CONTROL OF GASHOLDER LEVEL BY TREND PREDICTION BASED ON TIME-SERIES ANALYSIS AND PROCESS HEURISTICS

Young-Hwan Chu[1], Jeong Hwan Kim[1], Seung Jae Moon[2], In Su Kang[2], S. Joe Qin[3], Chonghun Han[1,†]

[1]*Department of Chemical Engineering, Pohang University of Science and Technology*
Hyoja-Dong, Nam-Gu, Pohang, Kyungbuk, Korea 790-784
[2]*Environment-Energy Team, Pohang Iron and Steel Company*
Goidong-Dong, Nam-Gu, Pohang, Kyungbuk, Korea 790-300
[3]*Department of Chemical Engineering, The University of Texas at Austin*
Austin, Texas, USA 78712

Abstract: A novel method to control gasholder levels in an iron and steel company with accurate prediction of future trend is presented. Although various gasholders are used to recycle by-product gases generated during iron-making, coke-burning and steel-making process, the capacity of the gasholders are insufficient to handle large amount of the gases. To overcome this problem, tight control of the gasholder level should be conducted by predicting their anticipated changes. However, the current prediction logic cannot show satisfactory results due to the lack of characterization of relevant processes. In the proposed method, time-series modeling and heuristics of 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 of discrepancy between predicted values and actual values has been observed. The method is expected to be adopted in the prediction system of POSCO.

Keywords: Level control, Time-series modeling, Prediction, Iron and steel making process, Heuristics

1. INTRODUCTION

For 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 various materials generated from many plants (Makkonen *et al.*, 2002; Worrell *et al.*, 1997; Kim, 1998). These efforts are also significant from the viewpoint of environmental protection as well as cost saving (Sridhar *et al.*, 2002). In particular, by-product gases generated from iron-making, coke-burning and steel-making process, called as BFG (Blaster Furnace Gas), COG (Coke Oven Gas), and LDG (Linz-Donawitz Gas), respectively, are worthy of being used as a fuel since they include considerable amount of CO and H_2 (Bojic and Mourdoukoutas, 2000; Prokop and Kohut, 1998; Markland, 1980). 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 relatively small capacity of the gasholders, 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, the size of the gasholders should be increased so as to mitigate the variation of the holder levels or the holder levels should be controlled in advance by predicting future levels of the gasholders based on the present patterns of gas generation and consumption. Since increasing capacity of the gasholders requires enormous costs, most steel companies are trying to solve the problem with the latter method under the management of energy center. However, most prediction logics being used in the energy center of the companies show low performance since the characteristics of the processes influencing the levels of the gasholders are not sufficiently reflected in the systems. Therefore, modification of the prediction logics is urgently required by investigating reasons for

† To whom correspondence should be addressed.
E-mail: chan@postech.ac.kr

the deterioration of the prediction capability and correcting the problems.

In this paper, we present new prediction logic for level changes of three gasholders in Pohang Iron and Steel Company (POSCO) based on time-series analysis and heuristics of industrial operators (Box *et al.*, 1994; Pandit and Wu, 1983). Due to practical aspects of the problem, we relied on the real data set obtained from various plants related with the by-product gases and interviews with industrial operators. This is the reason why the two techniques are mainly used in the proposed method. The time-series analysis is used to model the periodic properties of the processes connected to the BFG and COG holders. The operators' experiences are effectively utilized to know LDG generation time of next operation in the steel-making process, which is randomly changed because of frequent process delays. The randomness of the delays in the duration and occurrence time makes correct prediction of LDG holder level nearly impossible without their prior knowledge. By applying the proposed method to off-line data set, prediction performances for the three gasholders were remarkably improved. Through additional on-line test based on this success of off-line test, the proposed logic is expected to be adopted as a real system in the POSCO.

This paper is organized as the followings. In the first section, the general framework for the prediction of gasholder level in 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.

2. THEORETICAL BACKGROUND

2.1 General Framework for Prediction of Gasholder Levels.

The logics for predicting future changes of the three gasholder levels are based on the periodicity of relevant processes, although there are some exceptions depending on the processes. Therefore, if we know the cycle time, present position in the process cycle and the rate of gas generation or consumption for each interval in the cycle, we can know the future trend of gasholder level within one prediction horizon. To obtain prediction values for the holder level, prediction values for gas generation and consumption rates of relevant processes are separately calculated in advance for a prediction horizon. Once this procedure is completed, 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 gas generation rate to and subtracting the first prediction value of gas consumption rate from the present gasholder level.

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

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

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

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

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

Trend Prediction of BFG Holder Level. BFG is generated as a by-product gas during an 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: combustion and exchange phase. Since a BFG generation rate and duration time for each phase is maintained at fixed values as shown in Fig. 1, they are set as constant parameters. Prediction of BFG generation rate is performed based on the parameters. To start prediction, we should know where the present time is located in the process cycle. For this purpose, criterion parameters with which we can know the present phase are used. Therefore, 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 the whole prediction values for BFG generation rate within a prediction horizon can be obtained from the present time based on the parameters. It should be noted that the prediction values for total BFG generation rate are derived by adding the values of each BFG generation rate predicted for the five BFs.

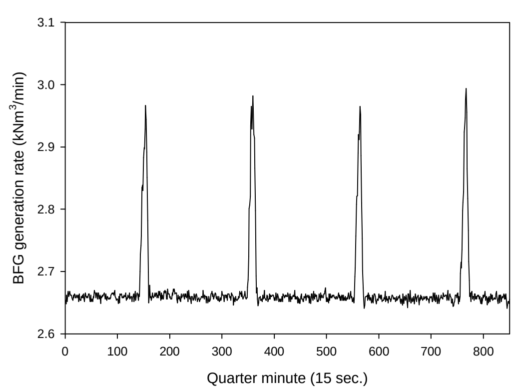

Fig. 1. Typical BFG generation pattern in BF 1.

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

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

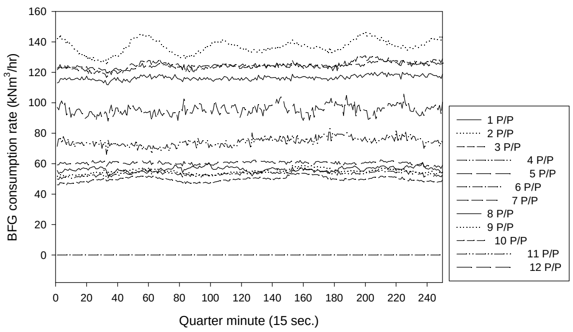

Fig. 2. Typical BFG consumption pattern for twelve power plants.

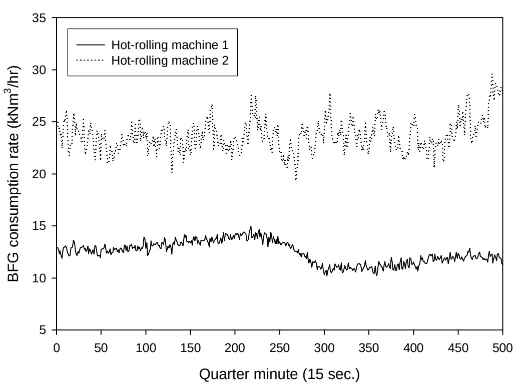

Fig. 3. Typical BFG consumption pattern for two hot-rolling machines.

Trend Prediction of COG Holder Level. COG is generated during a coke oven process. Cokes are used as a heat source for an iron-making process and they are lightly burned in the coke ovens as a preprocessing. During this process, significant amount of by-product gases are generated and they contain high percentage of CO and H_2 in themselves. Therefore, this gas is recycled as an energy source for many plants via COG holders. Unlike the BFG holders, the sizes of two COG holders are sufficiently large and much more plants are connected with the COG holders. Due to the relatively large capacity of the holders and averaging-out effect in the variation of holder level, they keep almost constant level as shown in Fig. 4. This fact means that the prediction of COG holder level is less important than those for the other kinds of gasholders since future COG holder level will be similar to the present one. For this reason, prediction logic for COG holder level is simpler than those for BFG or LDG holder level. In case of the prediction for COG generation rate, the present value is simply used for the prediction values within a prediction horizon under the condition that the present value should be in a normal range.

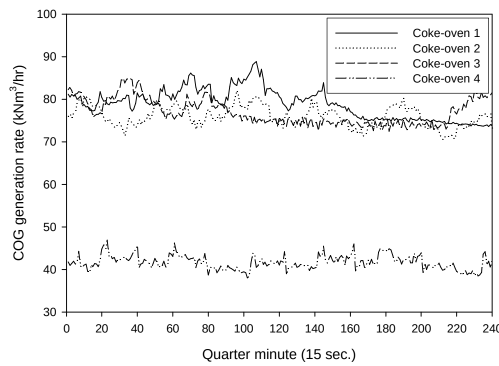

Fig. 4. Typical pattern for COG generation rate.

The plants which use the BFG as 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 of BFG consumption rate by a ratio constant. Using the Eqn. (1) and (2), the future changes of the COG holder level can be predicted if all generation and consumption rates predicted are given to us.

Trend Prediction of LDG Holder Level. LDG is a by-product gas generated in steel-making processes. In POSCO, two steel-making plants are operated and there exists a LDG gasholder for each steel-making plant. Three converters in each steel-making plant are sequentially used to continuously produce impurity-free steel by blowing oxygen to 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 a maintenance work.

Since the steel-making process also has a periodicity, the prediction for LDG generation rate is implemented in a similar way to the cases of BFG generation rate. The only difference is that four phases exist in one cycle of the process: start of oxygen-blowing, LDG recovery, end of oxygen-blowing and tapping. LDG is generated only in LDG recovery phase and the quantity of generation is nearly constant. In current prediction logic, the time required for completion of each phase is fixed as a constant although they are frequently changed due to unexpected process delays in fact.

Therefore, significant gap between the parameters and real values for the duration time of each phase necessarily occurs and this difference causes a serious deterioration in prediction performance. We tried to solve this problem by updating the duration parameters at every process cycle based on operator's heuristics. The details will be explained in the following sections.

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

2.2 Problems of the Current Prediction Logic and the Proposed Method as a Solution.

Although we explained outline of the existing prediction logic for each by-product gasholder, there are several problems that deteriorate prediction performance. The 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 condition. In fact, industrial operators have not updated the parameters for several years even if the actual process condition has changed significantly. To improve the prediction performance, we systematically analyzed the problems of the current prediction logic for each gasholder by investigating the characteristics of relevant processes based on historical data set and interviews with industry personnel. As a result, we have found out the following problems.

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

(b) In the prediction of COG generation rate, it is too simplified method to use the present value for the prediction values until the end of a horizon. Figure 4 which shows considerable variations in COG generation rate supports this fact.

(c) The pattern for BFG consumption rate in the coke oven 1 shows obvious periodicity as shown in Figure 5. Nevertheless, the current prediction logic does not consider this characteristic.

(d) The patterns for BFG and COG consumption rate in 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.

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

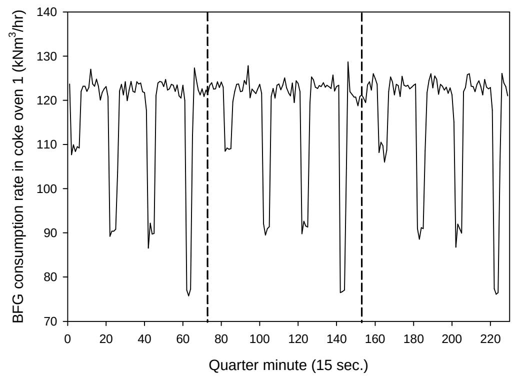

Fig. 5. Typical pattern for BFG consumption rate in coke oven 1.

We have approached these problems with time-series modeling and operator's heuristics. The schematic diagram for the proposed method together with the corresponding problems is given in Fig. 6. First of all, for the problems (b), (c) and (d), we modified the current prediction logic so that the past values can be reflected into the future values via 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 makes undetected past trend automatically reflected in the prediction values.

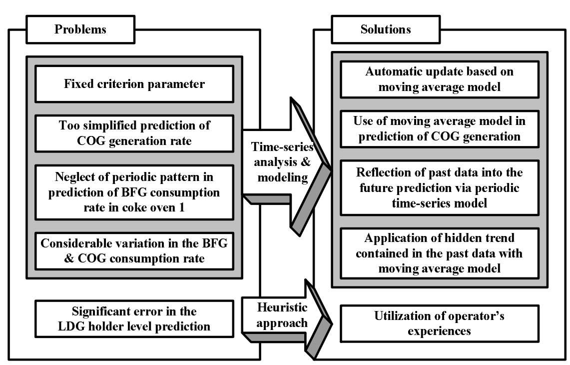

Fig. 6. Schematic diagram for the proposed method.

Of various kinds of time-series model, we used the moving average model such as Eqn. (3) for the problem (b) and (d). Although the variations for them are not so severe, we can improve the prediction performance by reflecting long-term trend of 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 process.

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

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

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

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

Problem (a) can be solved also with the moving average model such as Eqn. (3). By using the data during the past 60 minutes for this moving average model (k = 120), recent process condition can be reflected into the criterion parameters. This means that the parameters are automatically updated at each prediction.

Finally, we handled the problem (e) assisted by the heuristics of industrial operators in the steel-making process. Because of process delays occurred 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 on how to detect the delay in advance as a crucial point of this problem. There were so many causes for the changes of the process condition and too much time and efforts were expected to perfectly consider all the process changes and build a model including all the information. Fortunately, we found out correct prediction of LDG generation rate is possible with the aid of industrial operators. It was revealed that only the operators of converters know beforehand whether the unexpected process delay occurs as well as the duration time of the delay based on their heuristic judgement resulted from the present condition of steel-making process. Therefore, we modified the current prediction logic for LDG generation rate so that the operators send the information on the process delay to energy center at each process cycle to improve prediction performance.

3. RESULTS OF OFF-LINE TEST

We applied the proposed logic to the off-line data to validate its performance. Fig. 7 shows a result of prediction at 15:00:00 on Mar. 3, 2002 based on both of the existing and the proposed logics for LDG 1 holder level. From this figure, we can see the gap between the real data and the prediction data has been remarkably reduced by using the proposed logic. In Table 1 and 2, it is shown that the proposed logic surely produces better prediction values for most cases although the degree of improvement decreases as the prediction data are far from the present.

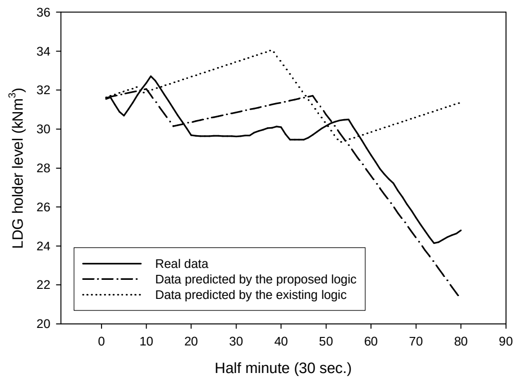

Fig. 7. Comparison between real data and both prediction data based on the existing and proposed logic for LDG 1 holder level. (implemented at 15:00:00 on Mar. 3, 2002)

4. CONCLUSIONS

In this paper, we proposed an improved logic for prediction of three kinds of by-product gasholder levels using time-series modeling and industrial heuristics. The results of off-line test showed that the proposed logic outperforms the existing logic on the average. By virtue of the success in 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 efficient use of by-product gases will contribute to enhancement of the overall productivity of POSCO.

REFERENCES

Bojic, M. and P. Mourdoukoutas (2000). Energy saving does not yield CO_2 emissions reductions: the case of waste fuel use in a steel mill. *Applied Thermal Engineering*, **20**, 963-975

Box, G. E. P., G. M. Jenkins and G. C. Reinsel (1994). *Time series analysis: forecasting and control*. Prentice Hall, Englewood Cliffs, NJ, USA.

Kim, K. (1998). Recycling technology of waste plastics in iron and steel industry. *Fuel energy abstr.*, **39**, 234

Li, C., H. Mi, W. Lee, W. You and Y. Wang (1999). PAH emission from the industrial boilers. *J. hazard. mater.*, **69,** 1-11

Makkonen, H. T., J. Heino, L. Laitila, A. Hiltunen, E. Pöyliö and J. Härkki (2002). Optimisation of steel plant recycling in Finland: dusts, scales and sludge. *Resour. conserv. recycl.,* **35**, 77-84

Markland, R. E. (1980). Improving fuel utilization in steel mill operations using linear programming. *J. oper. manage.,* **1**, 95-102

Pandit, S. M. and S. Wu (1983). *Time series and system analysis, with applications.* Wiley, New York, USA.

Prokop, L. and K. Kohut (1998). Process and apparatus for production of mixed combustion gas. *Fuel energy abstr.,* **39**, 188

Sridhar, S., D. Sichen, U. B. Pal and S. Seetharaman (2002). Abating Environmentally Harmful Waste Gases, *JOM,* **54**, 30-33

Worrell, E., L. Price, N. Martin, J. Farla and R. Schaeffer (1997). Energy intensity in the iron and steel industry: a comparison of physical and economic indicators. *Energy Policy,* **25**, 727-744

Table 1. Result of off-line test for BFG and COG holder level prediction after 1000 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. Result of off-line test for LDG holder level prediction after 1000 executions

		After 10 min.	After 20 min.	After 30 min.	After 40 min.
LDG (operation only with 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