Optimal Design of Combined Heat and Power System Using a Genetic Algorithm

Yoichi Tanaka[1], Yoshito Umeda[1], Tomoyuki Hiroyasu [2] and Mitsunori Miki[2]

1. Fundamental Research Department, Toho Gas Co.,Ltd, Tokai, Japan
2. Department of Knowledge Engineering and Computer Sciences, Doshisha University , Kyoto, Japan

Abstract: Combined heat and power (CHP) systems generate electric power by means of engine, turbine and fuel cell, and also supply the thermal energy produced through power generation.
Therefore, they are expected to be widespread and contribute to boost total efficiency and save energy.
The optimal design problem of CHP systems is a combinatorial optimization problem involving generators, thermally-activated machines, boilers, chillers and heaters. To solve this problem, the optimal operation of the designed CHP system must be achieved.
In this paper, we formulate the CHP system optimization problem and apply a genetic algorithm with a two stage optimization strategy: the first stage consists of combinatorial optimization, and the second stage consists of operation optimization. Numerical experiments show that the proposed method is effective for the optimal design of CHP systems.

Keywords: Combined heat and power, Genetic algorithm, Engineering Optimization, Optimal design , Optimal operation

1. INTRODUCTION

Combined Heat and Power systems (hereinafter abbreviated as CHP systems) are power generation systems that are installed in locations requiring electrical power from which both electrical power and thermal energy are obtained at the same time. In recent years, they have been receiving attention because of heightened interests in energy conservation. CHP systems have a generator such as an engine or gas turbine for driving a generator, thermally-activated machines such as an absorption chiller or an exhaust heat boiler that utilizes the exhaust heat from the generator, as well as a supplemental boiler used when the exhaust heat does not produce enough hot water or steam.

Design optimization problems in CHP systems involve the problem optimizing the combination of generators, thermally-activated machines, and supplemental boilers. However, in order to determine the suitability of a given combination, it is necessary to solve an operation optimization problem for electrical demand, cooling demand, heating demand, and hot water demand, all of which change over time.

Ito and Yokoyama proposed a method where the CHP systems design optimization problem is divided into the operational optimization problem and the system configuration design optimization problem, and is then solved in stages. In Ito and Yokoyama's method, the operation optimization problem was solved as a mixed-integer linear programming problem, and the system configuration design optimization problem was solved by using a gradient method after being simplified [1].

In addition, Fujita et. al pointed out that CHP systems design problem is a complex combinatorial optimization problem, and reported a method to solve the system configuration design optimization problem using a genetic algorithm and to solve the operation optimization problem as a mixed integer linear programming problem using the branch-and-bound method[2].

Although the performance of most machines making up CHP systems is linear, there are some exceptions to this; i.e. machines with efficiencies that drop off dramatically below a certain load factor. When operation optimization is taken as a mixed-integer linear programming problem, handling with this type of exceptional machines is difficult, and this is problematic. For this reason, metaheuristics have been proposed as an approach to the CHP systems operation optimization problem. Ohara et. al proposed a method of using genetic algorithms to solve the operation optimization problem for CHP systems made up of fuel cells and heat pumps[3]. However, few examples have been reported of design optimization of CHP systems containing machines with nonlinear performance. In particular, there have been no examples reported in which both the system configuration design and operation are optimized with the nonlinear performance of the machine.

With the CHP systems design problem investigated in this paper, system configuration design was regarded as combination optimization problem to select the optimal machines out of the available candidates, while operation was regarded as a nonlinear optimization problem by approximating machine efficiencies with quadric functions. By laying out the problem in this way, this CHP systems design optimization method under development makes it possible to flexibly correspond to a wider variety of machines.

A genetic algorithm was used to solve these problems. It was natural for us to make the attempt adopting the genetic algorithm with a track record in solving combinatorial optimization problems[4] for the optimization of the configuration making up the CHP systems. Moreover, it would have been conceivable that it is effective to adopt a genetic algorithm for operation optimization as

Corresponding author: H. Kimura, isets07@esi.nagoya-u.ac.jp

well if taking machine performance to be nonlinear. Thus, a genetic algorithm specialized for CHP systems design optimization problem was developed, that is able to simultaneously optimize system configuration design and operation, and the effectiveness of this algorithm was verified.

2. FORMULATION OF CHP SYSTEMS OPTIMIZATION PROBLEM

Figure 1 shows the system configuration of the applicable CHP systems to be optimized. μ is the energy demand that the CHP systems must satisfy, and this is applied as a design parameter.

P is a location where a generator is installed, Q is a location where a boiler is installed, and R is a location where a thermally-activated machine is installed.

ξ is the total energy input from outside the system into the generators and boilers. υ is the energy required to compensate for insufficient energy input into the thermally-activated machines. ζ is the energy amount used to compensate for any differences between energy demand and the energy coming out of the CHP systems. The purpose of this optimization problem is to minimize the total energy input (ξ, υ, and ζ).

D^I is the energy input into the generators, D^O is the energy output from the generators, E^I is the energy input into the boilers, E^O is the energy output from the boilers, F^I is the energy input into the thermally-activated machines, and F^O is the energy output from the thermally-activated machines. In addition, Φ is the total energy output from the generators and boilers, while Ω is the total amount of energy out of Φ and υ that does not input into the thermally-activated machines. Ψ is the total energy output of the thermally-activated machines.

The energy amounts described above are vectors made up of 8 components (e_1, e_2, e_3, e_4, e_5, e_6, e_7, and e_8). Here, e_1 is electrical power [kW], e_2 is heat for heating [kW], e_3 is heat for cooling [kW], e_4 is heat for heating water [kW], e_5 is exhaust heat in the form of hot water [kW], e_6 is exhaust heat in the form of gas emissions [kW], e_7 is exhaust heat in the form of steam [kW], and e_8 is the latent heat in municipal gas [kW].

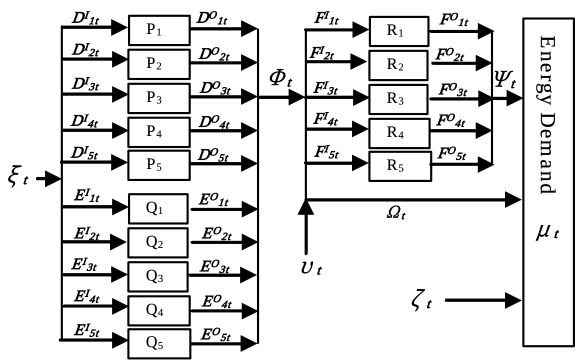

Fig.1 Configuration of CHP system

2.1. Allocation of machines

A generator is chosen from a set G and located on a element of P, where the set G = $\{g_1,g_2,g_3,\ldots,g_L\}$ is the set of generators and the set P=$\{P_1,P_2,P_3,\ldots,P_I\}$ is the set of the locations of generators. Same kind of generator can be chosen any times.

A boiler is chosen from a set B and located on a element of Q, where the set B = $\{b_1,b_2,b_3,\ldots,b_M\}$ is the set of boilers and the set Q=$\{Q_1,Q_2,Q_3,\ldots,Q_J\}$ is the set of the locations of boilers. Same kind of boiler can be chosen any times.

A thermally-activated machine is chosen from a set H and located on a element of R, where the set H = $\{h_1,h_2,h_3,\ldots,h_M\}$ is the set of thermally-activated machines and the set R=$\{R_1,R_2,R_3,\ldots,R_K\}$ is the set of the locations of thermally-activated machines. Same kind of thermally-activated machine can be chosen any times.

The 0/1 variables x,y and z are defined as below

$$x_{ij} = \begin{cases} 1: g_j \text{ is located at } P_i \\ 0: g_j \text{ is not located at } P_i \end{cases} \quad (1)$$

$$y_{ij} = \begin{cases} 1: b_j \text{ is located at } Q_i \\ 0: b_j \text{ is not located at } Q_i \end{cases} \quad (2)$$

$$z_{ij} = \begin{cases} 1: h_j \text{ is located at } R_i \\ 0: h_j \text{ is not located at } R_i \end{cases} \quad (3)$$

Only one machine can be located at each location.

On the actual CHP design, there would be the locations where any machine is located. Therefore virtual generator g_1, which does not have energy input and output, is introduced. To locate g_1 at P_i means that nothing is located at P_i. Similarly, virtual generator b_1 and virtual thermally-activated machine h_1 are introduced to denote that the locations where these machines are located are empty.

When g_1s are located at every P_i (i=1,2,3,…,I), the system can not be seen as CHP, therefore the constraint shown below is added.

$$\sum_{i=1}^{I} x_{i1} < I \quad (4)$$

2.2. Scheduling of machines

2.2.1. Startup time and stop time

It is not desirable that machines are started and stopped frequently. Therefore, we assume that one startup and stop in the scheduling period, which is a day or a week, is allowed.

Let τ be the last time of the scheduling period. The driving time of the generator located at P_i (i=1,2,3,…,I) is defined as below.

$$S_i = \{t : s_i^s \le t \le s_i^f\}$$
$$s_i^s, s_i^f \in \{1,2,3,\ldots,\tau\} \quad (5)$$

Where s^s_i and s^f_i are the startup time and the stop time of the generator respectively.

Similarly, the driving time of the boiler located at Q_i (i=1,2,3,…,J) is defined as below.

$$T_i = \{t : t_i^s \le t \le t_i^f\}$$
$$t_i^s, t_i^f \in \{1,2,3,\ldots,\tau\} \quad (6)$$

Where t^s_i and t^f_i are the startup time and the stop time of the boiler respectively. The driving time of the thermally-activated machine located at R_i (i=1,2,3,…,K) is defined as below.

$$U_i = \{t : u_i^s \le t \le u_i^f\}$$
$$u_i^s, u_i^f \in \{1,2,3,...,\tau\} \tag{7}$$

Where u^s_i and u^f_i are the startup time and the stop time of the thermally-activated machine respectively.

Let *X*,*Y* and *Z* denote the 0/1 variables which show the machines are running or not.

They are defined as below.

$$X_{it} = \begin{cases} 1 & t \in S_i \\ 0 & t \notin S_i \end{cases} \tag{8}$$
(i=1,2,…,I,t=1,2,…,τ)

$$Y_{it} = \begin{cases} 1 & t \in T_i \\ 0 & t \notin T_i \end{cases} \tag{9}$$
(i=1,2,…,J,t=1,2,…,τ)

$$Z_{it} = \begin{cases} 1 & t \in U_i \\ 0 & t \notin U_i \end{cases} \tag{10}$$
(i=1,2,…,K,t=1,2,…,τ)

2.2.2. Load factor

Load factor *u*,*v*,*w* and minimum load factor γ,β,η are defined as below.

u_{it} : The load factor of the generator located at P_i (i=1,2,…,I, t=1,2,…,τ)
v_{it} : The load factor of the boiler located at Q_i (i=1,2,…,J, t=1,2,…τ)
w_{it} : The load factor of the thermally-activated machine located at R_i (i=1,2,…,K, t=1,2,…,τ)
γ_j : The minimum load factor of the generator g_j (j=1,2,…,L)
β_j : The minimum load factor of the boiler b_j (j=1,2,…,M)
η_j : The minimum load factor of the thermally-activated machine h_j (j=1,2,…N)

On the CHP optimal design problem, the design variables are *u*,*v* and *w*. γ,β and η are the constants. *u*,*v* and *w* satisfy the following constraints.

$$\sum_{j=1}^{L} x_{ij}\gamma_j \le u_{it} \le 1 \tag{11}$$
(i=1,2,…,I, t=1,2,…,τ)

$$\sum_{j=1}^{M} y_{ij}\beta_j \le v_{it} \le 1 \tag{12}$$
(i=1,2,…,J, t=1,2,…,τ)

$$\sum_{j=1}^{N} z_{ij}\eta_j \le w_{it} \le 1 \tag{11}$$
(i=1,2,…,K, t=1,2,…,τ)

2.3. Evaluation function

ξ_t is the total fuel input on the time t (t=1,2,…,τ). It is defined as below.

$$\xi_t = \sum_{i=1}^{I} D_{it}^I + \sum_{i=1}^{J} E_{it}^I \tag{14}$$

Φ_t is the sum of the all generators output and the all boiler output. It is defined as below.

$$\Phi_t = \sum_{i=1}^{I} D_{it}^O + \sum_{i=1}^{J} E_{it}^O \tag{15}$$

υ_t is the compensation for the shortage of the energy for the all thermally-activated machines. It is written as below.

$$\upsilon_t = \left[\sum_{i=1}^{K} F_{it}^I - \Phi_t\right]_+ \tag{16}$$

Where $[.]_+$ shows the vector which is made by replacing the negative elements of the vector in the brackets with zeros.

Ω_t is the energy which isn't put to thermally-activated machines.

$$\Omega_t = \Phi_t + \upsilon_t - \sum_{i=1}^{K} F_{it}^I \tag{17}$$

ψ_t is the sum of output of the total thermally-activated machines.

$$\Psi_t = \sum_{i=1}^{K} F_{it}^O \tag{18}$$

The energy which can't be satisfied by the energy supply from the CHP on the time *t* (t=1,2,…,τ) is ζ_t. It is written as below.

$$\zeta_t = [\mu_t - \Psi_t - \Omega_t]_+ \tag{19}$$

The total energy consumption is written as below.

$$A = \sum_{t=1}^{\tau} (\xi_t + \upsilon_t + \zeta_t) \tag{20}$$

The objective function is defined as below.

$$V^{EV} = \sum_{j=1}^{8} C_j a_j \tag{21}$$

Where a_j is the j^{th} element of *A*, and C_j is the constants.

2.4. Input and output of machines

Input energy and output energy of a machine such as generator, a boiler and a thermally-activated machine are functions of the load factors.

These functions are named as below.

Input energy of generator g_j : $\Gamma^I_j(u)$
Output energy of generator g_j : $\Gamma^O_j(u)$
(j=1,2,…,L), *u*: load factor

Input energy of boiler b_j : $\Lambda^I_j(v)$
Output energy of boiler b_j : $\Lambda^O_j(v)$
(j=1,2,…,M), *v*: load factor

Input energy of thermally-activated machine h_j : $\Theta^I_j(w)$
Output energy of thermally-activated machine h_j : $\Theta^O_j(w)$
(j=1,2,…,N), *w*: load factor

Using these functions, D^I,D^O,E^I,E^O,F^I and F^O are written as below.

$$D^I_{it} = \begin{cases} \sum_{j=1}^{L} x_{ij}\Gamma^I_j(u_{ij}) & \text{if} \quad X_{it} = 1 \\ 0 & \text{if} \quad X_{it} = 0 \end{cases} \tag{22}$$

$$D^O_{it} = \begin{cases} \sum_{j=1}^{L} x_{ij}\Gamma^O_j(u_{ij}) & \text{if} \quad X_{it} = 1 \\ 0 & \text{if} \quad X_{it} = 0 \end{cases} \tag{23}$$

$$E^I_{it} = \begin{cases} \sum_{j=1}^{M} y_{ij}\Lambda^I_j(v_{ij}) & \text{if} \quad Y_{it} = 1 \\ 0 & \text{if} \quad Y_{it} = 0 \end{cases} \tag{24}$$

$$E^O_{it} = \begin{cases} \sum_{j=1}^{M} y_{ij}\Lambda^O_j(v_{ij}) & \text{if} \quad Y_{it} = 1 \\ 0 & \text{if} \quad Y_{it} = 0 \end{cases} \tag{25}$$

$$F^I_{it} = \begin{cases} \sum_{j=1}^{N} z_{ij}\Theta^I_j(w_{ij}) & \text{if} \quad Z_{it} = 1 \\ 0 & \text{if} \quad Z_{it} = 0 \end{cases} \tag{26}$$

$$F^O_{it} = \begin{cases} \sum_{j=1}^{N} z_{ij}\Theta^O_j(w_{ij}) & \text{if} \quad Z_{it} = 1 \\ 0 & \text{if} \quad Z_{it} = 0 \end{cases} \tag{27}$$

2.5. Evaluation function and design variables

In this problem, design variables are x,y,z which denote the allocation, and s^s,s^f,t^s,t^f,u^s,u^f which denote the startup and stop, and u,v,w which denote the load factors of the machines. And other variables are dependent variable.

The evaluation function is the equation 21. The aim of this problem is to search the design variables with which the evaluation function takes the minimum value.

3. GENETIC ALGORITHM THAT WAS APPLIED

The CHP systems design optimization problem set out in this paper has non-linear evaluation function with a large number of design variables with discrete values makes it difficult to find the strict optimum.

For this reason, we attempted to use a genetic algorithm, which is a versatile optimization method, to solve this problem.

3.1. Two-state genetic algorithm

If all the design variables are handled in the same way and simply lined up to create the gene code, the crossovers would destroy the relationship between machine load factor, startup times, start times, and machine types, which prevents the effective use of the genetic algorithm.

To overcome this problem, the 2-stage algorithm described below was devised.

3.1.1. Gene code

The concept of the gene code used in this Two-stage genetic algorithm is shown in Figure 2. The variables x, y, and z, which express equipment installation, together with the variables s^s, s^f, t^s, t^f, u^s, and u^f, which express start and shutdown times for each equipment, as the integer design variables.

The variables u, v, and w express load factors and are the real number design variables.

In this code, the rows correspond to the installation locations of the equipment. The 1st row shows the values indicating the installed equipment and the 2nd row shows the startup times. The 3rd row shows the end time, while the 4th row and below indicate the load factors at each time value.

Figure 3 shows a specific example of installation location Pi for design variables layout on the genetic code.

The characteristics of this code are as follows:

(1) For each equipment, the equipment type, startup time, end time, and load factor are one set.
(2) The variables are divided into integer design variables and real number design variables, and optimization is executed alternating between the two sets as shown in Figure 4.

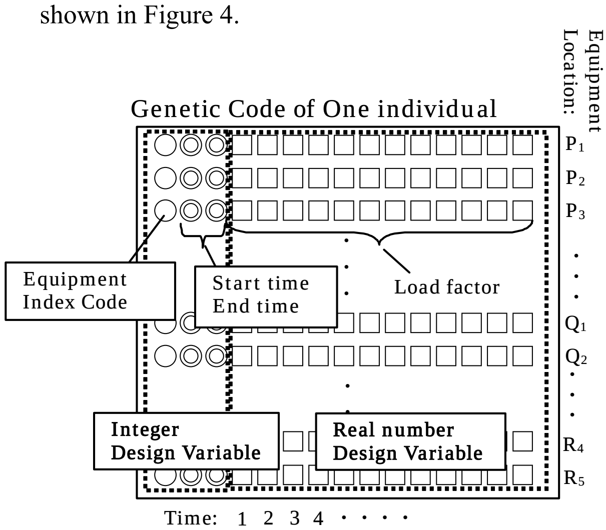

Fig.2 Structure of genetic code

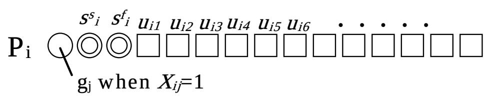

Fig.3 Genetic code of one equipment

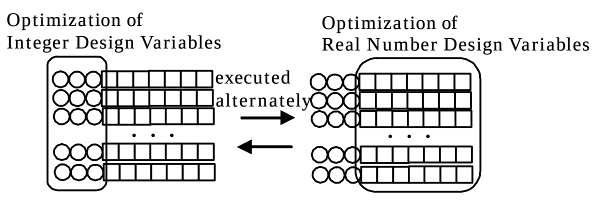

Fig.4 Optimization execution

3.1.2. Mutations

Mutations are introduced as a certain probability of changes to the integer design variables and real number design variables. The integer design variables are subjected to mutations during integer design variable optimization, while the real number design variables are subjected to mutations during real number design variable optimization. The change values are plausible values for each design variable.

3.1.3. Crossovers

During integer design variable optimization, two randomly selected rows are switched as shown in Figure 5. During real number design variable optimization, only the real number design variables are switched at random as shown in Figure 6.

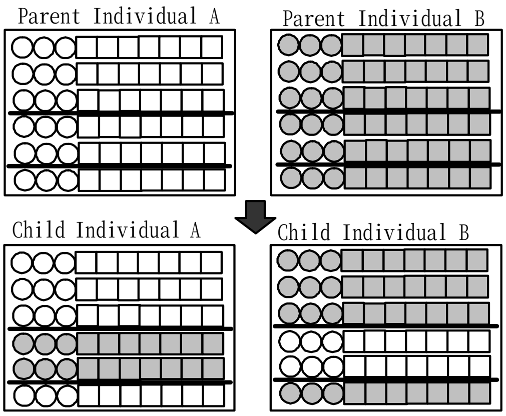

Fig.5 Crossover on integer design variables optimization stage

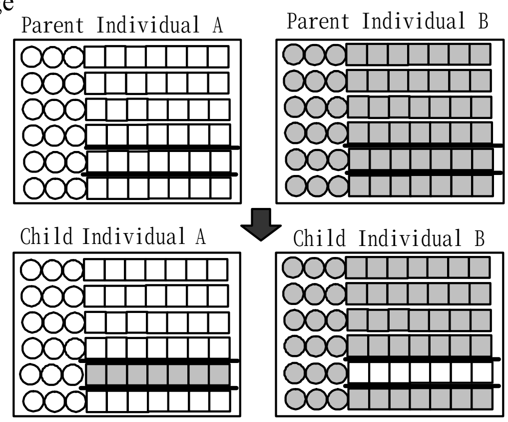

Fig.6 Crossover on real number variables optimization stage

3.1.4. Penalties

Those individuals not satisfying the equation (4) have the maximum value of energy consumption amount applied so that they are not selected.

3.1.5. Design of distributed genetic algorithm

A distributed genetic algorithm[5] was adopted as the basic algorithm.

The best individual was chosen using a tournament selection. In addition, a bit conversion was not used for the encoding method. Instead, the integer values were used for the integer design variables, while real number values were used for the real number design variables.

Here, the “int” type variables were used for the integer values and “double” type variables were used for the real number values (effective digit: 15 decimal digits).

For both integer design variable optimization and for real number design variable optimization, during one optimization operation, the selection of fit individuals is carried out on all of the individuals, followed by crossover on the selected individuals, which is followed by mutations on each of the individuals generated during the crossover step. Both integer design variable optimization and real number design variable optimization are carried out continuously in the same way until they reach the prescribed final number of generations, when a switch is carried out to another method.

4. PARAMETERS FOR NUMERICAL EXPERIMENT

4.1. Types of machines

In this numerical experiment, the generators were selected from those shown in Table 1, the boilers were selected from those shown in Table 2, and the thermally-activated machines were selected from those shown in Table 3.

Table 1. Set of generators

G	Generator type	Capacity [kW]	Exhaust heat type
g_1	No generator		
g_2	Gas engine	6	Hot water
g_3	Gas engine	25	Hot water
g_4	Gas engine	110	Hot water
g_5	Gas engine	200	Hot water
g_6	Gas engine	350	Hot water
g_7	Gas engine	740	Hot water
g_8	Gas turbine	27	Steam
g_9	Gas turbine	27	Exhaust gas
g_{10}	Gas turbine	60	Steam
g_{11}	Gas turbine	60	Exhaust gas

Table 2. Set of boilers

B	Boiler type	Capacity [kW]
b_1	No boiler	
b_2	Steam boiler	60
b_3	Hot water boiler	60
b_4	Steam boiler	470
b_5	Hot water boiler	470
b_6	Steam boiler	1250
b_7	Hot water boiler	1250

Table 3. Set of thermally-activated machines

H	Thermally-activated machine type	Capacity [kW]	Exhaust heat type
h_1	No machine		
h_2	Absorption refrigerator	150	Hot water
h_3	Absorption refrigerator	300	Hot water
h_4	Absorption refrigerator	450	Hot water
h_5	Absorption refrigerator	150	Steam
h_6	Absorption refrigerator	300	Steam
h_7	Absorption refrigerator	450	Steam
h_8	Absorption refrigerator	150	Exhaust gas
h_9	Absorption refrigerator	300	Exhaust gas
h_{10}	Absorption refrigerator	450	Exhaust gas
g_{11}	Heater	500	Hot water
h_{12}	Heater	500	Steam
h_{13}	Hot water boiler	500	Hot water
h_{14}	Hot water boiler	500	Exhaust gas
h_{15}	Hot water boiler	500	Steam

4.2. Machine efficiency

The functions for the energy output of the machines (Γ^O, Λ^O, and Θ^O), the energy input into the machines (Γ^I, Λ^I, and Θ^I) were decided as follows.

The power output from the generators is obtained by multiplying the rated power generation output by the load factor. The input of municipal gas is obtained by dividing the power generation output by the power generation efficiency. Exhaust heat output is obtained by multiplying the input of municipal gas by the exhaust heat collection efficiency. The power generation efficiencies of various generators are shown in Figure 7, while the exhaust heat recovery efficiencies of various generators are shown in Figure 8. The relationship between the efficiency and load factor was approximated as a quadratic function and used.

The calculations were performed assuming a fixed efficiency for the boilers and thermally-activated machines.

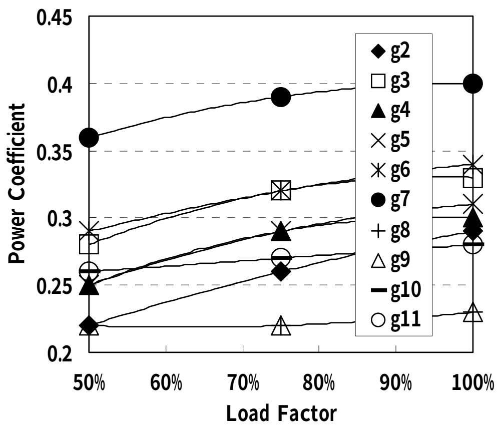

Fig.7 Power generation coefficient

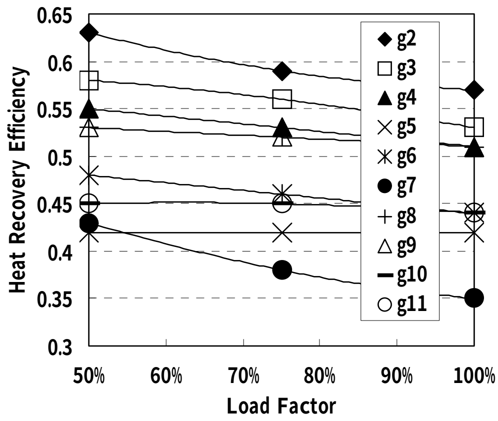

Fig.8 Heat recovery efficiency

4.3. Energy demand

In this numerical experiment, the final operation time $\tau = 24$, and energy demand μ_t ($t = 1, 2, 3, \ldots 24$) was set out as shown in Figure 9. Of the elements for μ_t, every element other than e_1 (electrical power), e_3 (cooling), e_4 (hot water) were set to zero for all time values.

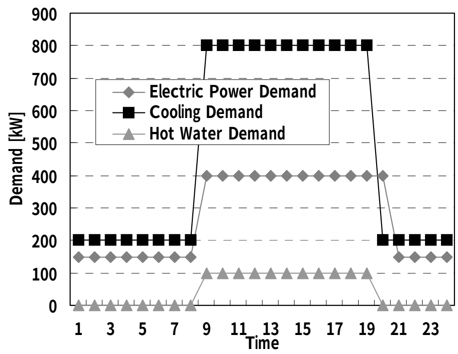

Fig.9 Energy demand

4.4. Weighting constants of consumed energy

The energy utilization weighting constants C_j for evaluation function (21) ($j = 1, 2, \ldots, 8$) are as follows:
C_1=2.86, C_2=0.952, C_3=0.952, C_4=1.25, C_5=1.25, C_6=1.0, C_7=1.25, C_8 = 1.0.

These values are set out from the standpoint of how much primary energy is required to generate a unit amount of the required energy.

4.5. Parameters for genetic algorithm

The parameters for the genetic algorithm are shown in Table 4.

5. RESULTS OF NUMERICAL EXPERIMENT

5.1. Trial Results

A summary of all 50 trials is shown in Figure 10. The evaluation values in the figure are values obtained by equation (21) divided by $\tau = 24$, and its physical meaning is an average energy input. The best, median, and worst value shown in the figure indicate the best, median, and worst values in the 50 trials in each generation. The solid line in the figure is the median value.

The average energy input without a CHP systems is 1295kW, and in each of the test runs, a better solution than not having CHP systems was selected before 50 generations.

Table 4. Parameters of genetic algorithm

item	value
Trials number	50
Number of islands	20
Migration rate	0.5
Migration interval	5
Population size	10
Number of generations	500
Number of generations(integer design variables optimization)	30
Number of generations(real design variables optimization	60
Tournament size	4
Crossover rate	1.0
Mutation rate(integer design variables optimization)	0.0222
Mutation rate(real design variables optimization)	0.002778

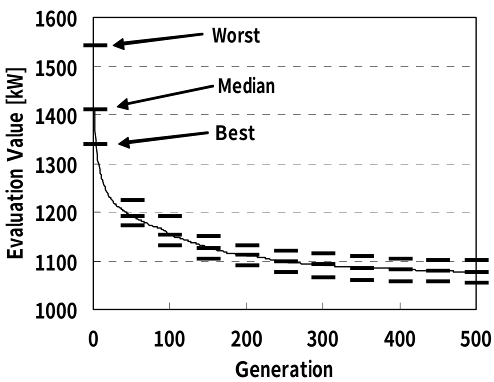

Fig. 10 Transition of evaluation value

5.2. Validity of the solution obtained

Table 5 shows the selected machines. Figure 11 shows the output of the power generation, and Figure 12 shows the exhaust heat utilization status. CHP systems have higher efficiencies if power is generated from the generators when there is no surplus in both power output and exhaust heat output. The solution obtained from the genetic algorithm also had a minimal surplus of exhaust heat, which is a characteristic of high-efficiency CHP systems.

In actual systems, the boiler is installed as a supplemental role. However, the use of boilers is disadvantageous from the standpoint of energy efficiency. Boilers and generators are what produce the energy used by thermally-activated machines, and generators output power in addition to the exhaust heat output, which makes it possible to reduce the electrical power element of ζ. Because of this significant effect, if there is a boiler output, it is more efficient to install a generator that is able to produce the same amount of exhaust heat.

In the numerical experiment carried out for this paper, there were no boilers being installed at al and this is a valid result.

Table 5. Selected machines

Location	machine	Startup time	Stop time
P_1	g_1	3	12
P_2	g_{11}	1	10
P_3	g_{11}	1	12
P_4	g_7	10	21
P_5	g_1	10	15
Q_1	b_1	1	10
Q_2	b_1	1	12
Q_3	b_1	13	20
Q_4	b_1	17	23
Q_5	b_1	1	8
R_1	h_4	11	21
R_2	h_9	6	19
R_3	h_8	1	19
R_4	h_3	10	20
R_5	h_8	1	19

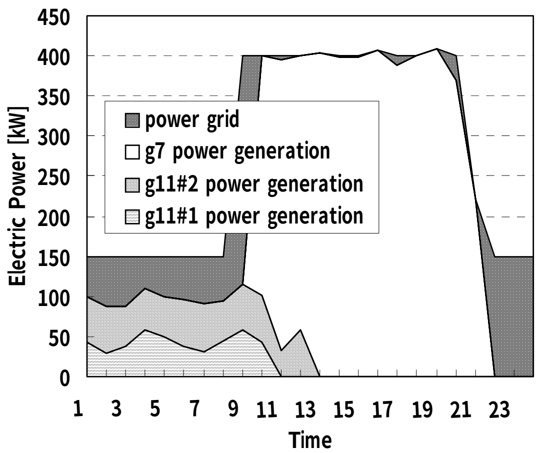

Fig. 11 Schedule of generators

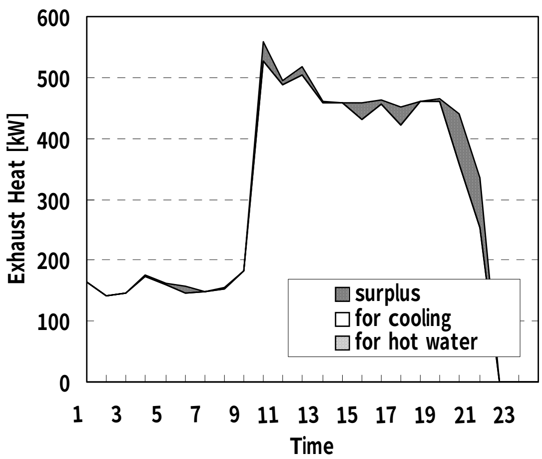

Fig. 12 Usage of exhaust heat

6. CONCLUSION

A genetic algorithm was used on the problem of design optimization in CHP systems that have nonlinear energy inputs and outputs. It verifies that good results were obtained.

The problem of design optimization in CHP systems was simplified using the points below.

(1) In this experiment, an optimization was performed on 24 hours of energy, but in reality, an optimization in consideration of energy demand for 1-year need to be performed.
(2) In this experiment, there were only 30 types of machines considered, but in reality, there are several hundred machines.

REFERENCES

1. Yokoyama,R., Ito,K. and Akagi, S., 1st Reoprt, Optimization Method and Its Effect, Transactions of the Japan Society of Mechanical Engineers, Series C, Vol.56, No.522(1990), pp. 263--270

2. Fujita,K., Akagi,S., Hirokawa.,N. and Yoshida,K., Optimal Planning Method of Energy Plant Configurations based on a Genetic Algorithm, Transactions of the Japan Society of Mechanical Engineers, Series C, Vol.64, No.617(1998), pp.354--361

3. Obara,S. and Kudo,K., Multip-purpose Operational Planning of Fuel Cell and Heat Pump Compound System using Genetic Algorithm, Transactions of the Society of Heating, Air-Conditioning and Sanitary Engineers of Japan, Vol.91(2003), pp.65--75

4. Kitagawa,S., Genetic Algorithm（in Japanese）, Vol.1,(1993), p.133, Sangyo-Tosho

5. Miki,M., Hiroyashu,T., Hatanaka,K. and Yoshida,J., Effectiveness of the availability of Parallel Distributed Genetic Algorithms, Transacitions of the Japan Society for Computational Engineering and Sience, No.20000038(2000)