and energy cost of power plants can be calculated by the model. In this model, the output of hydropower and renewable energy can be input as a fixed value per hour. Summation of EP generation ratios of all power plants is set to 1.

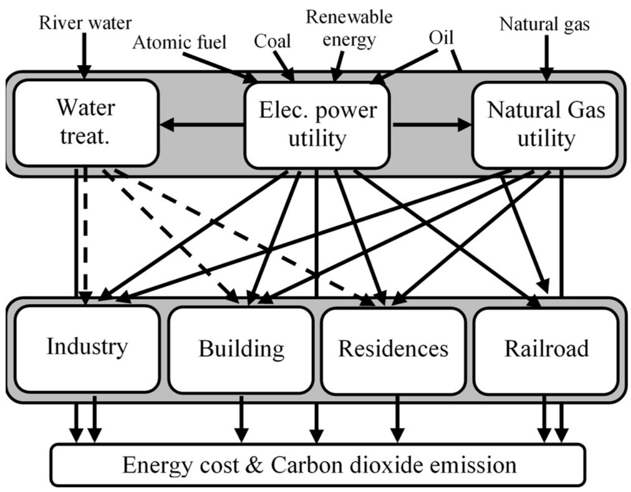

Fig. 1. A SC model configuration.

In the WWTP sector, the quantities of required demand response (DR) and renewable generation are set to fixed values. In the DWTP sector, required DR, water demand, and renewable power generation are set to fixed values.

C. Demand-Side Sectors

Railway, residence, building, and industry sectors belong to the demand side which interacts with the supply side [19]. EP supply facilities such as gas turbine generators (GTGs) are dealt with in the demand side model. By the supply side sectors, the secondary energies are mainly provided to power supply facilities, and the tertiary energies are supplied to various kinds of power loads through the power supply facilities in the model. Consequently, if all kinds of hourly load values of 24 hours a day are given in the demand side sector models, required secondary energy values are provided by the supply side sector models.

An industrial model has a variety of batteries, solar power systems, energy facilities, and the quantity of required DR.

A building model is utilized for shopping centers and offices, and they are are regarded as energy loads. It also has energy supply facilities which are also included in the industrial model. In addition, the quantities of various hourly energy loads and required DR are also dealt with by the model.

A residence model can handle apartments and detached houses. Both apartments and detached houses utilize a model with different input data. In the model, batteries, a tank less water heater, a fuel cell, a heat storage tank, and a heat pump water heater are treated. These facilities provide heat, EP, and hot water.

III. FORMULATION OF AN OVERALL OPTIMIZATION PROBLEM OF SMART CITY

A. Decision Variables

The following are the DecVars:

(a) DWT plant model: water inflow of river, water inflow of reservoir, output power of generator, and charge and discharge power of battery.

(b) WWT plant model: output power of the combined generator, quantity of water pumped to the wastewater treatment plant, and charge and discharge power of battery.

(c) Industrial model: turbo refrigerator heat output, steam refrigerator heat output, GTG power generation, and charging and discharging power of battery.

(d) Building model: turbo refrigerator heat output, steam refrigerator heat output, and GTG power output.

(e) Residential model: power output of fuel cell, charge and discharge of battery, and heat output of heat pump water heater.

(f) Railway model: average speed per hour, train average running distance per hour, the number of trains per hour, the number of cars per set, passenger average running distance per hour, passenger capacity per a car, the number of passengers per hour.

Since DecVars have to be prepared for 24 hours, there are 816 DecVars in a whole SC. Therefore, this problem can be regarded as a LSOP.

Members of IEE of Japan SC Model Development Committee include this paper's author. According to the committee, SC is defined as a kind of local area, like local governments and industrial parks.

B. Objective Function

Following three terms compose of the objective function:

(1) Energy cost minimization: summation of energy costs in all sectors except EP and NG sectors.

(2) Peak load minimization: summation of shifted real EP peak loads in the whole SC during peak load time.

Real EP peak load per hour is composed of the quantity of original EP loads, converted EP to other energies per hour, and battery charging. Peak load time refers to the time when the sum of real EP loads of sectors is more than an average of the sum of real EP loads of a whole day.

(3) Carbon dioxide emission minimization: summation of carbon dioxide emissions of all sectors in the supply chain except EP and NG sectors.

The objective function is composed of the above three terms with a weighted function as follows:

$$min\left\{w_1\sum_{s=1}^{S}\sum_{t=1}^{T}(PuG_{st}\times GU_{st}+PuE_{st}\times EU_{st})\right.$$
$$+w_2\sum_{s=1}^{S}\sum_{t=bplt}^{lplt}(GL_{st})$$
$$\left.+w_3\sum_{s=1}^{S}\sum_{t=1}^{T}(PuG_{st}\times GC+PuE_{st}\times EC)\right\}\quad(1)$$

where w_1, w_2, and w_3 are weighting factors and the sum of them is 1, S is the number of sectors except NG and EP sectors, T equals 24 (one day), PuG_{st} is the quantity of NG purchase of sector s at time t, GU_{st} is a NG price of sector s at time t, PuE_{st} is the quantity of EP purchase of sector s at time t, EU_{st} is a EP price of sector s at time t, $lplt$ is the last time of real EP peak load time, $bplt$ is the beginning time of real EP peak load time, GL_{st} is an real EP load of sector s at time t, GC is a coefficient of a relationship between the quantity of purchased NG and carbon dioxide emissions, EC is a coefficient of a relationship between the quantity of purchased EP and carbon dioxide emissions.

After the DecVars are determined, the dependent variables such as purchased EP and NG can be calculated. Therefore, if the dependent variables exceed the allowed limit values, penalty values are added to the objective function value.

C. Constraints

(1) Supply-demand balances of energies: for balances of EP, steam, and heat energies, the following equations are utilized:

$$g_{sr}(\boldsymbol{p},\boldsymbol{q})=0,\qquad(s=1,\dots,S,r=1,\dots,R_s)$$
$$\boldsymbol{p}=(p_1,\dots,p_L)^T,\boldsymbol{q}=(q_1,\dots,q_L)^T\qquad(2)$$

where $g_{sr}(\boldsymbol{p},\boldsymbol{q})$ is an energy balance of energy r in sector s, p_i is shutdown or start-up status for DecVar i, q_i is an output or input real value for DecVar i, R_s is the number of energies in sector s, and L is the number of DecVars.

(2) Characteristics of facility: characteristics of facilities can be expressed using the following equations. Lower and upper bounds of various kinds of facilities in each sector can be also expressed as follows:

$$h_{sf}(\boldsymbol{p},\boldsymbol{q})\le 0,\qquad(s=1,\dots,S,f=1,\dots,F_s)\qquad(3)$$

where $h_{sf}(\boldsymbol{p},\boldsymbol{q})$ is the facility characteristic functions that are composed of a character and lower / upper bounds of facility f in sector s, F_s is the number of facilities in sector s.

IV. Multi-population Global-best Brain Storm Optimization using Cooperative Coevolution for Overall Optimization of Smary City

A. Overview of GBSO

GBSO is one of improved BSO methods, which adopts a global best information (*gbest*) in individual updating and utilizes a fitness based grouping (FbG) algorithm in a clustering method. It was developed in 2017 by El-Abd [20].

If a certain condition is met, GBSO utilizes *gbest* (the current best individual among all individuals) to update individuals when generating a new individual (see Fig.2). In general, an early search phase should emphasize exploration in a larger searching area, while a final search phase should emphasize exploitation and update individuals in a smaller attractive area. Namely, when (5) is satisfied, utilize (6) in order to add *gbest* information to x_{ij}^{old} :

$$C=C_{min}+\frac{iter}{ITER}\times(C_{max}-C_{min})\qquad(4)$$

$$C>rand(1,0)\qquad(5)$$

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

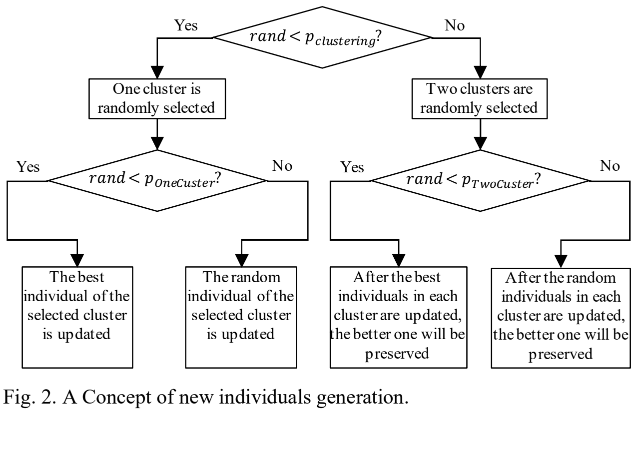

Fig. 2. A Concept of new individuals generation.

where, C_{max} and C_{min} are the maximum and minimum values of C, C is a parameter utilized to determine whether *gbest* information should be utilized or not.

The authors proposed to utilize new equations (5) and (6) [10] instead of using the original equations proposed in [20]. Although solution quality of GBSO is higher than that of BSO, it can be further improved by CC algorithm [11].

B. Overview of Cooperative Coevolution

CC algorithms divide a high-dimensional problem into several low-dimensional sub-problems and solve each sub-problem in order. The high-dimensional problem has a large number of DecVars, which are divided into the variables of the sub-problem. While dealing with a certain sub-problem, only DecVars of the current sub-problem are updated and DecVars of other sub-problems are treated as fixed variables. An objective function value is calculated using all DecVars (updated and fixed values) of all sub-problems by the same algorithm.

C. Overview of Multi-population

The authors found that standard deviations by CCGBSO for the overall optimization of SC were quite large compared with the conventional methods [11]. As described above, MP has a possibility to improve solution quality. Therefore, in this paper, the authors improve the CCBSO algorithm using a MP algorithm to reduce standard deviation and average values of the optimization results by the conventional CCGBSO based method.

MP is an algorithm to divide search individuals of a population into several subpopulations and an optimization algorithm is performed at each subpopulation. A migration model is a kind of MP models. It makes individuals exchange, and replace among subpopulations every certain interval.

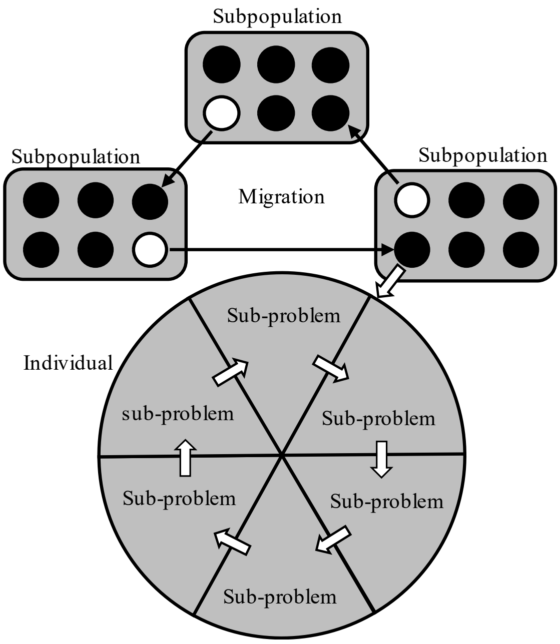

Fig. 3. A Concept of MP-CCBSO.

Hyperparameters of the MP model in this paper is explained as follows. Firstly, "the number of subpopulation" is the number of subpopulations independently executing CCGBSO. Secondly, "Subpopulation architecture" is a network architecture among subpopulations. A ring architecture can be utilized for two subpopulations and among more than two subpopulations. A triangle cone architecture can be utilized for four subpopulations. a cube architecture can be utilized for eight subpopulations. A hypercube architecture can be utilized for 16 subpopulations. Thirdly, "Migration interval" is frequency of migration. Fourthly, "Migration policy" is a policy that can explain which individuals should be migrated in the subpopulation of a sending side and which individuals should be replaced in a receiving side. For example, a Worst-Best (W-B) policy replaces the worst individual in the receiving side subpopulation with the best one in the sending side subpopulation, a Worst-Random (W-R) policy replaces the worst individual in the receiving side population with a random one in the sending side population, a Random-Random (R-R) policy replaces a random individual in the receiving side population with a random one in the sending side population (R-R), and a Random-Best (R-B) policy replaces a random individual in the receiving side population with the best one in the sending side population (R-B).

D. Overview of MP-CCGBSO

In each divided subpopulation, DecVars of each individual are divided into several sub-problems and updated by the CCGBSO algorithm. When the number of iterations reaches a preset iteration, individual migration among different subpopulations is carried out (see Fig.3 and Fig.4).

E. Overall Optimization of SC by MP-CCGBSO

Step.1 ***Initialization***: Initial individuals are generated at

Algorithm: The procedure of the MP-CCGBSO

```
Randomly initialize n individuals at each subpopulation
OutLoop = 1
while OutLoop ≤ Max_OutLoopNum do
  subpop = 1
  while subpop ≤ Max_SubpopNum do
    s = 1
    while s ≤ Max_SectorNum do
      Evaluate the n individuals
      InLoop = 1
      while InLoop ≤ Max_InLoopNum do
        Cluster n individuals into m clusters using FbG
        Find the best and worst individuals in each cluster
        Update the best and worst individuals at InLoop with GBSO
        InLoop = InLoop + 1
      end do
      Update the best and worst individuals in s
      s=s+1
    end do
    Update the best and worst individuals in subpop
    subpop = subpop+1
  end do
  if OutLoop % Migration == 0 then
    Compare the best individual of two neighboring subpopulations
    Replace the worst individual with the better one
  end if
  Update the global best individual
  OutLoop =Outloop+1
end do
Return the best individual
```

Fig. 4. An example of MP-CCGBSO algorithm using the W-B policy.

random in all subpopulations.

Step.2 According to the initial individuals of each subpopulation, objective function values considering carbon dioxide emissions, peak hour actual power loads, and energy costs are calculated. If operation variables are out of the constraint, penalty values are added to the objective function value. $Outloop = 1$ (current outer loop number).

Step.3 $subpop = 1$ (subpopulation number).

Step.4 $s = 1$ (sector number).

Step.5 $InLoop = 1$ (current inner loop number).

Step.6 ***Clustering***: FbG is utilized in all subpopulations in order to divide all individuals into clusters.

Step.7 ***New individual generations***: DecVars of a current sector sp are updated under preset conditions as explained in IV-A. DecVars of other sectors is fixed with the current values.

Step.8 ***Selection***: Using newly generated DecVars of sector sp and fixed DecVars of other sectors, individuals' objective function values are calculated. Current individuals' objective function values are compared with those of newly generated individuals with a same individual number. Individuals with better values are stored as current ones.

Step.9 ***Evaluation***: New current individual objective function values are calculated. If an individual objective function value is better than that of a global best individual of previous generations, the global best individual is updated.

Step.10 When $InLoop$ reaches the preset maximum inner loop number, go to the next step. Otherwise, $InLoop = InLoop + 1$ and go back to Step.6.

Step.11 When s reaches the preset maximum sector number, go to the next step. Otherwise, $s = s + 1$ and go back to Step.5.

Step.12 When $subpop$ reaches the preset maximum subpopulation number, go to the next step. Otherwise, $subpop = subpop + 1$ and go back to Step.4.

Step.13 ***Migration***: When the $loop$ reaches preset migration interval, the migration is performed.

Step.14 When $OutLoop$ reaches the preset maximum outer loop number, go to the next step. Otherwise, $Outloop = Outloop + 1$ and go back to Step.3.

Step.15 Final output contains DecVars of the final global best individual and its objective function value.

V. SIMULATIONS

A. Simulation Conditions

A model of Toyama City, a typical medium-sized SC in Japan, is utilized for an application of the proposed method. In this paper, we set a certain number of models for various sectors based on energy consumption values of real sectors in Toyama city as follows:

Residential: 45000, Industry: 15, Railroad: 1, Building: 50, DWTP: 1, WWTP: 1.

Based on comparison of simulation results of the conventional methods including GBSO and DEEPSO based methods with those of the conventional CCGBSO based method, we found that CCGBSO is the most effective among the methods [11]. Therefore, in this paper, the proposed MP-CCGBSO based method with 2, 4, 8 and 16 subpopulations are compared only with the conventional original CCGBSO based method with one population.

This paper sets up three cases. Case 1 is to minimize the energy cost (e.g. purpose of industrial park). Case 2 is to minimize carbon dioxide emissions (e.g. purpose of local government). Case 3 is to minimize the actual power load, carbon dioxide emissions and energy costs during peak load time equally. The weighting factors for each case are as follows:

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

Parameters for the conventional CCGBSO based method are as follows:

C_{max}: 0.9, C_{min}: 0.1, $p_{clustering}$: 0.5, $p_{generation}$: 0.5, $p_{OneCluster}$: 0.2, $p_{TwoCluster}$: 0.2.

Parameters for the proposed MP-CCGBSO based method are as follows:

- The number of subpopulation (NSP) are set to 2, 4, 8, and 16.
- A migration interval is set to 10 for all cases.
- Subpopulation architecture: Ring (2 subpopulations), triangle cone (4 subpopulations), cube (8 subpopulations), and hypercube (16 subpopulations) architectures are utilized.
- The number of total individuals is set to 160. For example, there are 40 individuals in each subpopulation when there are 4 subpopulations.
- Migration policy: the W-B policy is utilized.

The number of trials is set to 50. The maximum inner loop number is set to 100. The maximum outer loop number is set to 100. Therefore, the maximum iteration is 10000. The initial search point is randomly generated. A simulation environment on a PC (Intel Xeon E5-2670 (2.60GHz)) using C language (gcc version 5.3.7) is utilized.

B. Simulation Results

Table 1 shows comparison results of mean, the minimum, the maximum and standard deviation of objective function values by the conventional original CCGBSO (NSP = 1) based method and the proposed MP-CCGBSO based methods with 2, 4, 8, and 16 subpopulations for all cases. According to the table, all values are the most reduced by the proposed method with 4 subpopulations. Especially, the standard deviation values are greatly reduced.

Table 2 shows results of mean ranks and *p*-values among the conventional original CCGBSO (NSP = 1) based method and the proposed MP-CCGBSO based methods with 2, 4, 8, and 16 subpopulations by Friedman test. Mean ranks of 4 subpopulations are the best for all cases. The results show that there are significant differences among the methods at 0.05 significance level.

Table 3 shows comparison of optimal operation in an industrial model by the conventional original CCGBSO based method and the proposed MP-CCGBSO based methods with 2, 4, 8, and 16 subpopulations for Case 1. Column A shows the quantity of EP output of GTGs and column B shows the quantity of purchased EP from an EP utility. Between 8:00 and 22:00, prices of EP output of the GTGs per hour are lower than prices of purchased EP per hour. Therefore, in order to reduce the energy cost, it is necessary to increase the EP output of the GTGs. The results show that the proposed MP-CCGBSO based method with 4 subpopulations can maximize the EP output of the GTGs. Therefore, the proposed method can reduce the energy cost the most.

TABLE I. COMPARISON RESULTS OF MEAN, THE MINIMUM, THE MAXIIMUM, AND STANDARD DEVIATION OF OBJECTIVE FUNCTION VALUES BY THE CONVENTIONAL ORIGINAL CCGBSO BASED METHOD AND THE PROPOSED MP-CCGBSO BASED METHODS WITH 2, 4, 8, AND 16 SUBPOPULATIONS FOR ALL CASES.

Case	NSP	Mean	Min.	Max.	Std.
Case 1	1	100.00	98.89	101.72	1.06
	2	98.91	98.86	100.05	0.17
	4	**98.87**	**98.85**	98.90	**0.01**
	8	99.19	99.08	99.44	0.06
	16	99.24	99.10	99.77	0.11
Case 2	1	100.00	99.43	100.72	0.51
	2	99.47	99.39	100.66	0.18
	4	**99.42**	**99.38**	99.46	**0.02**
	8	99.64	99.56	99.75	0.04
	16	99.63	99.55	99.72	0.03
Case 3	1	100.00	99.69	100.47	0.30
	2	99.70	99.69	100.03	0.05
	4	**99.69**	**99.69**	99.70	**0.00**
	8	99.78	99.74	98.87	0.02
	16	99.79	99.75	99.93	0.03

*: The mean of the original CCGBSO is set to 100% and all values are ratios for the value.

Table 4 shows comparison of optimal operation in an industrial model by the conventional original CCGBSO based method and the proposed MP-CCGBSO based methods with 2, 4, 8, and 16 subpopulations for Case 2. GC is less than EC in (1). Therefore, in order to reduce carbon dioxide emissions, the EP output of the GTGs should be increased all day. The results show that the proposed MP-CCGBSO based method with 4 subpopulations can maximize the EP output of the GTGs. Therefore, the proposed method can reduce the carbon dioxide emission the most.

VI. CONCLUTIONS

This paper proposes a new evolutionary computation method, namely multi-population global-best brain storm optimization using cooperative coevolution, called MP-CCGBSO, and overall optimization of smart city by the proposed MP-CCGBSO. The proposed MP-CCGBSO based methods with 2, 4, 8, and 16 subpopulations is compared with the conventional original CCGBSO based method with a model of Toyama city, a typical SC in Japan. The results show that the

TABLE II. RESULTS OF MEAN RANKS AND P-VALUES AMONG THE CONVENTIONAL ORIGINAL CCGBSO BASED METHOD AND THE PROPOSED MP-CCGBSO BASED METHODS WITH 2, 4, 8, AND 16 SUBPOPULATIONS BY FRIEDMAN TEST .

NSP	1	2	**4**	8	16	*p*-value
Case 1	3.98	1.86	**1.2**	3.84	4.12	3.02E-31
Case 2	3.92	2	**1.16**	4.08	3.84	1.01E-29
Case 3	3.96	1.88	**1.2**	3.92	4.04	9.49E-31

TABLE III. COMPARISON OF OPTIMAL OPERATION BY THE CONVENTIONAL ORIGINAL CCGBSO BASED METHOD AND THE PROPOSED MP-CCGBSO BASED METHODS WITH 2, 4, 8, AND 16 SUBPOPULATIONS FOR CASE 1.

NSP	1		2		**4**		8		16	
Hour	A	B	A	B	A	B	A	B	A	B
1	0.00	7.44	0.00	7.45	0.00	7.45	0.00	7.37	0.00	7.36
2	0.00	7.39	0.00	7.45	0.00	7.43	0.00	7.15	0.00	7.33
3	0.00	7.36	0.00	7.43	0.00	7.44	0.00	7.36	0.00	7.24
4	0.00	7.38	0.00	7.42	0.00	7.44	0.00	7.38	0.00	7.25
5	0.00	9.41	0.00	9.44	0.00	9.44	0.00	9.32	0.00	9.33
6	0.00	9.30	0.00	9.33	0.00	9.34	0.00	9.25	0.00	9.15
7	0.00	9.29	0.00	9.32	0.00	9.33	0.00	9.06	0.00	9.16
8	8.95	0.01	9.13	0.01	**9.19**	**0.00**	9.03	0.00	8.88	0.11
9	10.90	0.02	11.03	0.01	**11.07**	**0.00**	10.70	0.17	10.62	0.42
10	14.89	0.05	15.00	0.01	**15.05**	**0.01**	14.89	0.21	14.73	0.44
11	18.91	0.01	18.96	0.01	**19.01**	**0.00**	18.67	0.25	18.82	0.21
12	19.98	4.75	19.99	4.73	**19.99**	**4.77**	20.00	4.88	19.90	4.81
13	17.76	0.02	17.87	0.01	**17.88**	**0.01**	17.67	0.05	17.79	0.12
14	19.98	2.02	20.00	2.00	**19.99**	**2.01**	19.89	2.28	19.74	2.37
15	19.99	3.11	20.00	3.00	**19.99**	**3.01**	19.84	3.16	19.87	3.13
16	19.99	1.01	20.00	1.00	**19.99**	**1.01**	19.89	1.40	20.00	1.00
17	19.99	2.83	20.00	2.70	**20.00**	**2.70**	20.00	2.78	20.00	2.70
18	19.97	2.05	19.99	1.91	**19.99**	**1.91**	20.00	1.90	20.00	2.00
19	19.98	2.92	19.98	2.92	**19.99**	**2.91**	20.00	2.90	20.00	2.90
20	19.98	1.11	19.99	1.01	**19.99**	**1.14**	20.00	1.00	19.93	1.24
21	17.22	0.04	17.00	0.00	**16.99**	**0.01**	16.92	0.08	17.06	0.02
22	12.15	0.04	12.19	0.03	**12.13**	**0.00**	11.85	0.21	12.11	0.03
23	0.00	13.03	0.00	13.05	0.00	13.03	0.00	12.99	0.00	12.96
24	0.00	10.45	0.00	10.45	0.00	10.45	0.00	10.45	0.00	10.45
Total	260.66	19.97	261.13	19.36	**261.26**	**19.49**	259.35	21.27	259.46	21.50

*) A: The quantity of EP output of GTGs. B: The quantity of purchased EP. Total: Summation of values between 8:00 and 22:00.

TABLE IV. COMPARISON OF OPTIMAL OPERATION BY THE CONVENTIONAL ORIGINAL CCGBSO BASED METHOD AND THE PROPOSED MP-CCGBSO BASED METHODS WITH 2, 4, 8, AND 16 SUBPOPULATIONS FOR CASE 2.

NSP	1		2		**4**		8		16	
Hour	A	B	A	B	A	B	A	B	A	B
1	7.11	0.28	7.28	0.08	**7.34**	**0.03**	6.96	0.34	7.05	0.27
2	6.72	0.64	7.25	0.14	**6.82**	**0.52**	6.81	0.49	7.04	0.19
3	7.15	0.14	7.30	0.11	**7.29**	**0.07**	6.95	0.40	7.06	0.31
4	7.24	0.12	7.29	0.02	**6.86**	**0.53**	7.18	0.13	7.10	0.22
5	7.70	1.64	9.10	0.33	**9.31**	**0.03**	9.03	0.19	7.45	1.92
6	8.36	0.80	8.58	0.61	**8.72**	**0.52**	8.89	0.29	8.63	0.47
7	8.97	0.23	9.16	0.14	**8.67**	**0.56**	8.75	0.40	9.13	0.09
8	9.10	0.09	8.03	1.23	**9.22**	**0.05**	8.04	1.07	8.86	0.39
9	10.99	0.21	11.16	0.01	**11.12**	**0.03**	10.89	0.19	10.53	0.45
10	15.02	0.10	15.11	0.09	**15.10**	**0.04**	14.87	0.24	14.76	0.29
11	18.93	0.13	19.00	0.04	**19.01**	**0.07**	18.80	0.25	18.47	0.50
12	19.92	4.94	19.97	4.99	**19.98**	**5.00**	19.66	5.25	19.64	5.29
13	17.71	0.21	17.81	0.18	**17.91**	**0.03**	17.54	0.37	17.37	0.45
14	19.96	2.32	19.92	2.48	**19.97**	**2.25**	19.63	2.64	19.94	2.29
15	19.93	3.31	19.96	3.39	**19.68**	**3.71**	19.88	3.30	19.99	3.11
16	19.90	1.48	19.95	1.31	**19.98**	**1.33**	19.79	1.44	19.70	1.38
17	19.96	3.06	19.94	3.13	**19.96**	**3.10**	19.53	3.35	19.76	3.14
18	19.90	2.21	19.98	2.22	**19.97**	**2.27**	19.75	2.26	20.00	1.98
19	19.89	3.31	19.98	3.21	**19.98**	**3.28**	19.74	3.38	19.73	3.17
20	19.84	1.46	19.93	1.40	**19.97**	**1.31**	19.91	1.17	19.45	1.77
21	17.16	0.18	17.32	0.04	**17.36**	**0.05**	16.81	0.19	16.76	0.41
22	12.19	0.10	12.30	0.03	**12.34**	**0.01**	11.87	0.22	11.84	0.25
23	12.94	0.05	12.88	0.08	**12.98**	**0.01**	12.65	0.29	12.71	0.23
24	10.24	0.22	10.33	0.09	**10.41**	**0.04**	10.06	0.39	10.01	0.45
Total	336.83	27.23	339.53	25.33	**339.98**	**24.85**	333.98	28.26	332.96	29.03

*) A: The quantity of EP output of GTGs. B: The quantity of purchased EP. Total: Summation of values all day.

proposed MP-CCGBSO based method with 4 subpopulations can improve the solution quality and minimize the standard deviation value the most.

As future works, the authors will investigate more effective evolutionary computation methods for solving overall optimization of smart city. If an EV model as a moving battery is added to the SC model by IEE of Japan, an automobile sector will be considered.

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