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Optimal Operational Planning of a Cogeneration Plant Considering Load Forecasting Error

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Abstract - **In recent years, cogeneration systems (CGS) have been installed in various factories and buildings. In order to generate optimal operational planning for CGS, various load, for example, electric loads, air-conditioning loads, heating loads, and hot water loads, should be forecasted, and startup and shutdown status and input values for the facilities at each control interval should be determined using facility models. The authors have already developed optimal operational planning for CGS using particle swarm optimization (PSO), which is one of the meta-heuristic optimization methods. However, there have always been errors between load forecasting value and actual load value. Therefore, generated operational planning does not always be optimal considering load forecasting errors. This paper proposes optimal operational planning of a cogeneration plant by PSO considering load forecasting error. The proposed method is applied to a typical cogeneration system with promising results.**

I. INTRODUCTION

In recent years, cogeneration systems (CGS) have been installed in various factories and buildings. CGS is usually connected to various facilities such as refrigerators, reservoirs, and cooling towers, and produces various energies for electric loads, air-conditioning loads, heating loads, and hot water loads (Fig.1). Since daily load patterns of the various loads are different, optimal operation planning for CGS is a very important task for saving operational costs and reducing environmental loads.

In order to generate optimal operational planning for CGS, various loads should be forecasted, and startup and shutdown status and input values for the facilities at each control interval should be determined using facility models (Fig.2). Therefore, the optimal operational planning problem can be formulated as a mixed-integer linear problem (MILP) and mathematical programming techniques such as branch-and bound, decomposition method, and dynamic programming have been applied conventionally [8,13,14]. However, the facilities may have nonlinear input-output characteristic practically and operational rules, which cannot be expressed as a mathematical forms, should be considered in actual operation. Therefore, the problem should be formulated as a mixed-integer nonlinear problem (MINLP), and independent facilities models should be developed for practical use and the method for solving the MINLP problem has been eagerly awaited.

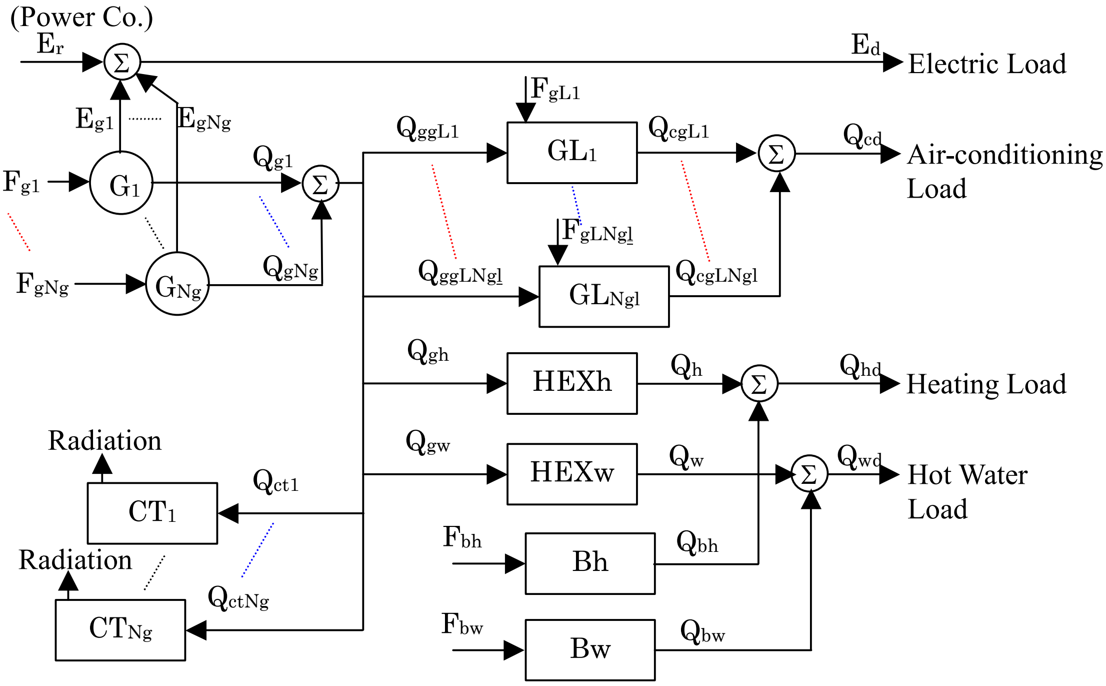
In these backgrounds, we have already developed optimal operational planning of cogeneration plant using particle swarm optimization (PSO), which is one of the meta-heuristic optimization methods [15]. PSO is one of the evolutionary computation (EC) techniques [10]. The method is improved and applied to various problems [1-5,7,10,11]. PSO can be expanded to handle the whole MINLP by itself easily and naturally, and it is easy to apply to various problems compared with conventional methods [6,12].

This paper proposes optimal operational planning of a cogeneration plant by PSO considering load forecasting error. Various loads should be forecasted in order to generate optimal operational planning for CGS. However, there have always been errors between load forecasting value and actual load value. Therefore, generated operational planning does not always be optimal considering forecasting error. We consider forecasting error as uncertainty, and propose a novel optimal operational planning method by PSO considering load forecasting error. The proposed method is applied to typical cogeneration planning problems with promising results.

II. PROBLEM FORMULATION

A. CONSIDERING METHOD OF LOAD FORECASTING ERROR

Generally, probability distribution of load forecasting error is expected to be expressed as normal probability distribution. Ideally, a number of simulation cases are performed by the considered normal probability distribution. However, performing a number of simulation cases is time-consuming. Therefore, limited number of types of load forecasting errors



Ng : Number of generator (Gen), Ngl : Number of genelink, G : Gen., GL : Genelink,
HEXh : Heat exchanger (HEX) for heat load, HEXw : HEX for hot water load,
CT : Cooling tower, Bh : Boiler for heating, Bw : Boiler for water supply,
E_r : Receiving/sending electric energy, F_g : CGS fuel, E_g : CGS electric power output,
E_d : Electric load, Q_g : CGS heat output, Q_{ggL} : GL input heat energy, F_{gL} : GL fuel,
QcgL : GL output heat energy, Q_{cd} : Air-conditioning load, Q_{gh} : HEXh input heat energy,
Q_h : HEXh output heat energy, Q_{hd} : Heat load, Q_{gw} : HEXw input heat energy,
Q_w : HEXw output heat energy, Q_{wd} : Hot water load, F_{bh} : Bh fuel, Q_{bh} : Bh output heat energy,
F_{bw} : Bw fuel, Q_{bw} : Bw output heat energy, Q_{ct} : Radiation value

Fig. 1 A typical GCS system

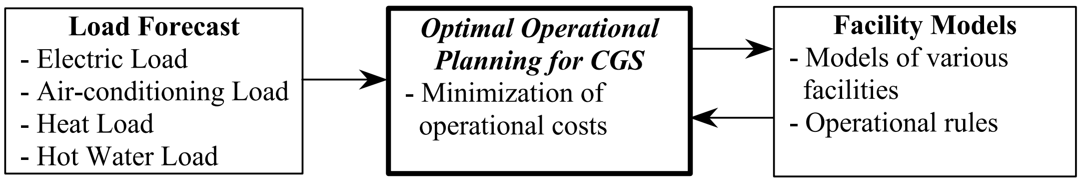


Fig. 2 A basic concept of optimal operational planning for CGS

is considered as the representative load forecasting values. The probability of the each considered representative load forecasting value is also defined considering probability distribution. Fig.3 shows example of three representative load forecasting errors, namely, no load forecasting error, upper load forecasting error, and lower load forecasting error. If load forecasting value equals to actual load value, load forecasting error equals to zero. In Fig.3, for example, the probability of the each representative load forecasting value is assumed to be the same value. Namely, the probability of each representative load forecasting error is assumed to be 1/3. We define σ as the standard deviation between load forecasting value and actual load. In normal probability distribution, the probability, which becomes lower than -0.43 σ, equals to 1/3, and the probability, which becomes upper than +0.43 σ, equals to 1/3. Therefore, the probability, which is contained between -0.43 σ and +0.43 σ, equals to 1/3. In Fig.3, if load forecasting error equals to zero, representative value (load forecasting error) is assumed to zero. On the other hand, if load forecasting error has minus value, representative value is assumed to -0.43 σ, and if load forecasting error has plus value, representative value is assumed to +0.43 σ.

B. STATE VARIABLES

State variables are electrical power output values of generator and heat energy output values of genelink and heat exchanger and heat energy input values of genelink per hour (24 points a day). Outputs of each facility for 24 points of the day should be determined. Moreover, two or three variables are required for one facility (startup and shutdown status (binary or discrete variables), and output or output/input values (continuous variables)). Therefore, one state variable for one facility is composed of vectors with 48 (24 points × 2 variables) or 72 (24 points × 3 variables) element. Therefore, for example, handling two generators, two genelinks, and two heat exchangers require 336 variables. In order to realize efficient search by PSO, reduction methods of number of state variables are required.

C. PROBLEM FORMULATION

(1) *Objective function*

The objective function is to minimize the operational expected costs of a day considering load forecasting error.

$$\min \left(P_0C_0+P_+C_++P_-C_-\right) \quad (1)$$

where, P_0 : probability which corresponds to zero load forecasting error, C_0 : total daily costs which corresponds to zero load forecasting errors, P_+ : probability which corresponds to plus load forecasting error, C_+ : total daily costs which corresponds to plus load forecasting error, P_- : probability which corresponds to minus load forecasting error, C_- : total daily costs which corresponds to minus load forecasting error.

(2) *Constraints*

a) *Demand and supply balance*: Summation of energies supplied by facilities such as electrical power, air-conditioning energy, and heat energy should be equal to each corresponding load.

b) *Facility constraints and operational rules*: Various facility constraints including the boundary constraints with state variables should be considered. Input-output characteristics of facilities should be also considered as facility constraints. For example, the characteristic of genelink is nonlinear practically and nonlinear characteristic should be considered in the problem. Examples of the operational rules are shown below:

- If the facility is startup, then the facility should not be shutdown for a certain period.
- If the facility is shutdown, then the facility should not be startup for a certain period.

(3) *Expansion of PSO for operational planning for CGS*

In order to reduce the number of state variables, the following simple expansion of PSO is utilized in this paper. Namely, all of state variables can be expressed as continuous variables. If the output value for a facility is less than or equal to the minimum output value, then the facility is recognized as shutdown. Otherwise, the facility is recognized as startup and the value is recognized as the output of the facility. The reduction method can reduce the state variables to half and drastic improvement of PSO search procedures can be expected.

III. APPLIED PSO TECHNIQUES

A. PSO WITH INERTIA WEIGHT APPROACH [10]

The basic PSO algorithm with inertia weight approach (IWA) can be expressed as follows:

1) *State variables* (*searching point*):

State variables (states and their velocities) can be expressed as vectors of continuous numbers. PSO utilizes multiple searching points for search procedures.

2) *Generation of initial searching points*:

Initial conditions of searching points are usually generated randomly within their allowable ranges.

3) *Evaluation of searching points*:

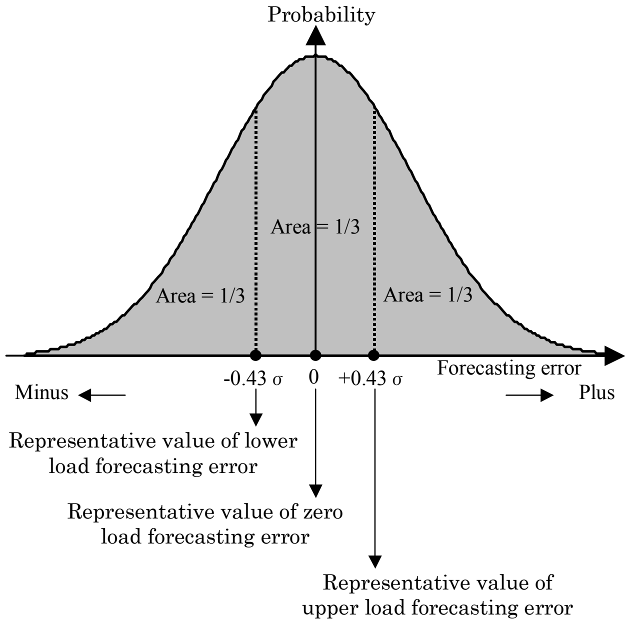


Fig. 3 Probability distribution of load forecasting error

The current searching points are evaluated by the objective function of the target problem. Pbests and gbest can be modified by comparing the evaluation values of the current searching points, and current pbests and gbest.

4) *Modification of searching points*:

The current searching points are modified using the state equations (3), (5) of PSO.

5) *Stop criterion*:

The search procedure can be stopped when the current iteration number reaches the predetermined maximum number. For example, the last gbest can be output as a solution.

In IWA, velocity of the state equations can be expressed as follows:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times (pbest_i - s_i^k) + c_2 rand_2 \times (gbest - s_i^k) \quad (2)$$

where, v_i^k : velocity of agent i at iteration k, w : weighting function, c_i : weighting coefficients, $rand_i$: random number between 0 and 1, s_i^k : current position of agent i at iteration k, $pbest_i$: pbest of agent i, $gbest$: gbest of the group.

IWA utilizes the following weighting function in (3):

$$w = w_{max} - \left(w_{max} - w_{min}\right)/iter_{max} \times iter \quad (3)$$

where, $w_{\max}$: initial weight, $w_{\min}$: final weight, $iter_{\max}$: maximum iteration number, $iter$: current iteration number.

The current position (searching point in the solution space) can be modified by the following state equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (4)$$

B. IMPROVED PSO [7]

The following points are improved to the basic POS with IWA.

- The search trajectory of PSO can be controlled by introducing the new parameters (P_1,P_2) based on the probability to move close to the position of (pbest, gbest) at the following iteration.

- The wv_i^k term of equation (3) is modified as equation (6). Using the equation, the center of the range of particle movements can be equal to gbest.
- When the agent becomes gbest, it is perturbed. The new parameters (P_1,P_2) of the agent are adjusted so that the new agent may move away from the position of (pbest, gbest).
- When the agent is moved beyond the boundary of feasible regions, pbests and gbest cannot be modified.
- When the agent is moved beyond the boundary of feasible regions, the new parameters (P_1,P_2) of the agent are adjusted so that the agent may move close to the position of (pbest, gbest).

The new parameters are set to each agent. The weighting coefficient is calculated as:

$$c_2 = 2/P_1, \quad c_1 = 2/P_2 - c_2 \tag{5}$$

The search trajectory of PSO can be controlled the parameters (P_1,P_2). Concretely, when the value is enlarged more than 0.5, the agent may move close to the position of pbest/gbest.

$$w = gbest - (\{c_1(pbest - x) + c_2(gbest - x)\}/2 + x) \tag{6}$$

Namely, the velocity of the improved PSO can be expressed as follows:

$$v_i^{k+1} = w_i + c_1 rand_1 \times (pbest_i - s_i^k) + c_2 rand_2 \times (gbest - s_i^k) \tag{7}$$

The improved PSO can be expressed as follows: (Step1 and 5 are same as PSO)

2) *Generation of initial searching points*:

Same as PSO. In addition, the parameters (P_1,P_2) of each agent are set to 0.5 or higher. Then, each agent may move close to the position of (pbest, gbest) at the following iteration.

3) *Evaluation of searching points*:

Same as PSO. In addition, when the agent becomes gbest, it is perturbed. The parameters (P_1,P_2) of the agent are adjusted to 0.5 or lower so that the agent may move away from the position of (pbest, gbest).

4) *Modification of searching points*:

The current searching points are modified using the state equation (7), (4) of improved PSO.

IV. NUMERICAL EXAPLES

A. SIMULATION CONDITIONS

The proposed method is applied to the typical CGS system shown in Fig.1. An office load model with 100000 [m^2] total floor spaces is utilized in the simulation. Two CGS generators and two genelinks are assumed to be installed. At most, two genelinks can be startup in summer season, one genelink in winter season, and one genelink in the intermediate season. The cooling tower is installed for each CGS generator. Number of agent is set to 200. The iteration number is set to 100.

B. SIMULATION RESULTS

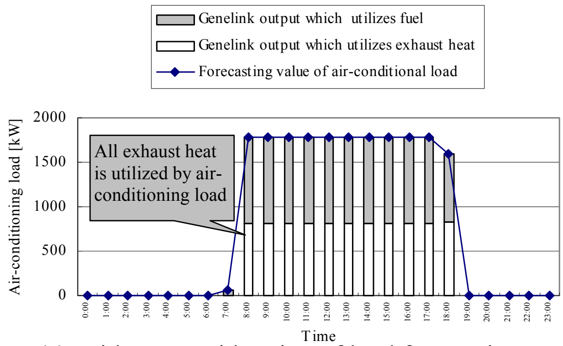
Fig. 5 shows comparison of optimal operational planning with or without consideration of load forecasting error against no load forecasting error. In Fig. 5, (1)-(a) shows optimal planning for air-conditioning load without consideration of load forecasting error and (1)-(b) shows optimal planning for air-conditioning load with consideration of load forecasting error. (2)-(a) shows optimal planning for heat load without consideration of load forecasting error and (2)-(b) shows optimal planning for heat load with consideration of load forecasting error. (3)-(a) shows optimal planning for exhaust heat without consideration of load forecasting error and (3)-(b) shows optimal planning for exhaust heat with consideration of load forecasting error.

According to the results, optimal operational planning with consideration of load forecasting error differs from optimal operational planning without consideration of load forecasting error. Namely, according to the results of air-conditioning load planning (Fig. 5 (1)), in the case of without consideration of load forecasting error, all exhaust heat is utilized by air-conditioning load. On the other hand, in the case of with consideration of load forecasting error, all exhaust heat is not utilized by air-conditioning load. Moreover, according to the results of heat load planning (Fig. 5 (2)), all heat loads utilize only boiler for heat load in the case of without consideration of load forecasting error, while heat loads utilize both exhaust heat and boiler for heat load in the case of with consideration of load forecasting error. Furthermore, according to the results of exhaust heat planning (Fig.5 (3)), all exhaust heat is utilized by only genelink in the case of without consideration of load forecasting error, while exhaust heat is utilized by both genelink and heat exchanger in the case of with consideration of load forecasting error.

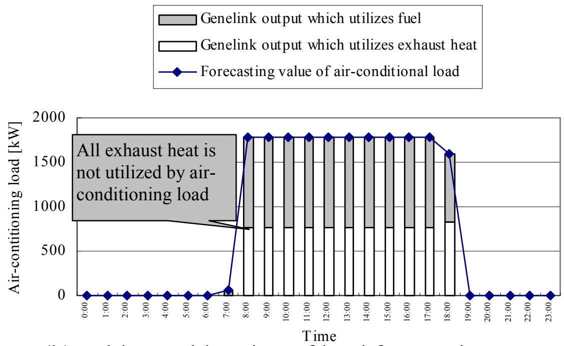
The difference of optimal planning between with and without consideration of load forecasting error is explained as follows. Genelink has a nonlinear characteristic shown in Fig.6. In the lower load factor areas, available exhaust heat is proportional to load factor. In the middle load factor areas, available exhaust heat is independent of load factor and has a constant value (maximum exhaust heat). The actual operation of CGS plant is shown in Fig.7. Firstly, the optimal operational planning is generated considering load forecasting value. Next, each facility receives set point corresponding to the optimal operational planning. However, there are load forecasting errors between load forecasting value and actual load value Therefore, each facility changes set point in order to balance supply and demand. The operation is called local control.

In Fig.6, we consider three load forecasting error. Namely, load condition (a) means no load forecasting error, load condition (b) means lower load forecasting error, and load condition (c) means upper load forecasting error. If we do not consider load forecasting error, only load condition (a) is considered. In such a case, utilization of all exhaust heat by genelink is the most efficient operational planning because we assume that efficiency of the genelink is better than efficiency of heat exchanger. Therefore, if we do not consider load forecasting error, all exhaust heat is utilized by only genelink. On the other hand, if we consider load forecasting error, load condition (a), (b), and (c) must be considered. In such a case, if load condition (a) changes load condition (b), local control of genelink is operated and load value becomes lower. Therefore, in load condition (b), available exhaust heat is lower than load condition (a) because of the nonlinear characteristic of genelink. If genelink utilizes all exhaust heat in load condition (b), exhaust heat difference Δ between load condition (a) and (b) shown in Fig.6 is wasted. The cooling tower must release the exhaust heat difference. On the contrary, if genelink does not utilize all exhaust heat, exhaust heat is not wasted. Therefore, if we consider load forecasting error, the optimal operational planning for exhaust heat is to be utilized by both genelink and heat exchanger.

Table.1 shows comparison of the operational expected costs of a day with or without consideration of load forecasting error. Case 1 in Table.1 represents the results shown in Fig. 5. Note that all of the value shown in Table.1 is the relative value when the value without consideration of load forecasting error is assumed to be 100 in each case. As shown in Table.1, the method with consideration of load forecasting error can reduce the operational expected costs compared to the method without consideration of load forecasting error. However, some cases are the same operational expected costs and operational planning between with and without consideration of load forecasting error. Namely, considering load forecasting error cannot always reduce the operational expected costs. However, considering load forecasting error can generate at least the same or cheaper operational planning compared to the method without consideration of load forecasting error. It indicates practical possibility of reduction of the operational expected costs considering load forecasting error.

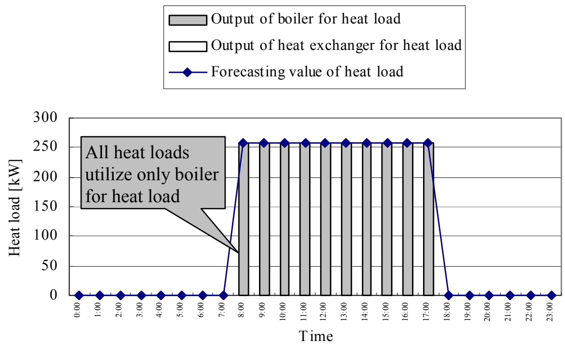


(a) Without consideration of load forecasting error

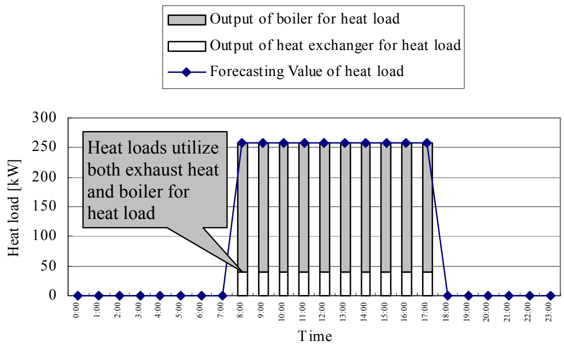


(b) With consideration of load forecasting error

(1) Optimal operational planning for air-conditioning load

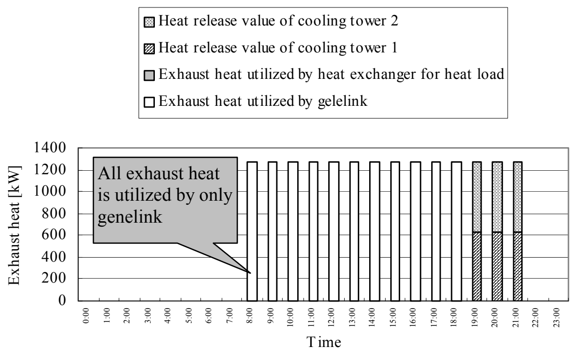


(a) Without consideration of load forecasting error

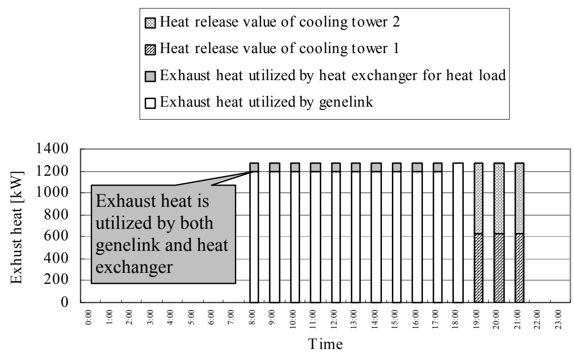


(b) With consideration of load forecasting error

(2) Optimal operational planning for heat load



(a) Without consideration of load forecasting error



(b) With consideration of load forecasting error

(3) Optimal operational planning for exhaust heat

Fig.5 Numerical results of typical CGS system

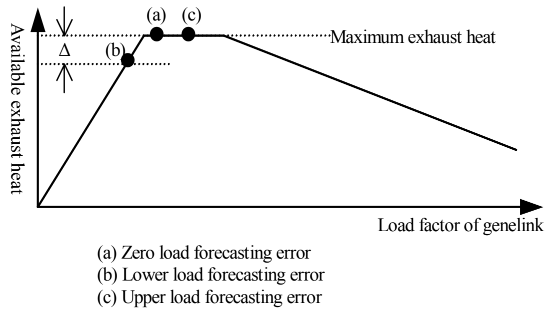


Fig.6 Characteristic of available exhaust heat vs. load factor in genelink

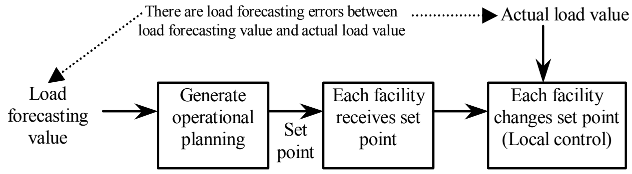


Fig.7 An actual operation of CGS plant

Table. 1 Comparison of the operational expected costs of a day with or without consideration of load forecasting error

Case no	Wo/ consideration of load forecasting error	W/ consideration of load forecasting error
1	100.00	99.94
2	100.00	99.98
3	100.00	99.98

According to Table.1, only about 0.02 to 0.06 % reductions are realized. However, the yearly total operational expected costs are large and the yearly actual prices of 0.02 to 0.06 % reductions are large enough.

V. CONCLUSIONS

This paper proposes optimal operational planning of a cogeneration plant by PSO considering load forecasting error. The proposed method is applied to typical cogeneration planning problem, which is formulated as a mixed-integer nonlinear problem. According to the results, the method with consideration of load forecasting error can reduce more operational expected costs compared with the method without consideration of load forecasting error. It indicates practical possibility of reduction of the operational expected costs considering load forecasting error. In future works, the proposed method will be applied to the actual cogeneration plants and the effectiveness of the proposed method will be verified.

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