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Comparison of metaheuristics and dynamic programming for district energy optimization

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Abstract. Metaheuristic optimization methods, as model-free methods, are expected to be applicable to practical issues (e.g., engineering problems). Although optimization methods have been proposed or improved through many theoretical studies, they should be tested using not only some benchmark functions, but also other models representing practical situations, such as those involving discrete control variables and equality or inequality constraints. Hence, differential evolution (DE)-based constrained optimization methods were applied to district energy optimization in this study. Several different types of DE-based methods and dynamic programming which was utilized to obtain theoretical results, were compared. The proposed DE-based method, ϵ -constrained DE with random jumping II (ϵ DE-RJ-II), proved capable of producing results differing by only 2.1% from the theoretical results in a computation time 1/457 of that required by dynamic programming. Therefore, ϵ DE-RJ-II has high potential to provide comprehensive district energy optimization within a realistic computation time.

1. Introductions

Metaheuristic optimization methods, also known as metaheuristics, have been continuously improved to obtain more accurate results within low computational costs. To improve the existing methods or develop new ones, benchmark functions have often been used to simplify the evaluation process [1–3].

However, it is also significant to apply and validate metaheuristics under practical conditions such as those existing in engineering optimization situations [4]. For example, engineering problems often involve nonlinear, discrete, and non-smooth characteristics. Additionally, the computation time is limited in practical use. Hence, it is important to apply metaheuristics to practical and complicated problems, and they can be expected to have high potential compared to classical mathematical programming methods such as mixed-integer linear programming and dynamic programming (DP) because they are model-free.

Many energy engineering research studies have been conducted in the interest of minimizing cost, CO₂ emissions, primary energy consumption, and so on [5–8]. However, limited numbers of decision variables and constraints were considered in those studies, and the variables were mainly continuous, although an important issue in practical engineering problems is the complexity of the decision variables and constraints. Hence, more comprehensive conditions should be considered.

In contrast, some efficient constrained metaheuristics have been proposed following theoretical studies such as those described in [9–13]. In particular, ϵ -constrained differential evolution (ϵ DE) proved to be an efficient constrained method with stable performance [14]. To apply constrained methods to practical engineering problems, continuous optimization often must be



transformed into discrete optimization because controlled variables such as mass flow rates, temperatures, and pressures are often discrete.

Hence, ϵ DE-based algorithms were employed for district energy optimization which consisted of many types of nonlinear characteristics in this research and parametric studies were conducted to evaluate the searching abilities of the algorithms by changing the parameter value combinations. To validate the accuracy of the algorithms, DP was utilized to derive theoretical results under discrete conditions.

Additionally, improved versions of ϵ DE called ϵ DE with random jumping I and II (ϵ DE-RJ-I and ϵ DE-RJ-II, respectively) were tested because classical DE and ϵ DE have the drawback of easily becoming trapped in local optima. ϵ DE-RJ-I was previously proposed by the author [15], and ϵ DE-RJ-II is a slightly improved version of ϵ DE-RJ-I.

2. Materials and methods

2.1. District cooling system

The target virtual district consisted of four buildings: two office buildings and two commercial buildings. The total floor areas of the buildings were as follows: office building 1 was 10,000 m², office building 2 was 15,000 m², commercial building 1 was 8,000 m², and commercial building 2 was 12,000 m². Fig. 1 illustrates the concept of the district cooling system. The plant had three heat source machines, two centrifugal refrigerators (CR1 and CR2) and an absorption refrigerator (AR), and one thermal energy storage (TES) unit to supply cooling heat to the buildings. The machine specifications are provided in Table 1. The total rated capacities of CR1, CR2, and AR were set to approximately 110% of the maximum cooling demand, 16,200 kW at 4 p.m., to ensure system stability. The inlet and outlet temperatures of the chilled water were fixed to 14 °C and 4 °C, respectively.

The system also included pumps, and their electricity consumptions were considered. Specifically, there were chilled and cooling water pumps for each heat source (CR1, CR2, and AR) and two pumps for the TES charging and discharging operations. The rated pump pressures of the chilled and cooling water pumps were set to 50 kPa and 200 kPa, respectively. The number of cooling towers was determined as follows. Firstly, the rated mass flow rate of one cooling tower was fixed to 2,000 L/min. Secondly, the number of cooling towers was determined to match the rated mass flow rate of the refrigerator. For example, when the rated mass flow rate of cooling water from CR1 is 16,950 L/min, nine cooling towers are required. The heat lost from the insulated pipes was considered negligible [16] and therefore ignored. The characteristics of each component were obtained from [17].

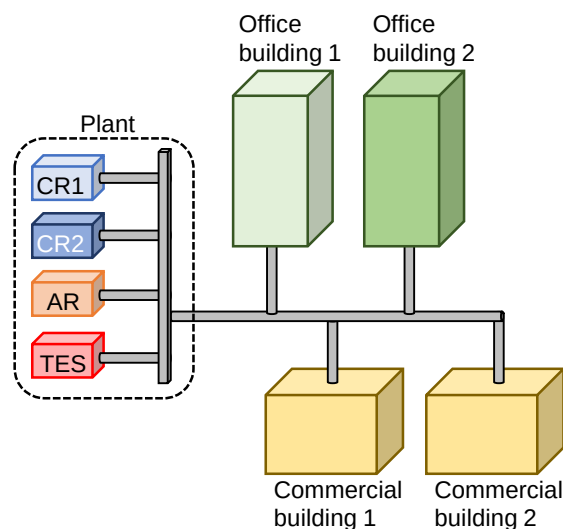


Fig. 1. Conceptual diagram of the district cooling system.

Table 1. Machine specifications.

CR1; CR2	Rated cooling capacity	5,000 kW
	Minimum partial load rate	20%
	Rated electricity consumption	861.5 kW
AR	Rated cooling capacity	8,000 kW
	Minimum partial load rate	25%
	Rated electricity consumption	68.8 kW
	Rated gas consumption	474.4 m ³
TES	Rated capacity	40,000 kWh
	Maximum charging or discharging rate	50%

2.2. Demand and price profiles

The calculation time horizon and time interval were set to 24 h and 1 h, respectively. The cooling demand profiles and the atmosphere temperature T_{atm} [°C] presented in Fig. 2 were obtained from [18] and [19], respectively. The electricity price p_e [yen/kWh], which is depicted as a red dotted line in Fig. 2, was considered to follow a time-of-use price system in which the price was quite high between 1 p.m. and 4 p.m. and relatively low otherwise. Hence, optimal operation was expected to involve charging cooling energy to the TES unit from 1 a.m. to 8 a.m. and discharging the energy to the district from the TES unit during the peak period. Additionally, the heat source machine was operated at efficient load rates to minimize the energy consumption and electricity price.

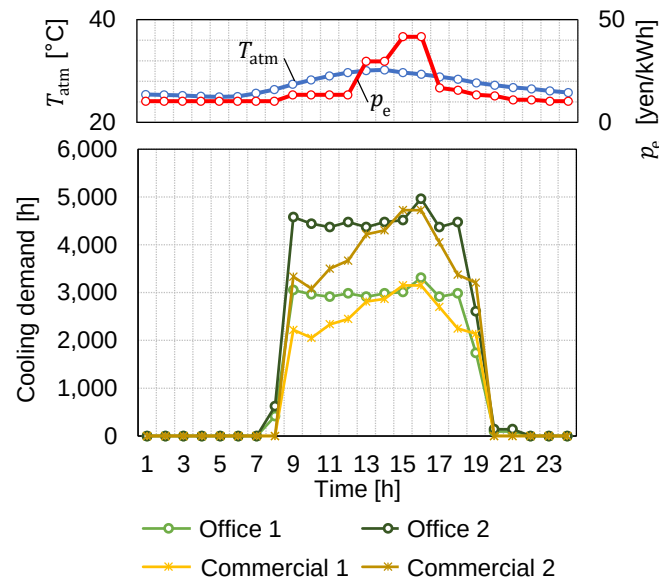


Fig. 2 Demand and price profiles.

2.3. Problem formulation

The objective function minimizing the daily operating costs of the district is as follows:

$$\text{minimize } f = \sum_{t=1}^{24} \left(p_e^t \sum_{m=1}^4 c_{e,m}^t + p_g c_g^t \right) \quad (1)$$

where p_e^t and p_g are the price of electricity [yen/kWh], which was changed dynamically, and the price of gas [yen/m³], which was fixed to 87.2 yen/m³, respectively. $c_{e,m}^t$ and $c_{g,n}^t$ are the electricity and gas consumption, respectively. $c_{e,m}^t$ incorporates the electricity consumption of the machine, cooling

tower fan, and pumps for cooling and chilled water. m denotes the machine number (1: CR1, 2: CR2, 3: AR, and 4: TES). The constraints are as follows:

$$Q_{CR1}^t + Q_{CR2}^t + Q_{AR}^t - Q_{TESc}^t + Q_{TESd}^t \geq D_c^t \quad (2)$$

$$Q_{CR1}^t, Q_{CR2}^t = 0 \text{ or } 1,000 \leq Q_{CR1}^t, Q_{CR2}^t \leq 5,000 \quad (3)$$

$$Q_{AR}^t = 0 \text{ or } 2,000 \leq Q_{AR}^t \leq 8,000 \quad (4)$$

$$0 \leq Q_{TESc}^t, Q_{TESd}^t \leq 8,000 \quad (5)$$

where Q_{CR1}^t , Q_{CR2}^t , and Q_{AR}^t denote the thermal outputs of CR1, CR2, and AR, respectively. Q_{TESc}^t and Q_{TESd}^t denote the thermal outputs of TES unit charging and discharging. D_c^t denotes the cooling demand.

There were 72 decision variables in total (3 machines (Q_{CR1}^t , Q_{CR2}^t , and S_{TES}^t which represented stored energy in TES unit [kWh]) $\times$ 24 h). If the full search algorithm was used, there would be $21^{3 \times 24}$ possible decision variable combinations, i.e., 21 operating load rates with 5% resolution, 3 machines, and 24 h, although the maximum number of combinations is not always tried in the DP and metaheuristic methods. The decision variables were standardized between 0 and 1, and the originally continuous variables were transformed into discrete variables with a resolution of 5% (e.g., 0, 0.05, 0.10, ..., 1.00) by rounding off to the nearest number in the metaheuristics.

3. Methods

3.1. DP

To confirm the accuracy of the ϵ DE-RJ results, DP was also used to derive theoretical optimal results. DP has advantages compared to other mathematical methods. In terms of application flexibility, DP can be employed to solve any configuration of functions, such as linear and higher-degree equations, while linear programming methods can only be used to solve linear configurations and nonlinear programming methods can be utilized to solve quadratic and cubic functions. Hence, DP is suitable for handling complex configurations of heat source machines. In terms of discrete optimization, it is easy to apply DP to discrete problems because DP originally handles discrete rather than continuous functions. In contrast, linear and nonlinear programming methods require specific methods to transform continuous functions into discrete functions, although district and building energy systems are controlled by discrete set points, such as pump speeds and temperatures. Therefore, DP is advantageous in this situation.

The computational complexity of DP can be expressed as follows:

$$\text{Computational complexity of DP} := N_{rs}^{2N_{dv}} \times N_t \quad (6)$$

where N_{rs} denotes the discrete resolution of the decision variables. In this case, N_r was 21 due to the 5% resolution from 0% to 100%. N_{dv} denotes the number of decision variables ($=3$), and N_t denotes the number of time steps ($=24$). Hence, the complexity was $21^{2 \times 3 \times 24}$, indicating that there were approximately one billion decision variable combinations. One negative aspect of DP is that it requires large amount of computational memory. In fact, the abovementioned complexity reached the computational limit of our computer due to its memory capacity (OS: Windows 10 64 bit, CPU: i7-4770 (3.40 GHz), RAM: 32 GB). All of the simulations including DP and the methods mentioned later were performed using MATLAB R2017a with a parallel computing toolbox (four workers).

3.2. ϵ -constrained differential evolution with random jumping (ϵ DE-RJ)

Differential evolution (DE) was first developed by Storn [20] and has been used often in many research fields [21–23]. However, the classical DE is not suitable when there are many constraints, especially in a high-dimensional searching space. To extend not only DE, but also other metaheuristic methods to develop more flexible constrained methods, many different types of constraint handling

methods have been proposed. In particular, Mallipeddi [14] compared several constraint methods with DE applied to an optimal power dispatch problem. In accordance with the paper, ϵ DE exhibited stability in different types of problems. ϵ DE was proposed by Takahama [9] and showed extensive capabilities. Although ϵ DE is usable in high-dimensional optimization problems, such as the 24- and 75-dimensional problems described in [24] and [14], respectively, it has a weak point related to searching for global optima because of the basic algorithm of classical DE. The weakness results from the classical DE mutation algorithm. Hence, the author proposed ϵ DE-RJ [15], which involves stochastically moving individuals to other searching points using uniformly distributed random numbers inspired by a classical genetic algorithm mutation method.

The ϵ DE-RJ algorithm is as follows. First, the classical DE mutation algorithm shown in Eq. (7) is performed:

$$v = x_{r1} + R_{mt}(x_{r2} - x_{r3}) \quad (7)$$

where v denotes a trial vector and x_{r1} , x_{r2} , and x_{r3} are randomly chosen individuals. R_{mt} is a mutation rate, called a scaling factor. When the values of the decision variables are the same, the differential variation ($x_{r2} - x_{r3}$) is exactly zero. Hence, the individuals are trapped in a local optimum. Then, the random jumping method is performed for every dimension as follows:

$$v_{i,j} = \begin{cases} x_{r1,j} + R_{mt}(x_{r2,j} - x_{r3,j}) & \text{when } |x_{r2,j} - x_{r3,j}| > 1.0 \times 10^{-3} \\ x_{r1,j} + \mathcal{U} & \text{otherwise} \end{cases} \quad (8)$$

where j denotes the dimension of the decision variables and $\mathcal{U} \in [0,1]$ denotes a uniformly distributed random number. However, the threshold ($|x_{r2,j} - x_{r3,j}| > 1.0 \times 10^{-3}$) was strict and difficult to apply. Thus, the following improvement was applied in this study:

$$v_{i,j} = \begin{cases} x_{r1,j} + R_{mt}(x_{r2,j} - x_{r3,j}) & \text{when } |x_{r2,j} - x_{r3,j}| > 1.0 \times 10^{-2} \text{ or } \mathcal{U}_1 \geq R_{RJ} \\ \mathcal{U}_2 & \text{otherwise} \end{cases} \quad (9)$$

where R_{RJ} denotes the random jumping rate and $\mathcal{U}_1 \in [0,1]$ and $\mathcal{U}_2 \in [0,1]$ are uniformly distributed random numbers. This improvement is expected to enable optimal combinations of decision variables to be searched globally by ϵ DE due to the threshold being changed to 0.01 from 0.001 and $\mathcal{U}_2$ being directly substituted for the trial vector. The key to the improvement is control of the random jumping execution frequency using random numbers as well. The newly added parameter R_{RJ} is a key factor determining the searching ability. The ϵ DE-RJ methods described by Eqs. (8) and (9) are referred to as ϵ DE-RJ-I and ϵ DE-RJ-II, respectively. The fundamental DE algorithm was DE/rand/1/exp. To evaluate the random jumping method, the other improved DE method, it was compared with the differential evolution with random local search (DERLS) method [25]. ϵ DERLS, the ϵ -constraint handling method associated with DERLS, was utilized in this research because the original DERLS did not include constraint handling methods. While the random jumping method is applied to each individual possible for the given R_{RJ} in ϵ DE-RJ-I and ϵ DE-RJ-II, the random number is applied only to the best individual in ϵ DERLS and the objective function should be generated repeatedly (e.g., 10 times) to replace the individuals every generation. Hence, the computational cost of ϵ DERLS can be greater than that of ϵ DE-RJ.

The fixed parameters were the number of generations ($N_g = 10,000$), the parameter controlling the crossover rate reduction exponentially as shown in Eq. (10), and the parameter controlling the relaxation reduction constraint ($cp = 3.0$):

$$R_{cs} = \exp(-k \times w_{cs}/N_g) \quad (10)$$

where R_{cs} is the crossover rate and k is the elapsed number of iterations. w_{cs} is a constant value controlling the crossover rate reduction. ϵ DE-RJ involves some parameters; however, there are no universally optimal combinations of these parameters.

4. Results and discussion

4.1. Comparison of DP and DE-based algorithm results

The daily operating cost of DP was 446,256 yen/day, and its computation time was 267,114 s (72 h 11 min 54 s) on the aforementioned personal computer. When the DE-based algorithms were first performed, N_{pop} and R_{mt} were fixed to 40 and 0.6, respectively. The optimization calculations were conducted 10 times to account for the randomness of the metaheuristics. Fig. 3 presents the boxplot results obtained using each DE-based algorithm. Although classical ϵ DE required the same computation time as ϵ DE-RJ-I and ϵ DE-RJ-II, it yielded the highest variation. ϵ DE-RJ-I exhibited relatively low variation, but its 50th percentile value was inferior to those of ϵ DERLS and ϵ DE-RJ-II. ϵ DE-RJ-II was the best method in this comparison due to its low variation, lowest 50th percentile value, and mean computation time, which was the same as that of ϵ DE. The best value in the ϵ DE-RJ-II results was the operating cost of 455,644 yen/day, which was only 2.1% higher than the theoretical DP result, although the computation time was reduced by 1/457.

ϵ DERLS required the longest computation time because iterative evaluation was conducted every generation in the RLS method. Additionally, the results exhibited greater variation than those obtained using the other two improved methods.

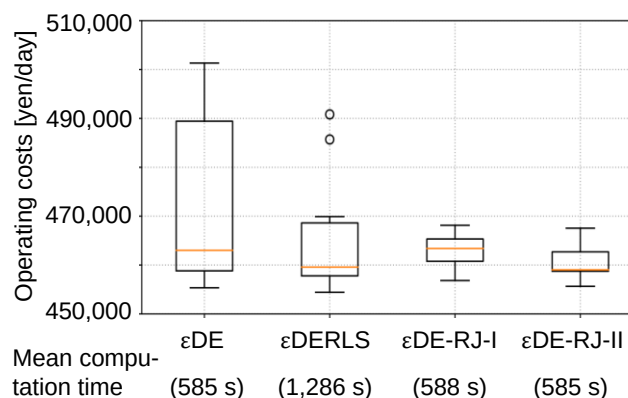


Fig. 3. Percentile analysis of various ϵ -constrained DE methods.

4.2. Optimal operating schedules obtained using DP and ϵ DE-RJ-II

Fig. 4 depicts the optimal operating schedules obtained using DP and ϵ DE-RJ-II. From 1 a.m. to 8 a.m., CR1 and CR2 generated cooling heat and the TES unit charges because the electricity price was low. At 9 a.m., the TES unit discharged cooling heat to meet the cooling demand because the sum of the rated capacities of CR1 and CR2 was not sufficient to meet it. From 10 a.m. to 11 a.m., CR1, CR2, and AR generated heat and the TES unit recharged to prepare for the next peak-time horizon, especially that from 1 p.m. to 4 p.m. During the peak-time horizon, the TES unit discharged drastically, as shown by the yellow bars in Fig. 4. Although AR usage to reduce electricity consumption could be expected in accordance with empirical operation, CR1 and CR2 were operated instead of the AR because of the complex characteristics. Thus, the optimization process yielded unusual solutions.

A significant difference between the DP and ϵ DE-RJ-II results lay in the operating schedule after 5 p.m. The DP results indicates that the TES unit charged and discharged alternately because it

allowed CR1 and CR2 to operate at efficient load rates at 8 p.m. Additionally, the alternating operation enabled CR1 to stop operating at 9 p.m. because the cooling demand was too low, and the TES unit discharged instead of CR1 being used. In contrast, the ϵ DE-RJ-II results show that the TES unit did not charge and discharge at all during the time horizon and that the heat source machines such as CR1, CR2, and AR were operated. Despite the abovementioned differences, the daily operating cost achieved using ϵ DE-RJ-II differs by only 2.1% from that obtained using DP.

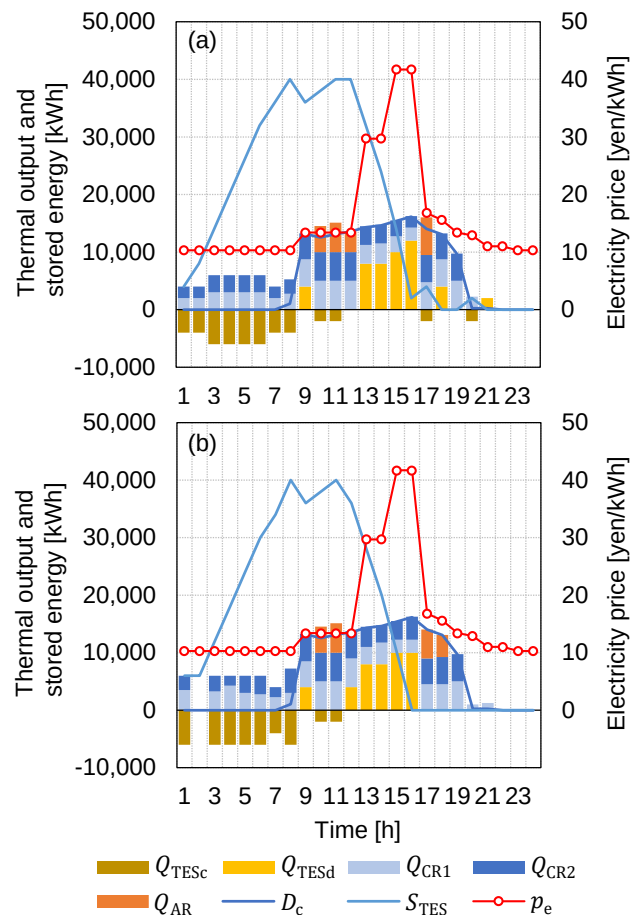


Fig. 4. Optimal operating schedules of the district energy plant: (a) DP and (b) ϵ DE-RJ-II results.

5. Conclusion

In this study, the performance of a constrained metaheuristic optimization method, ϵ DE-RJ, was validated with application to district energy optimization. ϵ DE-RJ was also compared to DP, which was used to derive a theoretical optimal solution; classical ϵ DE; and ϵ DERLS, which represents an improvement over classical DE due to the addition of randomness. Furthermore, ϵ DE-RJ-II was proposed as a slightly improved version of the original ϵ DE-RJ (called ϵ DE-RJ-I in this paper).

ϵ DE-RJ-II was superior to ϵ DE, ϵ DERLS, and ϵ DE-RJ-I in terms of the mean value of the objective function after 10 sets of calculations and produced results with the least variation. The ϵ DE-RJ-II result was 2.1% higher than the DP result, but the computation time was only 1/457 of that required by DP. Hence, ϵ DE-RJ-II has high potential to be used in actual district energy management because the practical situation required limited computation time on an ordinary computer.

Although ϵ DE-RJ-II could be improved further to minimize the difference of 2.1% from the theoretical result, it can be used practically with high accuracy and low computational cost.

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