Korean J. Chem. Eng., **28**(1), 16-21 (2011)
DOI: 10.1007/s11814-010-0340-2

Gasholder level control based on time-series analysis and process heuristics

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(*Received 31 December 2009 • accepted 31 May 2010*)

Abstract−A novel method to control gasholder levels in an iron and steel company with accurate prediction of the future trend is presented. Although various gasholders are used to recycle by-product gases generated during the iron-making, coke-burning, and steel-making processes, the capacities of these gasholders are insufficient to handle large amounts of gases. To overcome this problem, tight control of the gasholder level should be maintained by predicting their anticipated changes. However, the current prediction logic cannot show satisfactory results due to the lack of characterization of the relevant processes. In the proposed method, time-series modeling and heuristics from industrial operators are used to correctly reflect the process characteristics and deal with unexpected process delays. By applying the proposed method to an off-line data set, a significant reduction in the discrepancy between predicted values and actual values was observed. The method is expected to be adopted in the prediction system of POSCO.

Key words: Level Control, Time-series Modeling, Prediction, Iron and Steel Making Process, Heuristics

INTRODUCTION

In the iron and steel industries, it is very important to reduce energy costs due to their tremendous consumption of it. For this reason, they make every effort to recycle the various materials generated by their plants [1-3]. As well as having a cost saving benefit, these efforts are also significant from the viewpoint of environmental protection [4]. In particular, by-product gases generated from the iron-making, coke-burning, and steel-making processes, called BFG (blaster furnace gas), COG (coke oven gas), and LDG (Linz-Donawitz gas), respectively, are worthy of being used as fuel gases since they include considerable amounts of CO and H2 [5-7]. Therefore, these gases are now being supplied to many plants via gasholders, to be used as a fuel instead of expensive oil and LNG. The gasholders work as buffers that store the gases temporarily until the gas users need them as an energy source. However, due to the relatively small capacities of the gasholders, an overflow or lack of the by-product gases frequently occurs. As a result, many companies are interested in maintaining the levels of gasholders without severe variation for efficient utilization of the gases.

To achieve this goal, either the size of the gasholders should be increased or the holder levels should be controlled in advance by predicting future gasholder levels based on the present patterns of gas generation and consumption. Since increasing the capacities of the gasholders requires enormous costs, most steel companies are trying to solve the problem with the latter method under the management of an energy center. However, most of the prediction logic being used in the energy centers of companies shows low performance since the characteristics of the processes influencing the levels of the gasholders are not sufficiently reflected in the systems. Therefore, there is an urgent need to modify this prediction logic by investigating the reasons for the deterioration of the prediction capability and correcting the problems.

In this paper, we present new prediction logic for level changes in the three gasholders of the Pohang Iron and Steel Company (POSCO) based on time-series analysis and heuristics from industrial [8,9]. Due to the practical aspects of the problem, we relied on a real data set obtained from various plants related to the by-product gases and interviews with industrial operators. This is the reason why these two techniques are mainly used in the proposed method. The time-series analysis was used to model the periodic properties of the processes connected to the BFG and COG holders. The experience of the operators was effectively utilized to ascertain the LDG generation time of the next operation in the steel-making process, which changes randomly because of frequent process delays. The randomness of the delays in the duration and occurrence time makes correct prediction of the LDG holder level nearly impossible without their prior knowledge. By applying the proposed method to an off-line data set, prediction performances for the three gasholders were markedly improved. As additional on-line testing based on the success of this off-line test, the proposed logic is expected to be adopted as a real system by POSCO.

This paper is organized as follows. In the first section, the general framework for the prediction of gasholder levels at POSCO is introduced. Then, the problems of the existing logic and the features of the proposed method are given in the second section. Finally, the results of off-line application are shown in the third section, followed by conclusions

THEORETICAL BACKGROUND

1. General Framework for the Prediction of Gasholder Levels

The logic for predicting future changes in the three gasholder

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levels was based on the periodicity of the relevant processes, although there were some exceptions, depending on the processes. Therefore, if we know the cycle time, the present position in the process cycle, and the rate of gas generation or consumption for each interval in the cycle, we can determine the future gasholder level trend within one prediction horizon. To obtain prediction values for the holder level, prediction values for gas generation and the consumption rates of the relevant processes are separately calculated in advance for a prediction horizon. Once this procedure is completed, the calculation of prediction values for gasholder levels is implemented according to the following algorithm. Note that different prediction methods are used for gas generation and consumption, which will be explained.

Step 1. Calculate the first prediction value by adding the first prediction value of the gas generation rate to, and subtracting the first prediction value of gas consumption rate from, the present gasholder level.

$$l_p^1 = l_p + g_p^1 - c_p^1 \quad (1)$$

Step 2. Iteratively calculate the next prediction values based on the previous prediction values in the same way until the end of a prediction horizon.

$$l_p^n = l_p^{n-1} + g_p^n - c_p^n \quad (2)$$

where c_p^n is the n^{th} prediction value for the total consumption rate at the present, g_p^n is the n^{th} prediction value for the total generation rate at the present, l_p^n is the n^{th} prediction value for the gasholder level at the present, and l_p is the real value of the gasholder level at the present.

One prediction horizon is specified as 60 minutes for the BFG and COG holders, and as 40 minutes for the LDG holder, since these values are the cycle times of the corresponding processes. The details of the prediction logic for each of the three kinds of by-product gasholders are described in the following subsections.

1-1. Trend Prediction of BFG Holder Level

BFG is generated as a by-product gas during the iron-making process. In the process, five blast furnaces (BF) are operated to make molten pig-iron and two phases are continuously repeated for each BF operation: the combustion and exchange phases. Since the BFG generation rate and duration time for each phase are maintained at fixed values as shown in Fig. 1, they are set as constant parameters. The BFG generation rate is predicted based on these parameters. To start the prediction, we should know where the present time is located in the process cycle. For this purpose, criteria parameters with which we can know the present phase are used. By comparing the present BFG generation rate with the criterion value, we can know the present phase in the cycle. In addition, if the starting time of the present phase is recorded, the remaining time till the end of the present phase can be known. This means that all of the prediction values for the BFG generation rate within a prediction horizon can be obtained from the present time based on the parameters. It should be noted that all of the prediction values for the total BFG generation rate are derived by adding the values of each BFG generation rate predicted for the five BFs.

For predicting the BFG consumption rate, the following plants are considered as BFG users: five BFs, four coke ovens, twelve power plants, and two hot-rolling machines. The prediction of the BFG consumption rate for the BFs and coke ovens is implemented in the same way as the prediction of the BFG generation rate. For the other BFG-consuming plants, the present BFG consumption rate values are merely used for prediction values within a prediction horizon since the variation in the BFG consumption rate for these plants is not as severe as shown in Figs. 2 and 3.

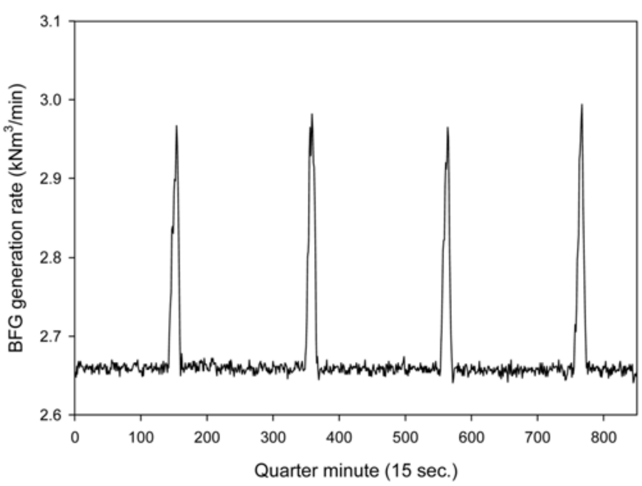

Fig. 1. Typical BFG generation pattern in BF 1.

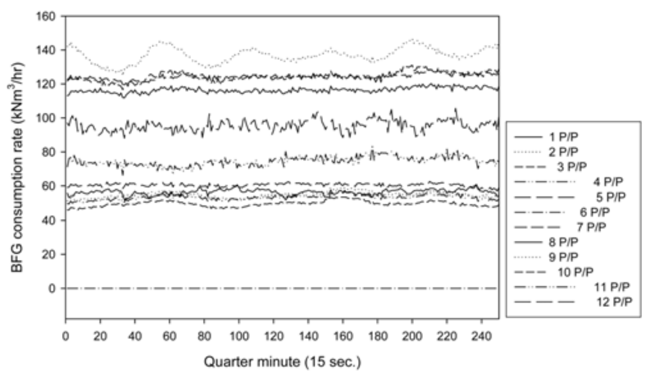

Fig. 2. Typical BFG consumption pattern for twelve power plants.

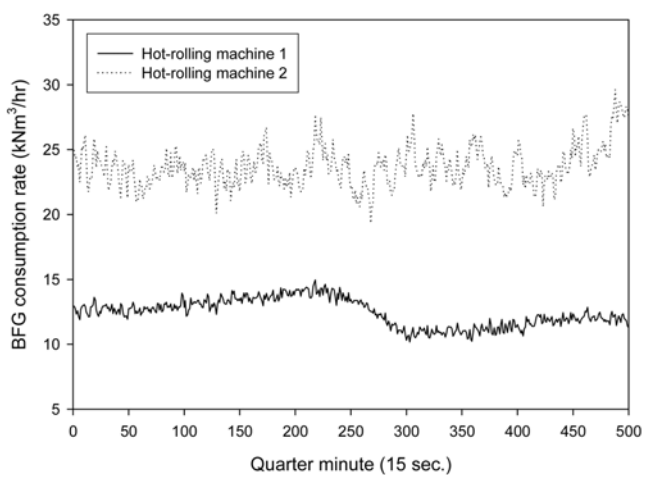

Fig. 3. Typical BFG consumption pattern for two hot-rolling machines.

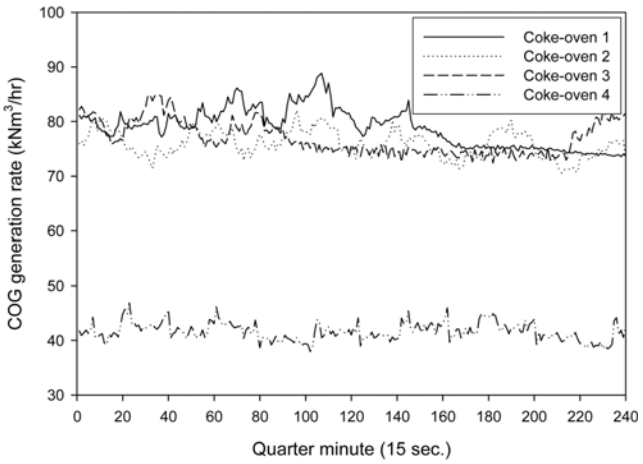

Fig. 4. Typical pattern for COG generation rate.

Note that this simple approximation is possible because only a small portion of the total BFG consumption rate takes place at these plants. Once the prediction values for the BFG generation and consumption rates are available, the future level changes for the two BFG holders can be calculated by Eqs. (1) and (2) till the end of a prediction horizon.

1-2. Trend Prediction for COG Holder Level

COG is generated during the coke oven process. Coke, which is used as a heat source in the iron-making process, is produced by baking, or partially burning, coal in a coke oven. During this process, significant amounts of by-product gases are generated. These contain high percentages of CO and H2. Therefore, this gas is recycled as an energy source for many plants via COG holders. Unlike the BFG holders, the two COG holders are sufficiently large and many more plants are connected to the COG holders. Due to the relatively large capacity of the holders and the averaging-out effect in the holder level variation, they stay at an almost constant level as shown in Fig. 4. This means that the prediction of the COG holder level is less important than those for the other kinds of gasholders since any future COG holder level will be similar to the present one. For this reason, the prediction logic for the COG holder level is simpler than that for the BFG or LDG holder levels. In the case of predicting the COG generation rate, the present value is simply used for the prediction values within a prediction horizon under the condition that the present value is in a normal range.

The plants that use the BFG as a fuel also use the COG because BFG and COG is supplied to them by way of a mixing station with a specific mixing ratio. Therefore, the prediction for the COG consumption rate is implemented by multiplying the prediction values for the BFG consumption rate by a ratio constant. Using Eqs. (1) and (2), the future changes in the COG holder level can be predicted if all of the generation and consumption rates predicted are given.

1-3. Trend Prediction for LDG Holder Level

LDG is a by-product gas generated in steel-making processes. At POSCO, two steel-making plants are operated and there is an LDG gasholder for each. Three converters in each steel-making plant are sequentially used to continuously produce impurity-free steel by blowing oxygen across the molten pig-iron. Although all three converters are usually operated in each steel-making plant, only two converters can be operated when one of them is under maintenance.

Since the steel-making process also has a periodicity, the LDG generation rate is predicted in a similar way to the cases of the BFG generation rate. The only difference is that four phases exist in one cycle of the process: the start of oxygen-blowing, LDG recovery, end of oxygen-blowing, and tapping. LDG is generated only in the LDG recovery phase and the quantity of generation is nearly constant. In the current prediction logic, the time required for the completion of each phase is fixed as a constant, although in actual practice these times are frequently changed due to unexpected process delays. Therefore, significant gaps between the parameters and real values for the duration times of each phase necessarily occur, and these differences cause a serious deterioration in prediction performance. We tried to solve this problem by updating the duration parameters at every process cycle based on operator heuristics. The details will be explained in the following sections.

While the prediction for the LDG generation rate is implemented by considering process characteristics, the prediction for the LDG consumption rate is simple and roughly approximated as an extension of the present value, since the LDG consumption rate shows no significant variation. The plants that use LDG as a fuel are the twelve power plants, two hot-rolling plants, and a wire-rod manufacturing plant. With the prediction values for the LDG consumption and generation rates, we can obtain prediction values for future LDG holder levels, also based on Eqs. (1) and (2).

2. Problems with Current Prediction Logic and the Proposed Method as a Solution

Although an outline of the existing prediction logic for each by-product gasholder has already been explained, there are several problems that deteriorate prediction performance. These problems are mainly caused by excessive approximation in calculating the prediction values or the fixed parameter values, which should be changed according to the process conditions. In fact, the industrial operators have not updated the parameters for several years even if the actual process conditions have changed significantly. To improve the prediction performance, we systematically analyzed the problems with the current prediction logic for each gasholder by investigating the characteristics of the relevant processes based on a historical data set and interviews with industry personnel. As a result, we have found the following problems.

(a) Since the values of the criteria parameters used to judge the exchange phase in the five BFs (both for generation and consumption) have not been updated, serious errors can occur in identifying the present phase. These errors make the prediction results deviate from the actual values.

(b) In the prediction for the COG generation rate, the method of using the present value for the prediction values until the end of a horizon is too simple. Fig. 4, which shows the considerable variation in the COG generation rate, supports this fact.

(c) The pattern for the BFG consumption rate in a coke oven one shows obvious periodicity as shown in Fig. 5. Nevertheless, the current prediction logic does not consider this characteristic.

(d) The patterns for the BFG and COG consumption rates in the power plants and hot-rolling plants also show some variations. However, only the present value is used as prediction values for these plants in the current prediction logic.

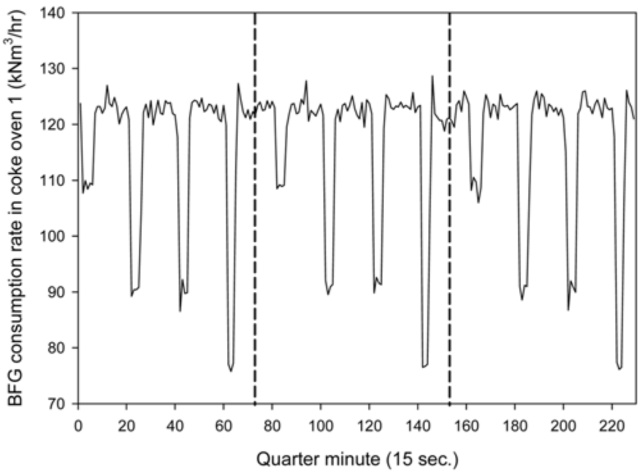

Fig. 5. Typical pattern for the BFG consumption rate in coke oven 1.

(e) Even though the actual duration time for each step in the steel-making process cycle changes severely depending on the process conditions, these times are fixed as constant parameters in calculating the prediction values for the LDG generation rate. This fact leads to prediction results that are very different from the real values.

We have approached these problems with time-series modeling and operator heuristics. A schematic diagram for the proposed method, together with the corresponding problems, is given in Fig. 6. First, for problems (b), (c), and (d), we modified the current prediction logic so that the past values can be reflected into the future values via a time-series model. If the past data set is used for the prediction of future values, more robust prediction can be accomplished. Namely, although the present value includes severe noise or disturbances, the prediction values can maintain the trend continued from the past. In addition, the time-series model ensures that an undetected past trend is automatically reflected in the prediction values.

Of the various kinds of time-series models, we used the moving average model, as described in Eq. (3), for problems (b) and (d). Although the variations in these are not so severe, we can improve the prediction performance by reflecting long-term trends from the past data into the future prediction values with the moving average model. Note that different values are used for k (the number of the past data) depending on the characteristics of the process.

$$\tilde{x}_t = x^1_{t-1} = \frac{1}{(k)}\sum_{i=t-k}^{t-1} x_i \tag{3}$$

Meanwhile, we applied a periodic time-series model in the form of Eq. (4) to solve problem (c), since the same pattern is obviously repeated with a specific period. Through more rigorous analysis of the actual data, the average value of the period was revealed to be 20.5 minutes. Since the prediction values are obtained at 30 second intervals, we built the periodic time-series model based on a unit of 30 seconds.

$$\tilde{x}_t = x^1_{t-1} = \frac{1}{14}(x_{t-82} + 6x_{t-81} + x_{t-42} + 6x_{t-41}) \tag{4}$$

In this equation, the weights have been empirically determined and two previous periods have been considered to obtain more generalized results.

Problem (a) can also be solved with the moving average model of Eq. (3). By using the data from the past 60 minutes for this moving average model (k=120), recent process conditions can be reflected in the criteria parameters. This means that the parameters are automatically updated at each prediction.

Finally, we handled problem (e) assisted by heuristics based on the experience of industrial operators in the steel-making process. Because process delays occur unexpectedly and frequently during the process, the prediction data obtained by fixed parameters give us no information on the future process trend. Therefore, we focused

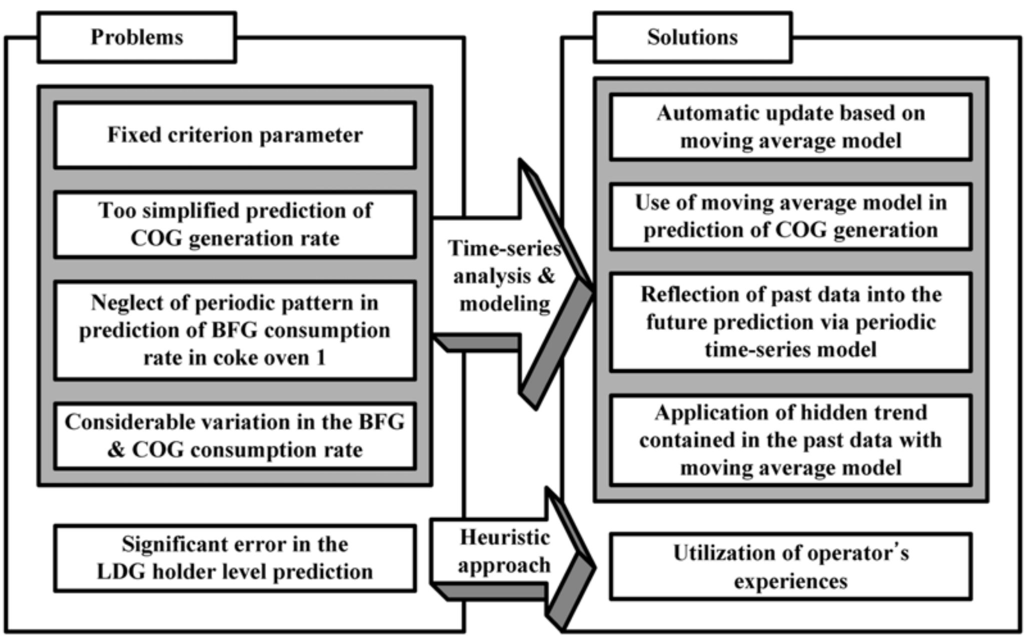

Fig. 6. Schematic diagram for the proposed method.

on how to detect the delay in advance as a crucial point of this problem. There were so many causes for the changes in the process conditions that it seemed like too much time and effort would be necessary to perfectly consider all the process changes and build a model that include all the information. Fortunately, we discovered that a correct prediction of the LDG generation rate was possible with the aid of industrial operators. It was revealed that only the operators of the converters know beforehand whether an unexpected process delay is going to occur, as well as the duration of the delay, based on their heuristic judgement considering the present condition of the steel-making process. Therefore, we modified the current prediction logic for the LDG generation rate so that the operators send the information on the process delay to the energy center at each process cycle to improve prediction performance.

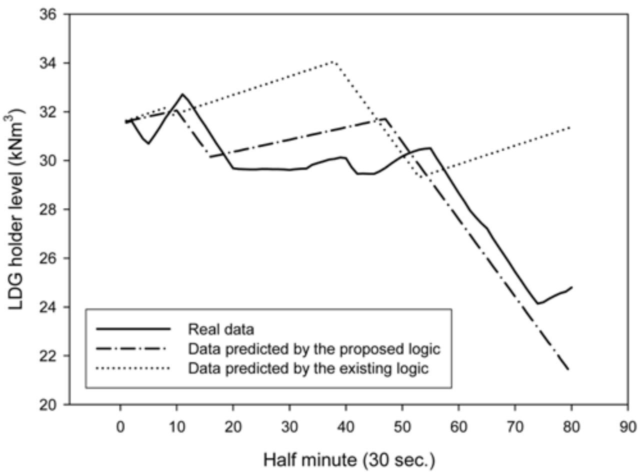

Fig. 7. Comparison between real data and prediction data based on both the existing and proposed logic for LDG 1 holder level.

RESULTS OF LINE TEST

We applied the proposed logic to the off-line data to validate its performance. Fig. 7 shows prediction results based on both the existing and the proposed logic for LDG 1 holder level. From this figure, we can see that the gap between the real data and the prediction data has been markedly reduced by using the proposed logic. Tables 1 and 2 show that the proposed logic definitely produces better prediction values for most cases, although the degree of improvement decreases as the prediction data become further from the present.

CONCLUSIONS

We have proposed an improved logic for the prediction of three kinds of by-product gasholder levels using time-series modeling and industrial heuristics. The results of an off-line test showed that the proposed logic outperformed the existing logic on average. By virtue of the success of the off-line test, the proposed logic is expected to be utilized in the actual prediction system of POSCO after rigorous on-line tests. If correct prediction of the future trend for each gasholder level is possible with the proposed logic, stable and safe management of the gasholders without waste or shortage of the gases can be achieved. Ultimately, significant reduction of energy costs via the efficient use of by-product gases will contribute to the enhancement of the overall productivity of POSCO.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the program for the con-

Table 1. Result of off-line test for BFG and COG holder level prediction after 1,000 executions

		After 2 min	After 4 min	After 6 min	After 8 min	After 10 min
BFG	Average difference for the existing logic (kNm^3)	4.20	6.05	6.96	8.9	10.7
	Average difference for the proposed logic (kNm^3)	2.43	2.89	3.12	3.56	3.82
	Relative improvement (%)	42.2	52.2	55.2	60	64.3
COG	Average difference for the existing logic (kNm^3)	1.07	1.9	3.0	3.6	5
	Average difference for the proposed logic (kNm^3)	0.6	1.0	1.9	2.6	3.1
	Relative improvement (%)	41.8	47.0	36.2	37.7	39.4

Table 2. Results of off-line test for LDG holder level prediction after 1,000 executions

		After 10 min	After 20 min	After 30 min	After 40 min
LDG (operation with only 2 converters)	Average difference for the existing logic (kNm^3)	157.0	469.5	349.2	428.7
	Average difference for the proposed logic (kNm^3)	67.2	102.8	170.0	463.9
	Relative improvement (%)	57.2	78.1	51.3	8.2
LDG (operation with all converters)	Average difference for the existing logic (kNm^3)	534.5	2518.7	2741.0	3042.7
	Average difference for the proposed logic (kNm^3)	133.7	175.2	244.9	225.6
	Relative improvement (%)	75.0	93.0	91.1	92.6

struction of Eco Industrial Park (EIP) which was conducted by the Korea Industrial Complex Corporation (KICOX) and the Brain Korea 21 project initiated by the Ministry of Education, Korea, Seoul R&BD Program, Energy Resources Technology Development Project provided through the Korea Energy Management Corporation/Ministry of Knowledge Economy, the Korea Science and Engineering Foundation provided through the Advanced Environmental Biotechnology Research Center (R11-2003-006) at Pohang University of Science and Technology, the program for Advancement of Plant Technology in 2008 "Gas Plant R&D Center-Development of Dynamic Process Design Simulator (08 Gas Plant B03)" conducted by Korea Institute of Construction &Transportation Evaluation and Planning provided through Ministry of Land, Transport and Maritime Affairs.

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