Optimal Operation System for Energy Plants

Tetsuya Koide
Kouji Matsumoto
Shinji Kitagawa

1. Introduction

Against a backdrop of healthy domestic and foreign demand, the steel industry is continuing its fundamental trend of increasing production for the manufacturing industry. Meanwhile, since the steel industry accounts for approximately 11% of final energy consumption in Japan, efforts to improve the efficiency of energy usage have been pursued actively for a long time. Since the first oil crisis, an energy savings of approximately 20% has been realized, and efforts to conserve energy have intensified with the recent recognition of the importance of preventing climate change on a global scale. Reducing the consumption of energy in manufacturing processes is a part of these efforts, and it is a goal to reduce energy consumption in fiscal 2010 to a level that is 10% lower than the energy consumption in fiscal 1990.

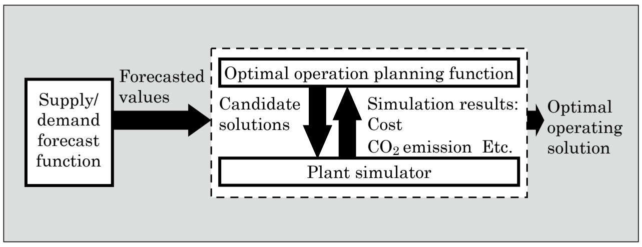
Fuji Electric was early to recognize the usefulness of energy management in steelworks, and continues to deliver "energy centers" which have become synonymous with energy management systems. The energy supply and demand configurations for steelworks are various, and have mutually complex relationships. A process computer-based real-time energy supply and demand forecast function and an optimal distribution function are essential parts of an energy center in order to supply energy stably and respond rapidly to the moment-by-moment changes in the energy supply and demand balance.

Based on these circumstances, this paper describes the application of Fuji Electric's FeTOP optimal energy operation system package to an energy plan in a steelworks (in cooperation with the JFE Steel Corporation) and the results of optimal operation that have been verified through simulations.

2. Optimal Operation of an Energy Plant

An energy plant supplies various forms of energy, such as electricity, heat and steam, to facilities in factories, business offices, hospitals, large buildings and the like. To supply the energy, various types of equipment are used, including electric generators, boilers and energy source facilities. To meet the demand for energy required at a facility, the energy – including electric power, gas and the like purchased externally – must be distributed and supplied to each piece of equipment.

Fig.1 Functions for realizing optimal operation of an energy plant



In particular, an energy plant in a steelworks can be utilized efficiently to realize energy savings by converting gas and heat by-products generated from production facilities into a form suitable for energy use. The conversion of energy must be implemented while carefully monitoring the balance between supply and demand, and with the appropriate combination and distribution, i.e., such that optimal operation enables a reduction in the externally purchasing cost and a lower burden on the environment. However, with a boiler and other such equipment, in addition to fuel that is externally purchased, multiple by-product gases are also used simultaneously as fuel, and various constraints exist for the allocated proportions of these gas by-products. An energy plant in a steelworks must operate in consideration of constraints that are more numerous and more complex than in energy plants of other industries.

Moreover, energy supply and demand are constantly changing, and for equipment such as a holder that stores by-product gases, the optimal operation in response to supply and demand fluctuations within a fixed interval must be determined. Accordingly, as shown in Fig. 1, the optimal operation of an energy plant is realized through the use of a supply/demand forecast function, an optimal operation planning function and a plant simulator. In other words, the supply/demand forecast function predicts the fluctuations in the supply and demand of various types of energy, including the quantity of generated by-product gases. Next, the optimal operation planning function uses the plant simulator to determine optimal operation that satisfies the forecasted energy supply and demand requirements in consideration of many various constraints.

3. FeTOP Optimal Energy Operation System Package

An overview of the main functions and a description of the elemental technology of FeTOP is presented below.

3.1 Forecasting function

The demand for energy, i.e., electricity and heat, and the amount of generated by-product gases have various characteristics which differ when affected by diverse conditions, i.e., factory operation and the weather, but also sometimes periodically exhibit the same trends. The following models are used mostly to simulate these characteristics.

(a) Physical model that uses physical characteristic equations for the energy consumption of equipment
(b) Statistical model that uses historical performance data
(c) Hybrid model that combines the physical model and statistical model

These models may be described in some cases with linear equations, but must be described with non-linear equations in other cases, and various forecasting methods should be considered in order to make forecasts with good accuracy.

FeTOP allows the use of multiple forecasting methods, such as a pattern forecasting method, a multiple regression method and a neural network method.

(a) The pattern forecasting method produces a forecast value by searching historical performance data for the closest fit to the present condition.
(b) The multiple regression method uses a linear equation to approximate the relationship between explanatory variables for heat, humidity and so on, and objective variables such as for the power demand to be forecast.
(c) The neural network method structures a non-linear forecasting model based on learned historical data to produce results most suitable to the present condition.

Of these methods, the analyzable structure neural network (ASNN) developed independently by Fuji Electric enables the forecasting reasons to be explained, which had been difficult to do with prior neural networks having a "black box" interior. As shown in Fig. 2, the network interior is structured for each input unit so that the forecasting reason can be explained, and the structure can be optimized since units and connecting weights that are not needed in the learning process may be eliminated.

3.2 Plant simulator

The plant simulator supports modeling of the plant characteristics using multiple methods, such as modeling with linear or non-linear characteristic equations based on physical models of the equipment and modeling using response surface methodology and neural networks. Moreover, plant characteristics may be modeled using various expressions such as logical equations for local control, such as quantity control, and plant-specific operating rules. Additionally, the plant simulator also supports modeling of the various constraints and objective functions needed when searching for optimal operation.

The plant model may be generated graphically on a monitor screen. Standard models for many types of equipment, such as boilers and turbines, have already been developed and are available for use as templates. A model for an entire plant can be generated by positioning and connecting these templates on a monitor screen. Parameters for the model characteristics and constraints can also be designed on-screen. Additionally, an objective function can be modeled and optimized on-screen by connecting the terminals of variables in the model. Figure 3 shows an example of the creation of a plant model.

Moreover, in addition to the case where used with an online optimal operation system, this simulator may also be used in offline simulations such as for engineering an optimal operation system or for reviewing an aspect of the plant design, such as equipment selection. As a result, the user is free to set which plant variables are input as independent variables, which variables are dependent variables (variables computed by computing the modeling equations), and which variables are the state variables to be determined according to the optimization. These settings, once configured, may be changed by simple onscreen operations. Based upon category setting information for these variables and upon equipment model connection information, a model computation algorithm is configured automatically inside the simulator.

Fig.2 Overview of structured neural network

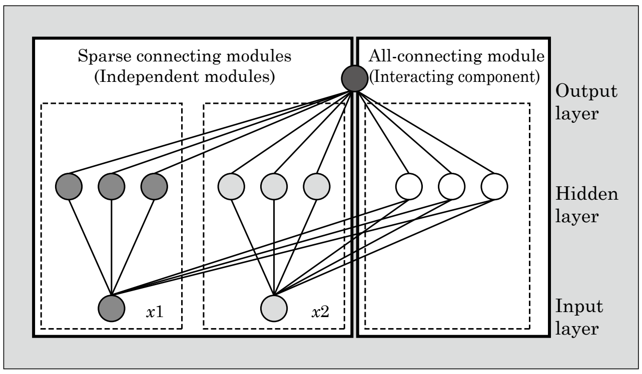
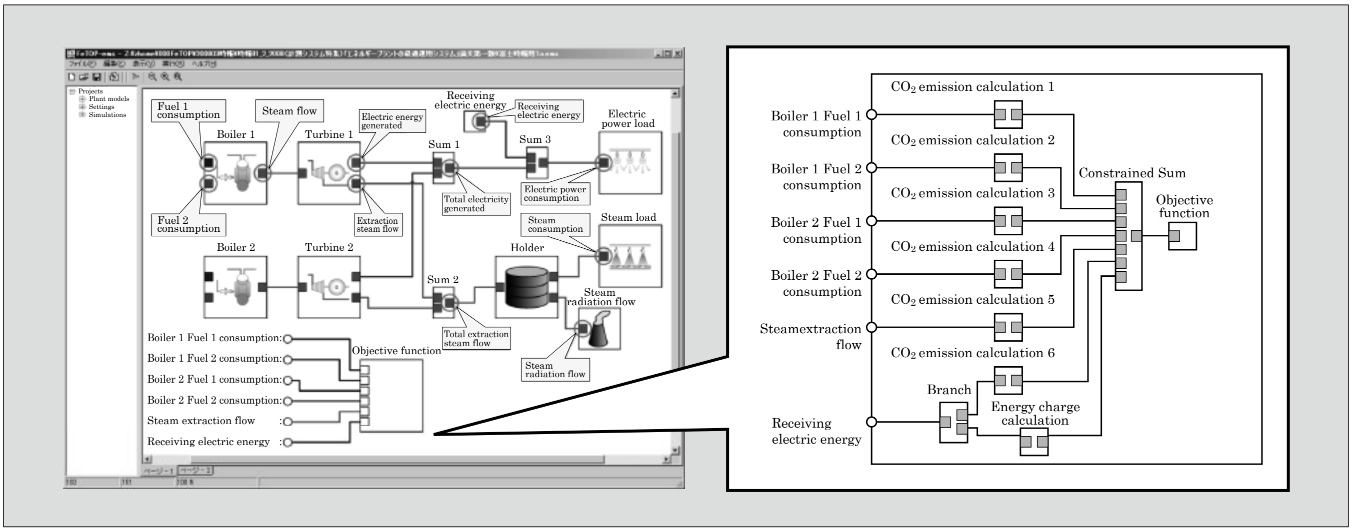


Fig.3 Example of creation of plant model with plant simulator



3.3 Offline simulation function

The FeTOP optimal operation planning function is realized using the above-described plant simulator. Accordingly, constraints and objective functions can be configured easily on the plant simulator screen, and the designation of which plant variables are to be set as state variables can also be implemented easily. As a result, in addition to performing online optimization simulations, offline optimization simulations can also be implemented using user-configured operating settings without having to perform various optimization calculations and optimization for various scenarios.

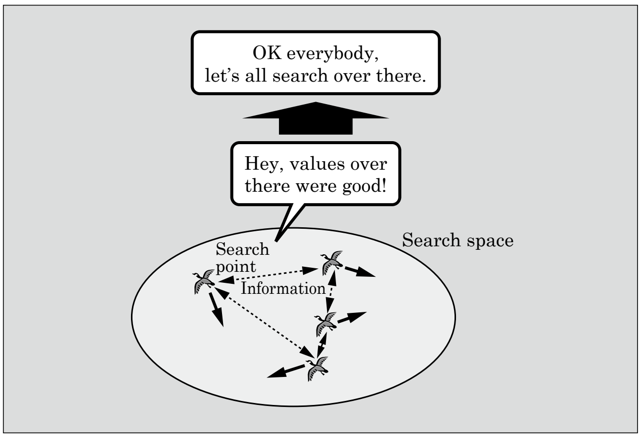
For example, simulations can be implemented for various study purposes, such as to compare optimal operation plans in order to minimize cost or minimize CO_2 emissions and to estimate the amount of by-product gas generation required for a certain operating state.

Furthermore, since the input conditions for multiple cases and the calculated results thereof can be saved collectively and reused, this function enables plans for improvement to be reviewed through the pre-assessment of operation plans and the verification of historical operation results, energy plant optimal operation plans to be drafted and the effects thereof to be verified, and plant design, including equipment selection, to be reviewed.

3.4 Optimal operation planning function

In order to realize optimal energy plant operation, the start-up and shutdown status (discrete values) and the power output (continuous values) of equipment such as generators must be determined simultaneously. Mixed-integer linear problems (MILP) that approximate device characteristics and operation conditions with a linear function have been formulated and solved previously. But, when applied to an actual plant, in addition to the non-linear characteristics of devices, logic equations for quantity control and other control logic and operational rules must also be considered. These considerations, in order to be handled directly, must be formulated as a non-linear mixed-integer problem and solved. An effective method for solving mixed-integer non-linear problems did not exist previously, but the use of a recent method known as meta-heuristics enables such problems to be solved. FeTOP implements an optimization function that uses PSO (particle swarm optimization), one such meta-heuristic technique[(1)].

Fig.4 Concept of PSO searching



PSO is a multi-point solution search technique that models the movement of a group of animals or other swarms to solve optimization problems. As shown in Fig. 4, an optimal solution is obtained by allocating multiple search points to a search space, sharing information of favorably evaluated search points, and based on that information, by repeating the migration of the search points. In recent years, various techniques for improvement have been proposed, and FeTOP allows the use of multiple improvement techniques.

Fuji Electric has delivered an optimal operation system using PSO to the energy plant for a mechanical part manufacturing factory, and this system has successfully contributed to achieving energy savings and reducing CO_2 emissions. However, generally in an energy plant in a steelworks, the amount used of each by-product gas is set as a state variable, the mutual interference among state variables is strong and the proportional allocation relationships thereof have many constraints, thus increasing the difficulty of finding a solution as an optimization problem. On the other hand, with FeTOP, the PSO search algorithm is simple, and with the characteristic feature of allowing the easy addition of proprietary improvements during searching, the configuration allows improvements unique to the target plant to be added.

In the optimal operation of an energy plant in a steelworks, for example, an enormous number of constraints must be considered, and these constraints are usually considered using the penalty function method. In other words, by adding, as a penalty term, the weighted sum of constraint violation values to an object function, a solution that satisfies the constraints can be obtained. In some cases, however, the addition of a penalty term causes a phenomenon whereby the search efficiency drops significantly. Therefore, this function is configured such that among the proprietary processes added during a search, and improvement process can be added for solution that eliminates specific constraint violations. For example, by implementing an improvement process so as to correct a conflicting operation solution, such as when gas is being purchased despite the holder capacity being at its maximum capacity and diffusing gas, the efficiency of solution searching can be improved. Additionally,

Fig.5 Modeled energy plant in a steelworks

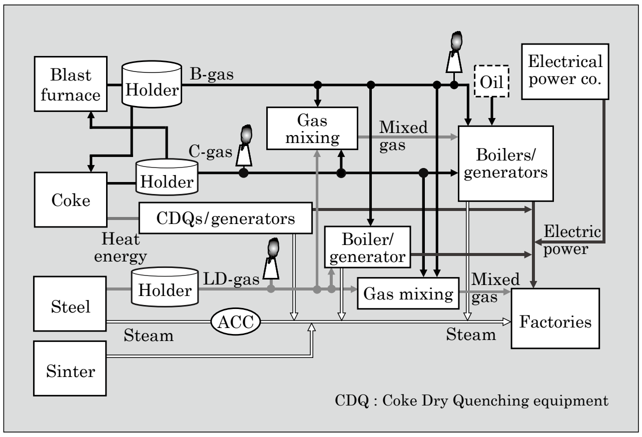


Fig.6 Example of effect of decreased energy consumption due to optimal operation

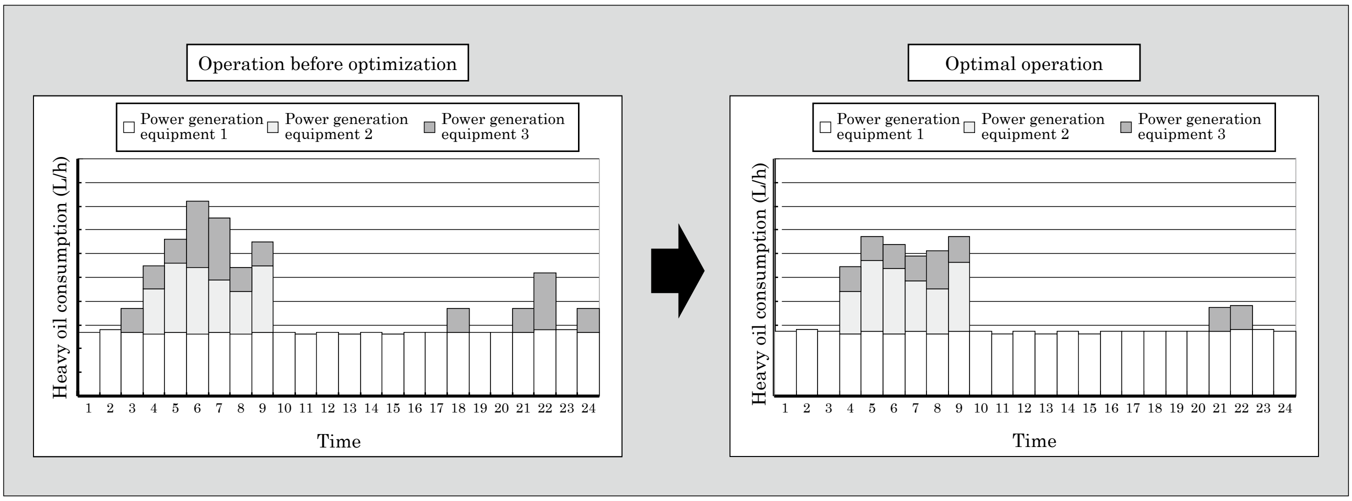
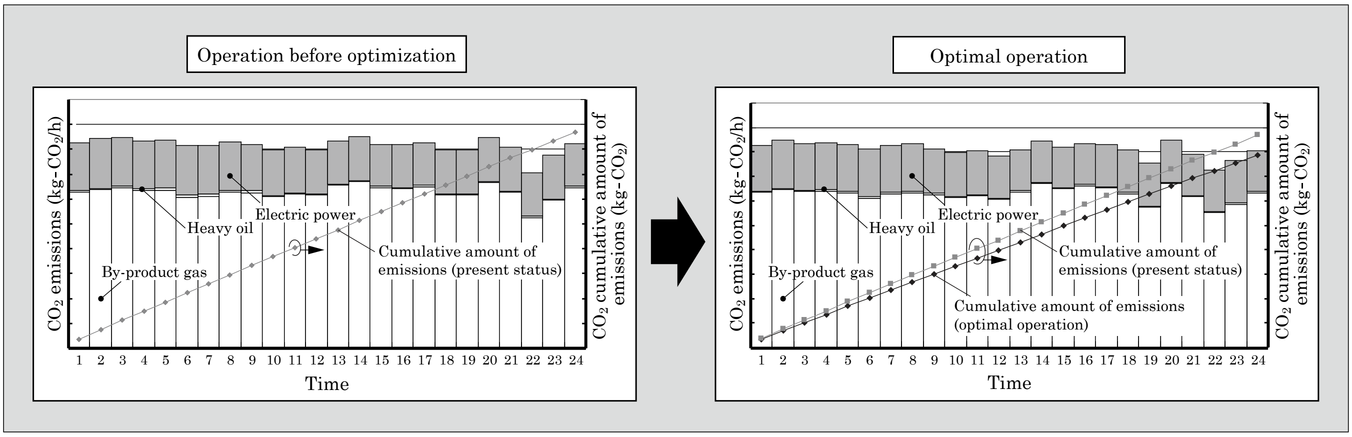


Fig.7 Example of effect of reduced CO_2 emissions due to optimal operation



when adding a penalty term, the weighting factor usually must be adjusted, but a function has also been added for automatically changing the weighing factor value according to the objective function value or the like while searching. As a result of these improvements, better searching efficiency is obtained.

4. Implemented Example

An example is presented below of an offline simulation modeling an energy plant in a steelworks.

We evaluated the optimization of the supply of energy sources such as gas and heat from an iron and steel making plant and the distribution of energy according to the demand for energy (electricity, gas, heat) required in manufacturing processes and downstream processes in order to minimize operating costs such the purchasing cost of heavy oil and to minimize CO_2 emissions. For the model plant shown in Fig. 5, the evaluation was implemented by comparing evaluation values, for the case where optimization was performed by simulating plant operation using performance data for energy demand and supply during unusual operating conditions, with evaluation values computed based on the actual operating state. From the simulation results of a number of cases that modeled several unusual operating conditions, we verified that optimization has the effect of reducing operating costs by of approximately 1 to 3% on average and reducing CO_2 emissions by approximately 72,000 t-CO_2 annually. Figure 6 shows the effect of reducing heavy oil consumption as an example of the result of minimizing operational cost, and Fig. 7 shows the effect of reducing CO_2 emissions as the result of minimizing CO_2 emissions.

5. Postscript

We have presented the verified results of optimal operation systems for energy plants, as represented by the iron and steel industry.

Leveraging these results, Fuji Electric intends to develop these systems further in order to satisfy user needs, and will continue to work to realize efficient and optimal energy operation and to help prevent climate change on a global scale.

Lastly, the authors wish to extend their deep gratitude to the JFE Steel Corporation for their tremendous cooperation and advice in verifying the efficiency of optimal operation of an energy plant in a steelworks.

Reference

(1) Kennedy, J. et al. Particle Swarm Optimization. Proceedings of IEEE International Conference on Neural Networks. Vol. IV, 1995, p. 1942-1948.