Development and Estimation of a Burden Distribution Index for Monitoring a Blast Furnace Condition

Young-Hwan Chu*, Tai-Hwa Choi** and Chonghun Han*

* Department of Chemical Engineering, Pohang University of Science and Technology, Pohang, Korea
(Tel : +82-54-279-2279; E-mail: chan@postech.ac.kr)
**Ironmaking Department, Pohang Works, POSCO, Pohang, Korea
(Tel : +82-54-220-0548; E-mail: choith@posco.co.kr)

Abstract: A novel index representing burden distribution form in the blast furnace is developed and index estimation model is built with an empirical modeling method to monitor inner condition of the furnace without expensive sensors. To find the best combination of index and modeling method, two candidates for the index and four modeling methods have been examined. Results have shown that 3-D index have more resolution in describing the distribution form than 1-D index and ANN model produces smallest RMSE due to nonlinearity between the indices and charging mode. Although ANN has shown the best prediction accuracy in this study, PLS can be a good alternative due to its advantages in generalization capability, consistency, simplicity and training time. The second best result of PLS in the prediction results supports this fact.

Keywords: Blast furnace, Estimation, Monitoring, Empirical modeling, PLS, ANN

1. INTRODUCTION

A blast furnace is essential equipment in an iron-and-steel making process since it produces pig iron in liquid phase as a base material for various final steel products. However, characteristics of the blast furnace process have not completely identified due to its complexity in physicochemical phenomena and excessively huge scale [1]. In particular, severely high inner temperature of the equipment makes it difficult to use sensors for measurement of various states. Although optical sensors based on an ultrasonic wave or laser are currently used as a measuring method, these methods still have disadvantages in costs, time, and accuracy. Therefore, a novel state-estimation method which replaces the direct measurement using physical sensors is required.

In this study, a method which estimates a burden distribution form in a blast furnace based on a data-driven model is proposed. The burden distribution form is very important in evaluating blast furnace condition because direction of high-temperature blast rising from bottom of the furnace is determined by the distribution form. Despite the importance of the burden distribution form, it has not been correctly measured due to difficulty in using sensors. Therefore, we propose the two-stage strategy to estimate it from charging program which can be manipulated. In the first stage, a burden distribution index is devised so that the form can be correctly reproduced from the index value. Then, in the second stage, empirical models between the index and charging mode are built to predict the actual index value from the charging mode.

Because we do not know which index and which modeling method show the best description for the burden distribution form and prediction performance, we try several combinations of the candidates for the index and modeling method. For the index, two candidates are considered: 1-D index and 3-D index. 1-D index is simple but does not have satisfactory resolution for the actual burden distribution form. On the other hand, 3-D index is more complex due to its increased dimension but has advantage in describing the form more accurately. As the modeling methods, 4 kinds are considered: partial least squares (PLS), artificial neural networks (ANN), polynomial PLS, and neural networks PLS (NNPLS) [2-5]. PLS is considered as a linear modeling method which can handle multi-collinearity. ANN is a nonlinear modeling method which has flexibility in determining modeling structure. Polynomial PLS and NNPLS are nonlinear PLS methods which have nonlinear inner relationship between principal components of predictor and predicted variables. Note that these two modeling methods are considered as a compromise between PLS and ANN. We will find out the best combination of the index and modeling method based on description capability of the index and prediction performance of the completed model.

This paper is organized as follows. In section 2, overview of a blast furnace operation is explained. Then, background of the development of a burden distribution index and its procedure is shown in the section 3. In section 4, various modeling methods are examined to find out the best one with the minimum RMSE value for test data. Finally, conclusions are given in section 5.

2. OVERVIEW OF A BLAST FURNACE OPERATION

A blast furnace operation is the most important in that it produces base material for final steel products. In this operation, cokes as both reductant and fuel are charged into the furnace from the top together with iron ores according to a charging program. Figure 1 shows outline of the blast furnace operation. Charging of input materials is periodically performed and the charged materials slowly go down. Meanwhile, high-temperature blast is blown into the furnace from the bottom to provide heat source for melting of the iron ores. The flow of the blast and the fall of the charged materials are countercurrently processed, and cohesive zone is generated in the middle of the furnace by phase equilibrium phenomenon. During this process, oxygen of the iron ore is taken by the blast gas through a combustion reaction and pure pig iron is produced at the bottom of the furnace. The blast gas after going through the charged materials leaves the furnace as a blast furnace gas (BFG) which is recycled as fuels. Finally, the pig iron in the liquid phase is intermittently tapped from the bottom of the furnace to be used for following processes.

Due to its complexity in physicochemical phenomena and enormous size, the static and dynamic behaviors inside of the furnace have not been clearly revealed. In addition, severely high temperature of the furnace is an obstacle to using sensors to monitor the inner condition. Currently, the whole furnace condition is inferred from measurement results of surface condition although expensive heat-resistant rods with measuring sensors are occasionally inserted into the inside of the furnace to directly measure the inner condition.

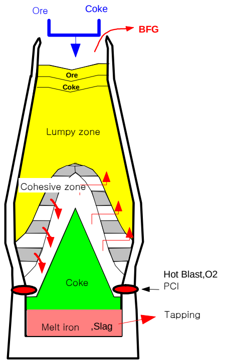


Fig. 1 Blast furnace operation.

The burden distribution form usually measured with ultrasonic wave or laser provides lots of information on the furnace condition. Because the high-temperature blast gas flows through interstices of coke pile, direction of the gas is critically determined by the burden distribution form. For example, if center side has more coke pile than wall side, the flow of the blast gas is biased into the center side (Case 1). On the other hand, if wall side has more coke pile than center side, the flow of the blast gas is biased into the wall side (Case 2). For Case 1, the pig iron finally produced by the operation decreases due to reduction of contacting area between the blast gas and iron ores, while heat load of the wall is relieved. Case 2 is the opposite situation of the Case 1. In this case, production rate of the pig iron increases while loss in equipment costs is occurred due to increased heal load on the furnace wall. Therefore, to know the burden distribution form is very important to effectively monitor and control the inner condition.

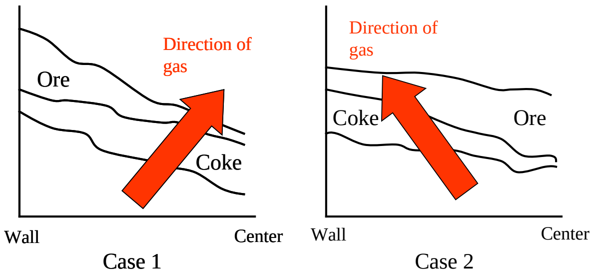


Fig. 2 Determination of gas direction according to the burden distribution form.

Until now, the form has been measured by optical sensors such as ultrasonic wave or laser. However, these methods also require considerable costs and time like other direct measuring methods. Therefore, it is needed to estimate the form from models which allows us to know the form in simple and fast way without additional costs. For this purpose, two kinds of works should be done. First one is to develop an index which correctly represents the burden distribution form, and the second one is to build an empirical model between the index and manipulated variables so that we can determine the form from the model.

3. DEVELOPMENT OF A BURDEN DISTRIBUTION INDEX

As a first step for estimation of the burden distribution form, an index which quantifies the form is developed. The developed index is used as a response variable for the index estimation model. It is required that the index should be simple and uniquely describe the burden distribution profile to radial direction. We propose two candidates for the index: 1-D and 3-D indices. While the 1-D index represents the profile form with only one number, the 3-D index represents with combination of three numbers. Equations (1) through (5) express these two indices, respectively.

$$1-D\ index = \frac{SORT}{SCRT}, \tag{1}$$

$$3-D\ index = [SORT\ SCRT\ SOCR] \tag{2}$$

where,

$$SORT = \sum_{i=1}^{n}(weight_i \cdot \frac{thickness_{ore,i}}{wall\ thickness_{ore}}), \tag{3}$$

$$SCRT = \sum_{i=1}^{n}(weight_i \cdot \frac{thickness_{coke,i}}{wall\ thickness_{coke}}), \tag{4}$$

$$SOCR = \sum_{i=1}^{n}(weight_i \cdot \frac{thickness_{ore,i}}{thickness_{coke,i}}). \tag{5}$$

In the equation (3), (4) and (5), SORT, SCRT and SOCR mean “Sum of Ore Relative Thicknesses”, “Sum of Coke Relative Thicknesses” and “Sum of Ore to Coke Ratios”, respectively. The indices have been devised based on the idea shown in Fig. 3. To consider all positions of the radial-direction profile, we divided it into 51 slices. Then, the three kinds of relative thickness sums have been proposed. SORT and SCRT reflect overall bias of ore and coke layers to wall or center side. If all thicknesses of ore or coke layer at the 51 sliced positions are the same, SORT or SCRT becomes 1. Otherwise, if thickness at center side is larger than wall side, SORT has a value larger than 1, and vise versa. On the other hand, SOCR considers ratios of ore and coke layer at all sliced positions. Therefore, if the thickness of ore layer is overall larger than coke layer, SOCR has a value larger than 1.

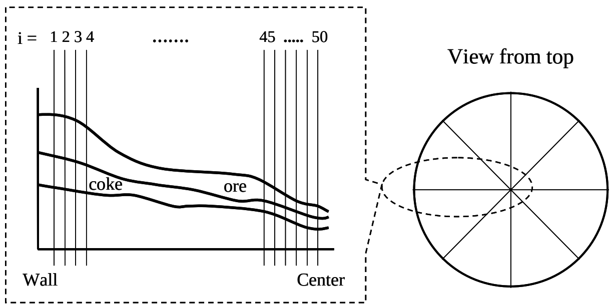


Fig. 3. Slicing of burden distribution profile.

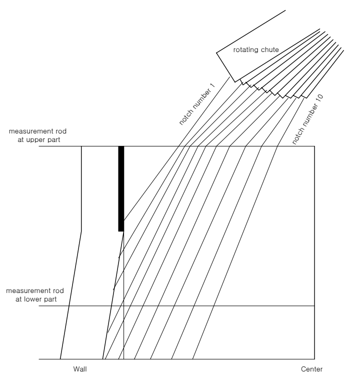
The 1-D index is defined as the ratio of SORT and SCRT. It is simple since the distribution form can be described only with one number. However, it does not have exact one-to-one relationship with the form because many distribution forms can be reproduced from one value. For instance, the ratio of SORT and SCRT can be maintained as the same value while SORT and SCRT have different values (i.e. the burden distribution profile of each layer has different shape). Nevertheless, the 1-D index has uniqueness to certain extent due to typical pattern of the operation.

The 3-D index is a combination of the three relative thickness sums. Since it considers them independently, more information on the profile form can be given to us. In addition, the uniqueness of the index can be guaranteed since only one shape can be constructed from one combination of the three values despite increase of dimension. To select better index from the two ones which provide correct reproducibility and prediction accuracy, we will further examine the performance of the two indices from the viewpoint of modeling in the next section.

4. EMPIRICAL MODEL BUILDING BETWEEN THE INDEX AND CHARGING MODE

4.1 Charging mode

Since the purpose of this study is to estimate the index value from a model without a measurement sensor, an empirical model is built based on historical data. In the model, charging mode is used as predictor variables because it critically determines the burden distribution form. Charging mode is a program in which the quantity of charged materials and charging positions are specified. Figure 4 shows how the charging mode is defined together with the structure of charging equipment. In this figure, ores and cokes are charged through the rotating chute which has 10 notch numbers depending on its tilted angle from the center axis. As the notch number decreases, the angle increases and the charged materials fall near the wall side. Although the burden distribution form is mainly determined by the charging mode, it is possible that the different form can be generated with the same charging mode. This problem is caused by large scale of the furnace, collision between the charged materials and the furnace wall, and rolling of the charged materials on the previous burden. This means that direct guess for the burden distribution form from the charging mode is difficult and thus modeling between them is required.



Notch number	Tilted angle(º)
1	48.5
2	46.5
3	44.5
4	42.0
5	39.5
6	37.0
7	34.5
8	31.5
9	25.0
10	17.0

Fig. 4 Structure of charging equipment and definition of charging mode.

4.2 Empirical modeling based on linear and nonlinear regression techniques

With the two kinds of developed indices, we build empirical models based on regression methods. To find out the best modeling method fitted to the characteristics of the relation among the variables, we examine four modeling methods: PLS, ANN, polynomial PLS, and neural net PLS. The reason for the selection of the four modeling methods is to check nonlinearity and multi-collinearity among the variables. Besides, simplicity and consistency are also important criteria for selection of the final method. Brief reviews for these four methods are given in the followings.

<u>4.2.1 PLS (Partial Least Squares)</u>

PLS is the most advanced one in the linear regression methods from the viewpoint of handling multi-collinearity among variables. Unlike the multiple linear regression (MLR) method, PLS projects both X and Y data on a latent space generated to the direction of largest variance to perform regression. The optimal number of principal components (PCs) used for predictor variables in the regression are determined by various criteria such as cross-validation. Based on the selected PCs, a regression model is built so that correlation between PCs of X and Y is maximized. As an algorithm for PLS, NIPALS and SIMPLS are the most widely used. [6, 7]

<u>4.2.2 ANN (Artificial Neural Networks)</u>

ANN is a representative nonlinear regression method that imitates a neural processing of human brain. It has flexibility in determining model structure, and thus any model can be built by adjusting its structure and parameters [8, 9]. The general structure of ANN is shown in Fig. 5. It is the most distinguished feature of the ANN that nonlinear transformation is performed via the hidden nodes. Although lots of training algorithms have been proposed to estimate parameters given to each arc connecting nodes, back-propagation algorithm is known to be the most efficient one to train a multi-layer perceptron such as Fig. 5. In this study, we use the Levenberg-Marquardt algorithm which is one of the best back-propagation algorithms as a training method.

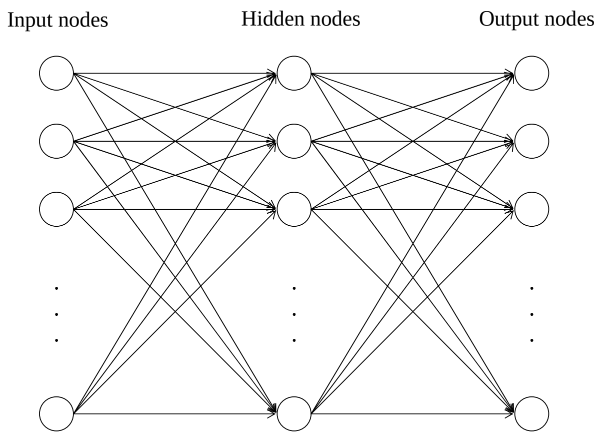


Fig. 5 General neural networks structure.

<u>4.2.3 Polynomial PLS</u>

To deal with nonlinearity in data structure together with multi-collinearity problem, various nonlinear regression techniques have been considered in inner relationship of PLS algorithm. These methods called as nonlinear PLS (NPLS) have compromising properties between PLS and ANN. Therefore, advantages of both methods can be seen in the NPLS. The most simple method that can be used for this purpose is a polynomial equation with orders equal to or larger than 2 [10]. Despite lack of freedom in changing model structure, polynomial equations can be effective for weak nonlinearity. In this study, the order of the equation is determined so that RMSE of the polynomial PLS model is minimized. Schematic diagram of the NPLS with polynomial inner relationship is shown in Fig. 6.

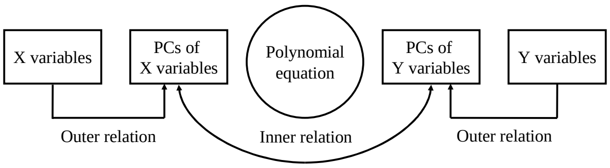


Fig. 6 Structure of polynomial PLS.

4.2.4 Neural Network PLS (NNPLS)

NNPLS can handle even severe nonlinearity by employing ANN structure in the inner relation of PLS. By using neural network structure in the inner relation, freedom in structural change of the model increases compared to polynomial PLS. NNPLS takes advantages of both PLS and ANN approaches. Therefore, it has increased model robustness and smaller prediction variance. This property of NNPLS comes from reduction of a MIMO network regression to a number of SISO network regression problems [11]. Although NNPLS has less flexibility in determining model structure than ANN, it can solve over-fitting problem of ANN to a certain degree due to this decomposition property. For this reason, NNPLS is popularly used instead of ANN or PLS when nonlinearity should be considered together with generalization capability.

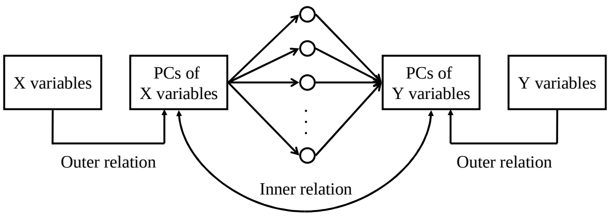


Fig. 7 Structure of NNPLS.

4.3 Results and analysis

We examined 8 cases as combinations of two developed indices and 4 modeling methods to select one with the minimum RMSE and the best reproduction capability. We shows 4 results related to the 1-D index followed by another 4 results related to the 3-D index.

4.3.1 Data validation

To build the index estimation model, 83 charging mode data were gathered. For corresponding charging mode data, the values of the two kinds of indices were calculated based on the past data measured with ultrasonic wave. For these data, data validation using PCA was performed to exclude abnormal data. Figures 8 and 9 show score and loading plots resulted from the application of PCA. Figure 8 shows that 67th and 83rd data are evidently outside of the ellipsoid representing 95% confidence level. Therefore, we did not include these two data and used only 81 data in the study. The 81 data were divided into 60 modeling and 21 test data.

Since rotation numbers at certain notch numbers do not change, variance information for the variables cannot be reflected in the model. Therefore, we considered only the 19 variables with nonzero variance for modeling. In Fig. 9, we can see that the loading values of the 19 variables are far from the center position. This means that all 19 variables can plays a significant role in explaining data variance for the index estimation model.

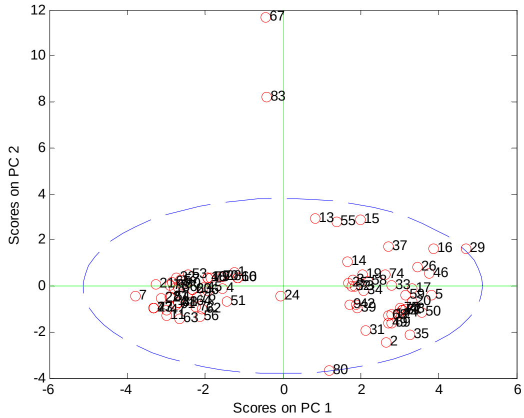


Fig. 8 PCA Score plot composed of the first two PCs.

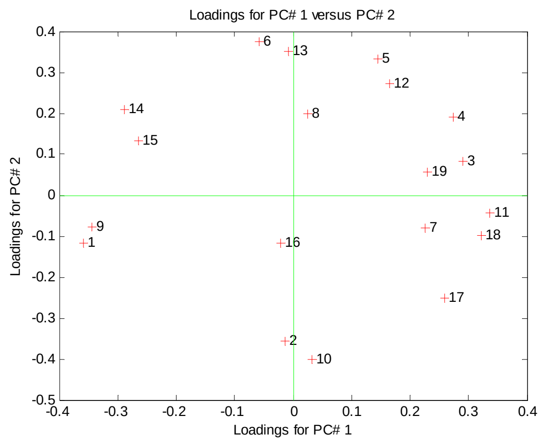


Fig. 9 PCA loading plot composed of the first two PCs.

4.3.2 Estimation results for test data

With the modeling data, index estimation models based on the four empirical modeling methods have been built. In each modeling, both of 1-D and 3-D indices were examined as response variables to select more predictive index. After completing the models, data predicted by the models were compared with real data with 21 test data. Fig. 10 shows the prediction results for 1-D index. In this figure, we can see visually that the data predicted by ANN model have the best prediction performance. It is also notable that PLS shows better prediction accuracy than the two NPLS methods. Fig. 11 which shows the predicted data for the 3-D index produced similar results to the cases of 1-D index. For all three elements, ANN model showed the best prediction results and the second best was the PLS model.

From these results, two facts can be inferred. First, superiority of ANN model to the other models in the prediction results means that there is nonlinearity between the charging mode and 1-D index. Besides, its flexibility in determining model structure may contribute to the outstanding prediction results. Second, it has been proved that PLS has a good generalization capability and robustness in predicting unknown data. Therefore, we can see that PLS can be applied to any data except severely nonlinear ones to achieve an empirical model with acceptable prediction performance.

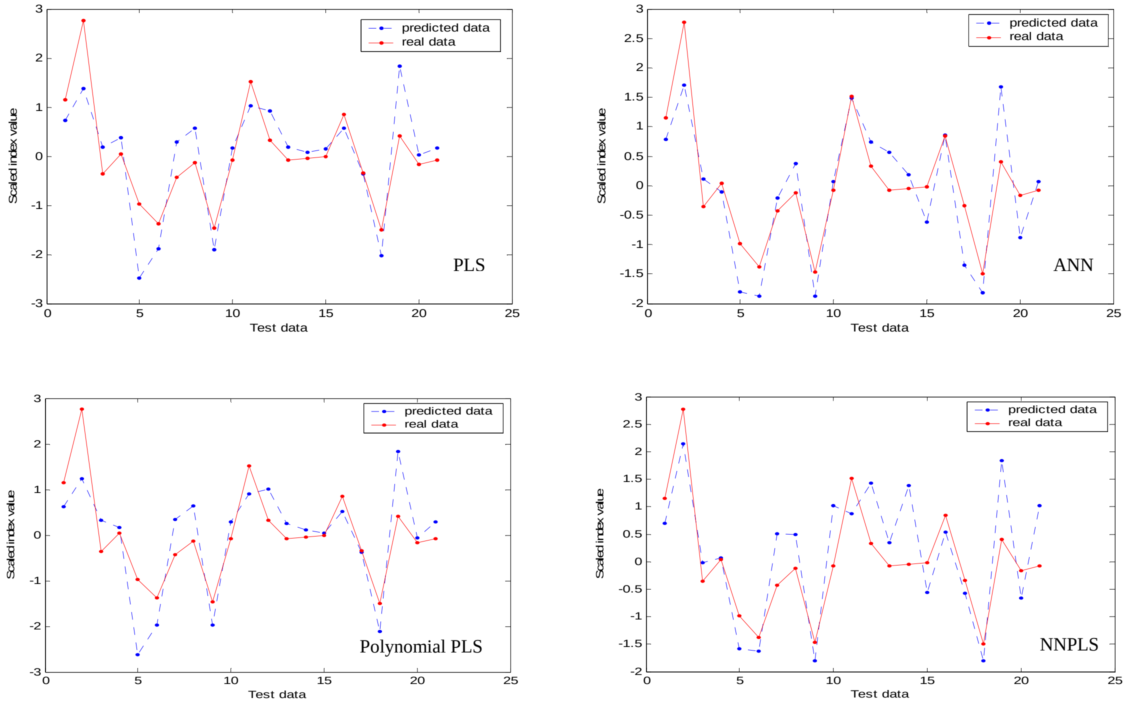


Fig. 10 Estimation results for the 1-D index.

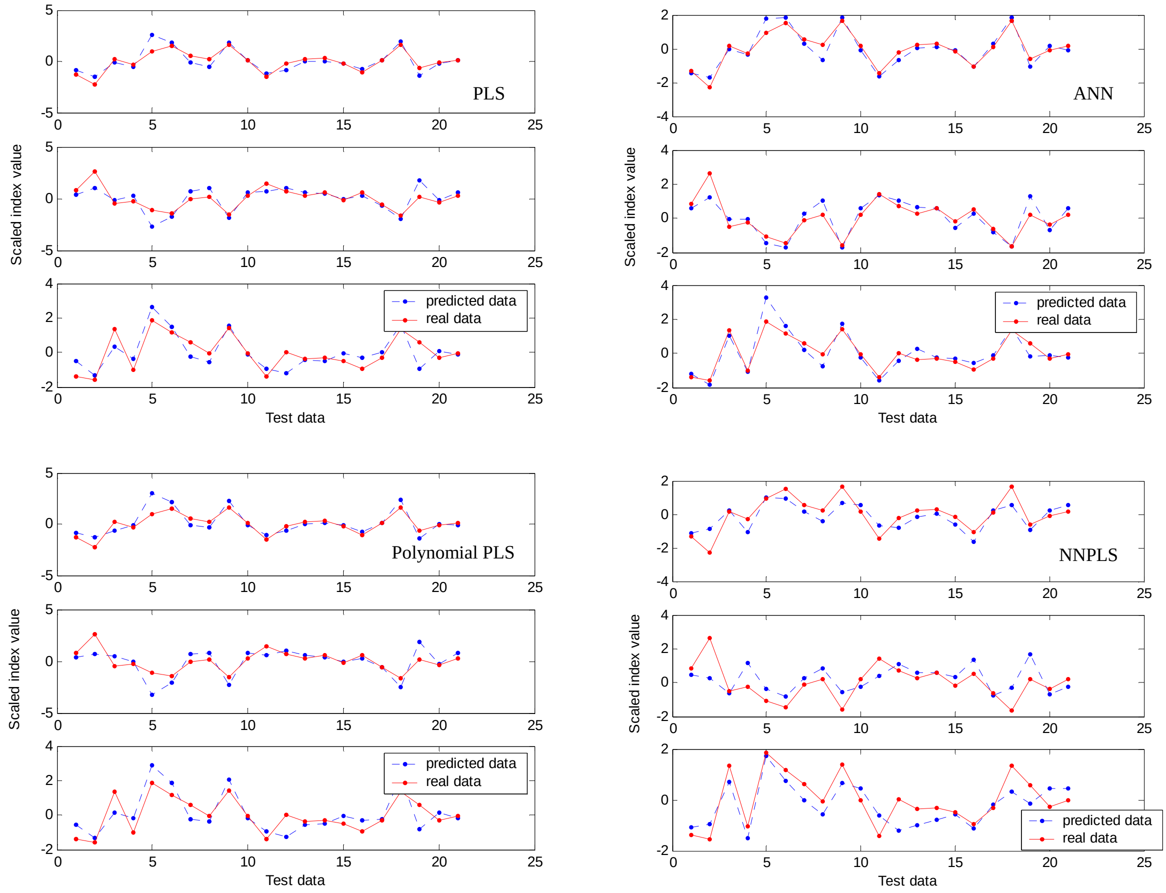


Fig. 11 Estimation results for the 3-D index.

Finally, for the case of 3-D index, it was a noticeable result that the last element of the 3-D index (SOCR) showed the largest gap between predicted and real data for all models. The reason for this result is that the ratio of ore thickness to coke thickness at each position is not definitely affected by charging mode. Nevertheless, SOCR is an important criterion to evaluate overall shape of coke and ore layers, and can be predicted satisfactorily with ANN model.

The RMSE values resulted from the predictions for those eight cases are shown in Table 1. Note that mean RMSE values for three elements have been used for comparison with the 1-D index. In this table, ANN produces the least RMSE values for both of the indices and the RMSE values by PLS are the second best as Figs. 10 and 11 previously showed. Besides, from this table, we can see that the combination of ANN and 3-D index gives the smallest RMSE. This result is desirable because 3-D index has exact one-to-one relationship with burden distribution form and nonlinearity of data can be effectively handled by ANN. However, it should be noted that training results of ANN can be different depending on initial parameter values because the training procedure is equivalent to solving a nonlinear optimization problem. Therefore, PLS can be a better alternative to ANN from the viewpoint of consistency as well as simplicity and training time.

Table 1 RMSE values for two indices and four modeling methods.

	RMSE			
	PLS	ANN	Poly. PLS	NNPLS
1-D index	0.6730	0.4781	0.7348	0.7418
3-D index	0.6586	**0.4465**	0.7660	0.7070

5. CONCLUSIONS

In this study, we developed a novel index representing the burden distribution form and estimated it with an empirical model to effectively monitor inner condition of the blast furnace without expensive ultrasonic sensors. Of the two kinds of indices, 3-D index had better accuracy in uniquely describing the distribution form. From the viewpoint of prediction accuracy, ANN showed the best performance among the four proposed empirical modeling methods for both indices. The results means that the indices have nonlinear relationship with charging mode used as input variables for the models. By comparing RMSE values of eight cases generated by combining the two indices and four modeling methods, combination of 3-D index and ANN has been revealed to be the best. However, the disadvantages of ANN in consistency, simplicity, and training time drive us to use PLS as the second best modeling method. Based on the results of this study, we can further consider an optimization problem in which the optimal charging mode can be found out so that productivity and equipment costs are optimally compromised. This problem will be dealt with in the future study.

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