ONLINE OPTIMAL OPERATION PLANNING AND CONTROL OF COGENERATION SYSTEMS

Shinji Kitagawa, Naoki Hayashi, Chikashi Nakazawa, Yoshikazu Fukuyama

Information & Control Technology Dept., Fuji Electric Advanced Technology Co., Ltd.
No.1, Fuji-machi, Hino, Tokyo 191-8502, JAPAN

Abstract: This paper proposes on-line optimal operation planning and control of cogeneration systems (CGS). CGS is usually connected to various facilities such as refrigerators, reservoirs, and cooling towers. In order to generate optimal operation planning for CGS, startup/shutdown status and/or input/output values of the facilities for each control interval should be determined. The facilities may have nonlinear input-output characteristics. Therefore, the problem can be formulated as a mixed-integer nonlinear optimization problem (MINLP). Particle Swarm Optimization (PSO) can be easily expanded to be utilized for MINLP. The proposed PSO-based methods are applied to typical cogeneration planning problems with promising results. *Copyright © 2005 IFAC*

Keywords: Plants, Planning, On-line control, Operators, Optimization problems,

1. INTRODUCTION

Recently, 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 operational planning for CGS is a very important task for saving operational costs and reducing environmental loads.

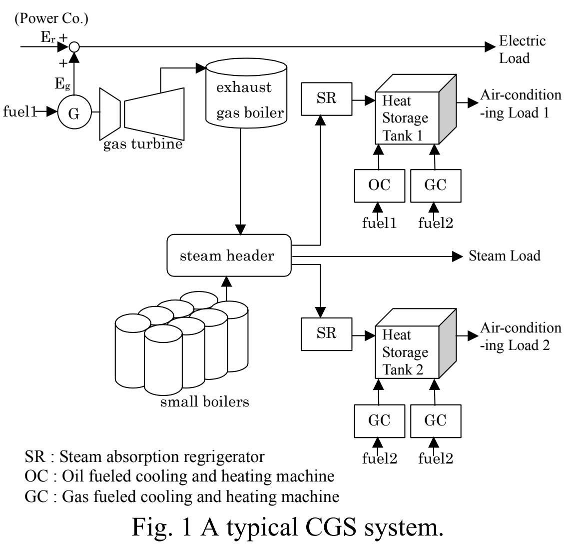


Fig. 1 A typical CGS system.

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 (Ravn, 1994; Ito, et al., 1994; Yokoyama, et al., 1996). 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 MINLP and independent facility models should be developed for practical use (as shown in Fig.1) and the method for

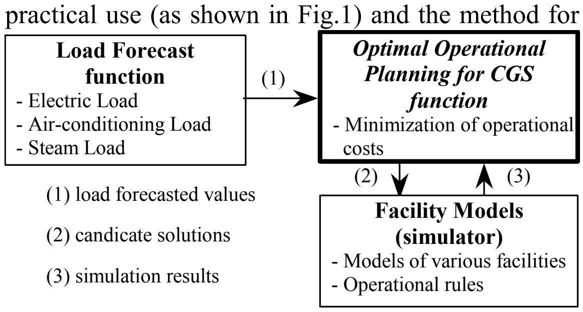


Fig. 2 A basic concept of optimal operational planning for CGS.

solving the MINLP problem has been eagerly awaited.

PSO is one of the evolutionary computation (EC) techniques (Kennedy and Eberhart, 1995). The method is improved and applied to various problems (Kennedy and Eberhart, 2001; Fukuyama, 2000; Fukuyama, 2002; Yasuda, et al., 2003; Miranda, et al., 2002a; Miranda, et al., 2002b). The original method is able to handle continuous state variables easily. Moreover, the author has expanded PSO in order to handle both continuous and discrete variables for a power system problem (Fukuyama, 2000). Various methods have been developed for a MINLP such as generalized benders decomposition (GBD) (Geoffrion, 1972) and outer approximation (OA/ER) (Kocis, et al., 1989). Using the conventional methods, the whole problem is usually divided to sub-problems and various methods are utilized for solving each sub-problem. Therefore, the whole algorithm has to solve each sub-problem alternately. On the contrary, 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 the conventional methods. Moreover, optimal CGS operational planning requires handling various operational rules and constraints that are difficult to be handled by linear models. In addition, independent facility models, which cannot be handled in the conventional method, must be handled in the optimal operational planning problem for CGS. PSO is expected to be suitable for the optimal operational planning for CGS because it can handle such operation rules, constraints, and independent facility models easily.

This paper proposes online optimal operation and control of cogeneration system using particle swarm optimization techniques. The original PSO, Adaptive PSO, and Evolutionary PSO based methods are compared. The methods are applied to typical cogeneration planning problems with promising results. Forecasting various loads is out of scope in this paper. However, the authors have developed the analyzable structured neural network (ASNN) and other forecasting methods. The accurate load forecasting can be realized for various loads (Fukuyama, et al., 2002).

2. PROBLEM FORMULATION

2.1 State Variables

State variables are on/off status per hour (24 points a day) of each controlled facility. The detailed variables and related constraints can be listed as follows:

i = 0, 1, 2, ... , 23 : index for time (hour),

n : i th facility of a specific equipment.

Steam absorption refrigerator: SR

The state variables of SR are as follows:

δ_{SRni} :On/Off status of the n th SR at the i th hour

where, n=1,…,N_{SR},

N_{SR} : Total number of SR.

Oil fueled cooling and heating machine: OC

The state variables of OC are as follows:

δ_{OCni} :On/Off status of n th OC at the i th hour

where, n=1,…,N_{OC}

N_{OC} : Total number of OC.

Gas fueled cooling and heating machine: GC

δ_{GCni} :On/Off status of the n th GC at the i th hour

All state variables are binary (0 / 1) variables and the formulation for summer season is utilized in this paper. For example, heat exchanger output values are continuous and the problem can be MINLP in winter season. The formulation can be easily expanded to MINLP. One state variable for one facility is composed of vectors with 24 elements (24 points at the day). Namely, all of state variables have 24 elements and one state in the solution space can be expressed as an array with number of all facilities multiplied by 24 elements.

2.2 Objective Function

The objective function is to minimize the operational costs. The operational costs can be obtained by calculation of the annual operational costs using daily operational costs of the representative days of summer, winter, and intermediate seasons).

$$\min(\alpha C_F + \beta P) \tag{1}$$

$$P = k_1 P_1 + k_2 P_2 + k_3 P_3$$

where,

C_F : Total fuel charges,

P : Total penalty costs,

α, β : Weighting factors of cost and penalty term,

k_i : Weighting factors of each penalty term,

P_i : Penalty terms (i=1,2,3).

The penalty term P_1 is related to the air-conditioning supply-demand balance constraints concerning the heat storage tank 1 (HST-1). The penalty term P_2 is related to the air-conditioning supply-demand balance constraints concerning the heat storage tank 2 (HST-2). The penalty term P_3 is related to the steam supply-demand balance constraints. As shown in (1), the objective function value can be obtained as the total costs of the fuel charges.

2.3 Constraints

Air-conditioning load balance

Summation of air-conditioning energies should be greater or equal to air-conditioning loads.

$$Q_{Pni} + Q_{HSTni} \geq Q_{AC\,ni} \tag{2}$$

where,

Q_{Pni} : Total heat output of the equipment connected to HST-n,

$Q_{HSTni} = Q_{HSTnTotali} - Q_{HSTnbase}$: Available heat quantity of the HST-n,

$Q_{HSTnTotali}$: Total heat quantity of HST-n,

$Q_{HSTnbase}$: Base heat quantity of HST-n,

Q_{ACni} :Air-conditioning load connected to HST-n,

n=1,2 : # of the heat storage tank.

i=0, 1, …, 23 : index for time (hour).

Steam load Balance

Summation of steam flow supplied from boilers should be greater or equal to steam demand.

$$S_{Pi} \geq S_{Li} + S_{Qi} \qquad (3)$$

where,

S_{Pi} : Total steam flow supplied from small boilers and exhaust gas boiler,

S_{Li} : Steam load flow,

S_{Qi} : Total consumed steam flow by steam absorption refrigerators,

i=0, 1, …, 23 : index for time (hour).

Facility Constraints and Operational Rules

Various facility constraints including the boundary constraints shown above with state variables should be considered. Input-output characteristics of facilities should be also considered as facility constraints. Examples of the operational rules are shown below:

- If the facility is startup, then the facility should not be shut downed for a certain period. (Minimum up time)
- If the facility is shut downed, then the facility should not be startup for a certain period. (Minimum down time)

Facility models are constructed using the facility constraints and the operational rules. The models are independent and all of CGS states are calculated when all of facility states are input from PSO. Then, the operational cost for the days can be calculated.

3. PARTICLE SWARM OPTIMIZATION TECHNIQUES

3.1 Original PSO (Kennedy and Eberhart, 1995, 2001)

The original PSO algorithm can be expressed as follows (See fig.3):

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* (Step.1 in fig.3)
   Initial conditions of searching points in the solution space are usually generated randomly within their allowable ranges.
3) *Evaluation of searching points* (Step.2 in fig.3)
   The current searching points are evaluated by the objective function of the target problem. Pbests (the best evaluated value so far of each agent) and gbest (the best of pbest) can be modified by comparing the evaluation values of the current searching points, and current pbests and gbest.
4) *Modification of searching points* (Step.3 in fig.3)
   The current searching points are modified using the state equations of PSO.
5) *Stop criterion* (Step.4 in fig.3)

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

Searching points can be modified (Step.3 in fig.3) as follows:

Velocity of the state equations can be expressed by

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times (pbest_i - s_i^k) + c_2 rand_2 \times (gbest - s_i^k) \qquad (4)$$

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.

The original PSO utilizes the following weighting function in (4). The way to utilize the function is called "inertia weights approach (IWA)":

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \qquad (5)$$

where,

wmax : Initial weight,

wmin : Final weight,

itermax : Maximum iteration number,

iter : Current iteration number.

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

$$s_i^{k+1} = s_i^k + v_i^{k+1} \qquad (6)$$

3.2 Adaptive PSO (APSO) (Yasuda, et al., 2003)

The following points are improved to the original PSO with IWA.

1) 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.
2) The wv_i^k term of (4) is modified as (8). Using the equation, the center of the range of particle

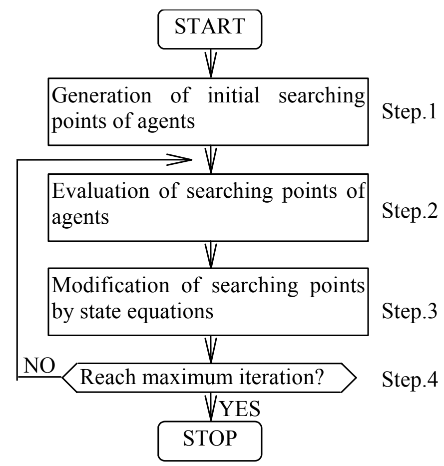


Fig.3 A general flow chart of PSO.

movements can be equal to gbest.

3) When the agent becomes gbest, it is perturbed. The new parameters (P_1, P_2) of the agent are adjusted so that the agent may move away from the position of (pbest, gbest).
4) When the agent is moved beyond the boundary of feasible regions, pbests and gbest cannot be modified.
5) 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 coefficients is calculated as:

$$c_2 = \frac{2}{P_1}, \quad c_1 = \frac{2}{P_2} - c_2 . \qquad (7)$$

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.

$$\begin{aligned} w &= gbest - \\ &\left(\{c_1(pbest - x) + c_2(gbest - x)\}/2 + x\right) \end{aligned} \qquad (8)$$

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

$$\begin{aligned} v_i^{k+1} &= w_i + c_1 rand_1 \times (pbest_i - s_i^k) \\ &\quad + c_2 rand_2 \times (gbest - s_i^k) \end{aligned} . \qquad (9)$$

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 equations (9), (6) of adaptive PSO.

3.3 Evolutionary PSO (EPSO) (Miranda, et al., 2002a, 2002b)

The idea behind EPSO is to grant a PSO scheme with an explicit selection procedure and with self-adapting properties for its parameters. At a given iteration, consider a set of solutions or alternatives that we will keep calling particles. The general scheme of EPSO is the followings:

1)REPLICATION - each particle is replicated R times
2)MUTATION - each particle has its weights mutated
3)REPRODUCTION - each mutated particle generates an offspring according to the particle movement rule
4)EVALUATION - each offspring has its fitness evaluated
5)SELECTION - by stochastic tournament the best particles survive to form a new generation.

The movement rule for EPSO is the following: given a particle s_i^k, a new particle s_i^{k+1} results from

$$s_i^{k+1} = s_i^k + v_i^{k+1} \qquad (10)$$

$$\begin{aligned} v_i^{k+1} &= w_{i0}^* v_i^k + w_{i1}^*\left(pbest_i - s_i^k\right) \\ &\quad + w_{i2}^*\left(gbest^* - s_i^k\right) \end{aligned} \qquad (11)$$

So far, this seems like PSO – the movement rule keeps its terms of inertia, memory and cooperation. However, the weights undego mutation

$$w_{ik}^* = w_{ik} + \tau N(0,1) \qquad (12)$$

Where, N(0,1) is a random variable with Gaussian distribution, 0 mean and variance 1; and the global best g b is randomly disturbed to give

$$gbest^* = gbest + \tau' N(0,1) \qquad (13)$$

The τ,τ’ are learning parameters (either fixed or treated also as strategic parameters and therefore also subject to mutation).

This scheme benefits from two “pushes” in the right direction: the Darwinistic process of selection and the particle movement rule and therefore it is natural to expect that it may display advantageous convergence properties when compared to ES or PSO alone. Furthermore, EPSO can also be classified as a self-adaptive algorithm, because it relies on the mutation and selection of strategic parameters, just as any σ-SA Evolution Strategy.

3.4 Expanded PSO for MINLP (Fukuyama, 2000; Kennedy and Eberhart, 1997)

A binary version of PSO has been developed (Kennedy and Eberhart, 1997). Although the PSO is useful only for binary problems, on/off status of facilities can be expressed by binary numbers. Using the binary version and the original continuous version of PSOs, the optimal CGS operational planning problem formulated as a MINLP can be handled.

As formulated in section 2, the optimal CGS operational planning problem can be formulated as a 0-1 integer nonlinear problem. In the binary version of PSO, the current position (searching point in the solution space) can be modified by the following state equation:

$$\begin{aligned} &if\ \left(rand(0,1) < S\left(v_i^{k+1}\right)\right) then\ s_i^{k+1} = 1; \\ &else\ s_i^{k+1} = 0 \end{aligned} \qquad (14)$$

where,

$$S\left(v_i^{k+1}\right) = \frac{1}{1 + \exp\left(-v_i^{k+1}\right)} . \qquad (15)$$

The authors have expanded PSO to handle discrete variables as follows (Fukuyama, 2000):

(a) Velocity can be discretized to existing values after calculation of (4) or (9) or (11),
(b) Searching points are discretized to existing values after calculation of (6) or (10).

The application of the expanded PSO for one of the MINLP in power systems has been shown in (Fukuyama, 2000). The expanded PSO can be also utilized for the optimal CGS operational planning problem.

4. OPTIMAL OPERATION PLANNING AND CONTROL FOR CGS USING PSO

Each agent keeps a state and a velocity in the solution space, and the state and the velocity are modified using state equations at each iteration. Using the above-mentioned expansion, x_l and v_l are composed of vectors with 24 elements. Namely, all of state variables have 24 elements and one state in the solution space can be expressed as an array with number of all facilities multiplied by 24 elements.

The whole algorithm can be expressed as follows:

Step.1 *Generation of initial searching points (states)*
States and velocities of all facilities are randomly generated. The upper and lower bounds of facilities are considered when the initial states are generated.

Step.2 *Evaluation of searching points*
The current states are input to facility models and the total annual operational costs are calculated as the objective function value. If the calculated value of the current state is better than the current *pbest*, *pbest* is updated. If the best *pbest* is better than the current *gbest*, *gbest* is updated.

Step.3 *Modification of searching points*
The current searching points (facility states) are modified using the state equations ((4)-(6) or (7)-(9) or (11)-(13)). The upper and lower bounds of facilities are considered when the current states are modified.

Step.4 *Stop criterion*
The search procedure can be stopped when the current iteration number reaches the predetermined maximum iteration number. Otherwise, go to step. 2. The last *gbest* (the state and the objective function value) is output as a solution for the optimal CGS operational planning.

The planning until 24 hours ahead is performed every 15 to 30 [min] with energy load forecasting results. The planning results are shown in display and the results for the next control interval are sent to DCS for online control. The operators can evaluate the control plans until 24 hours ahead and the plans may change gradually according to the modification of energy load forecasting results.

5. NUMERICAL EXAMPLES

The proposed method has been applied to typical cogeneration system planning problems. One numerical example is shown in this paper. Original PSO, APSO, and EPSO based proposed methods are compared.

5.1 Simulation Conditions

The proposed method is applied to the typical CGS system shown in fig. 1. A factory load model based on actual data is utilized in the simulation. One CGS generators and two heat storage tanks are assumed to be installed. At most, one steam absorption refrigerator is assumed to be installed to each heat storage tank. One oil fueled cooling and heating machine and one gas fueled cooling and heating machine are connected to heat storage tank 1. Two gas fueled cooling and heating machine are connected to heat storage tank 2. A summer load data is utilized. Number of agent is set to 200. The iteration number is set to 200. Twenty trials are compared. The numbers may be able to be optimized and the further investigation should be performed.

5.2 Simulation Results

Table 1 shows comparison of costs by Original PSO, APSO, and EPSO based method. All of the value in table 1 is the relative rate when the value of the original PSO method is assumed to be 100. According to the results, usage of fuel is improved. EPSO generates the best solution. APSO can generate the second result. In addition, EPSO and APSO can generate better average results than original PSO. According to the results, the followings can be observed:

(a) EPSO (Evolutionary PSO) and APSO (Adaptive PSO) can generate better results than Original PSO with IWA clearly.
(b) EPSO (Evolutionary PSO) can generate better results than APSO (Adaptive PSO).

Fig.4 shows comparison of results for HST-2 by three methods. According to the results, operation time for SR R-1 by Evolutionary and Adaptive PSO is longer than that by original PSO so that the total operational cost is reduced.

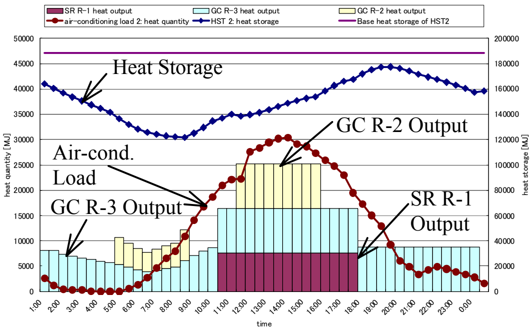
Table 1. Comparison of costs by the original PSO, APSO, and EPSO.

Method	Min.	Ave.	Max.
Original PSO	100.0	100.6	101.3
Adaptive PSO	98.7	99.4	101.3
Evolutionary PSO	96.7	97.5	100.5

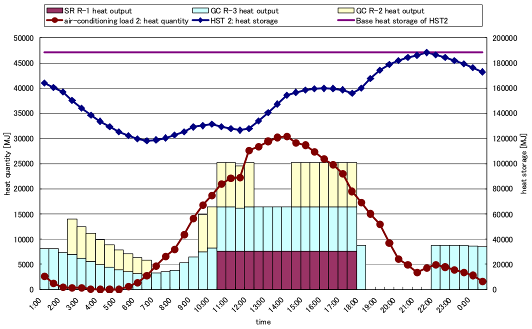
*) All of the value is the relative rate when the value of the original PSO method is assumed to be 100.

6. CONCLUSIONS

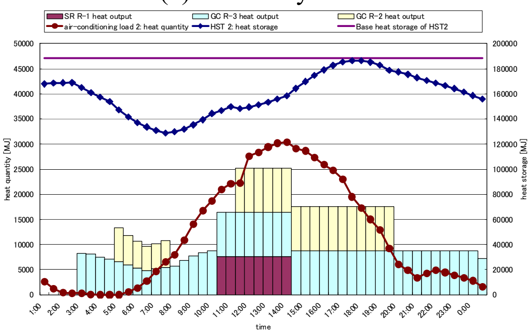
This paper proposes on-line optimal operation planning and control of cogeneration systems using particle swarm optimization. Three PSO based techniques: Original PSO, Adaptive PSO, and Evolutionary PSO are compared. The proposed methods are applied to a typical cogeneration planning problem and the results indicate practical applicability of PSO for the target problem. According to the results, Evolutionary PSO can generate better results than others. The PSO-based one-line optimal operational planning and control system has been used in the factories of Toyota motor corporation (Fukuyama, et al., 2004).



(a)Results by EPSO



(b) Results by APSO



(c) Results by original PSO

Fig.4 Comparison of Results for HST-2 by three methods.

There are many practical problems formulated as a mixed-integer nonlinear optimization problem. The practical tools such as PSO for the problem have been eagerly awaited. As shown in this paper, in the practical applications, number of state variables may be too large to be handled by the original PSO. There are some expansions of PSO for improving efficiency of the quality of solutions, APSO, EPSO and others (Kennedy and Eberhart, 2001). However, more powerful improvement is expected for practical use.

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