철강 생산 공정에서 Soft Computing 기술을 이용한 온도하락 예측 모형의 비교 연구

Comparative Analysis of Models used to Predict the Temperature Decreases in the Steel Making Process using Soft Computing Techniques

김 종 한, 성 덕 현*
(Jong-Han Kim and Deokhyun Seong)

Abstract : This paper is to establish an appropriate model for predicting the temperature decreases in the batch transferred from the refining process to the caster in steel-making companies. Mathematical modeling of the temperature decreases between the processes is difficult, since the reaction mechanism by which the temperature changes in a molten steel batch is dynamic, uncertain and complex. Three soft computing techniques are examined using the same data, namely the multiple regression, fuzzy regression, and neural net (NN) models. To compare the accuracy of these three models, a limited number of input variables are selected from those variables significantly affecting the temperature decrease. The results show that the difference in accuracy between the three models is not statistically significant. Nonetheless, the NN model is recommended because of its adaptive ability and robustness. The method presented in this paper allows the temperature decrease to be predicted without requiring any precise metallurgical knowledge.

Keywords : comparative analysis, predicting temperature decrease, steel making process

I. Introduction

The steel-making process is very important in integrated iron and steel-making companies, because the quality of the steel is mainly determined through this process, which is composed of two sub-processes, namely the converter and continuous caster sub-processes. The secondary refining of molten steel is performed in between these two sub-processes, in order to control the temperature and chemical compositions precisely. The secondary refining process has various functions, e.g., adjusting the temperature, homogenizing the chemical compositions, deoxygenating, desulphurization, degassing, and controlling for unwanted substances. Each facility listed in Table 1 performs an appropriate function as explained in the table, and almost every batch of molten steel passes through the proper facility to remove the impurities in the batch.

During continuous casting, ensuring that the appropriate temperature is maintained is critical for continuous processing. If the temperature is significantly lower than expected, productivity decreases or the nozzle becomes clogged. On the other hand, if the temperature is too high, inferior product quality or breakage of the slab during processing is highly likely, due to the consequent acceleration of the casting. The temperature is not controlled at the caster, rather the arrival temperature of the batch is determined from the previous refining process [1].

Transferring the hot batches from the refining process to the caster takes time and leads to a decrease in temperature. To ensure that the required temperature is maintained at the caster, accurate prediction of the temperature decreases is very important. In general, there are various metallurgical models used in the steel industry for predicting these temperature decreases. Nonetheless, most of these models have been proven to have limitations in their accuracy, because of the complex relationship among the factors affecting the temperature decreases. In order to develop an

표 1. 2차정련 설비와 그 기능.
Table 1. Secondary refining facilities and their functions.

Secondary refining facilities	Function				
	Degassing	Desulfurization	Agitation	Control chemical compositions	Increasing temperature
BB(Bubbling)	X	△	O	△	X
PI(Powder Injection)	X	◎	O	◎	X
RH(Ruhrstahl-Heraess)	◎	X	◎	O	O
LF(Ladle Furnace)	X	O	O	◎	◎

Note: ◎ : major function, O : minor , △: semi-minor, X : No function

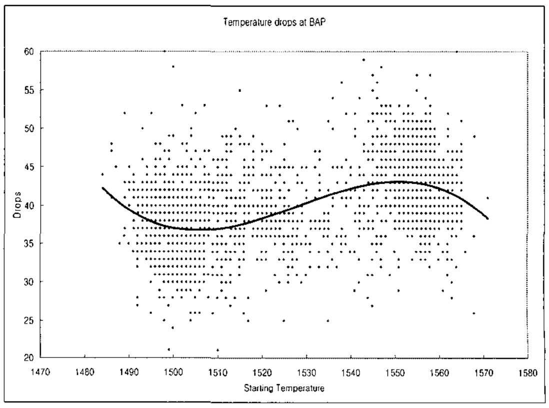


그림 1. LF에서 연주기로 이송 시 온도 하락.
Fig. 1. Temperature decreases of a batch from LF to caster.

* 책임저자(Corresponding Author)
논문접수 : 2006. 11. 2., 채택확정 : 2006. 12. 20.
김종한 : 포항산업과학연구원(kjh@rist.re.kr)
성덕현 : 부경대학교 경영학부(dhsung@pknu.ac.kr)

accurate model for predicting these temperature decreases, the influencing factors should first be clearly defined. Likewise, appropriate modeling is the next step toward prediction.

In general, the temperature decreases significantly with time or as a function of the starting temperature, however, this is not the case in metallurgy. Fig. 1 shows the decrease in temperature that occurs as a function of the starting temperature, and which is observed to exhibit non-linearity, i.e., lower starting temperature produces a slight decrease in the arrival temperature. On the other hand, higher starting temperature produce a significant decrease. This phenomenon is known to occur throughout the steel industry where the temperature of the batch is controlled through these processes.

Several methods of predicting these kinds of non-linear problems have been proven to be effective, namely multiple regression, fuzzy logic and neural networks. Each method has its own advantages. This paper aims to establish the appropriate model for predicting the temperature decreases in a batch transferred from the refining process to the caster, particularly from the LF to the caster. Specifically, a comparative analysis is conducted among the three methods, in order to assess the accuracy of each method. Actual data were gathered for three months in 2003, and these data were processed using each model in order to evaluate the accuracy of the predicted results.

Mathematical modeling of the temperature decrease in between the processes is difficult, since the reaction mechanism by which the temperature changes in a molten steel batch is dynamic, uncertain, and complex. Temperature control in a steel plant normally focuses only on the deformation of the metals. Traditionally, ordinary regression analysis is used for the prediction of problems of this kind. Recently, however, neural networks and fuzzy regression have also been used for similar types of problems. For process control, in particular, the neural network and fuzzy regression methods have been proven to be efficient by many researchers. Following the introduction of the fuzzy regression model by Buckley and Feuring [2] and Feuring et al. [3], Li et al. [4] examined and compared the use of regression and artificial neural network models for the estimation of wind turbine process control. They showed that the neural network performs better than the regression model under conditions in which there are complicated influencing factors. On the other hand, Chang and Ayyub [5] compared the fuzzy regression model with ordinary regression, providing extensive literature on the topic. Karlsruche [6] adopted the piecewise linear neural network model for process control. Finol et al. [7] used fuzzy logic to predict petrophysical rock parameters. Their modeling approach has significant advantages, since it does not require any previous assumption based on physical or experimental considerations of the problem.

The paper is organized as follows: Chapter 2 presents various attempts to predict temperature decreases through mathematical models; Chapter 3 provides a comparative analysis; and Chapter 4 presents the conclusion and recommendations for further research.

II. Modeling the temperature decreases

1. Independent variables

Based on metallurgical knowledge and expert experience, all of the factors affecting the temperature decreases of the batch from the LF to the caster are investigated. These factors can be categorized into four groups related to refining, casting, the ladle, and the species of steel. Only 12 out of the 38 potential influencing factors are deemed significant, based on the correlation coefficient between each factor and the temperature decrease. In addition, the functional type of each factor is determined using the scatter plot between the factor and temperature decrease. For example, a cubic expression of the arrival temperature is expected to predict the temperature decreases most accurately.

2. Regression model

For the independent variables, **x**, as the population model, assumes the following linear equation (the regression equation is estimated) [8]:

$$y = x\beta + \varepsilon$$
$$\hat{\beta} = (xx')^{-1}(x'y) \tag{1}$$
$$\text{where } \varepsilon_i \sim N(0,\sigma^2) \text{ and independent}$$

The arrival temperature at the caster is found to be the most significant factor among the independent variables. The scatter plot between the arrival temperature and the temperature decrease shows that the piecewise function will fit the relationship between these two factors. Therefore, three multiple linear regression models are developed according to the arrival temperature, viz. below 1505°C, over 1505°C and below 1551°C, and over 1551°C.

In the piecewise regression model, the independent variables are assumed to be included, without there being any interaction between them. The parameters are estimated using the maximum likelihood method, and the final regression equation is obtained. The ANOVA result shows that the multiple regression models are statistically significant: the p-values are all below 0.0001. Therefore, if the input values of the independent variables are set, the temperature decreases can be predicted using the regression equation. Note that it is necessary to replace the arrival temperature as the temperature required at the caster if the prediction model is to be used. The VIF (variance influence factor) for each independent variable is found to be below 5. This implies that there is no multicollinearity between the independent variables. In addition, the residual analysis shows that the assumptions made in the regression model are reasonable.

The temperature decreases for the field data are predicted using the equation in Table 3, and the resulting residuals between the predicted and actual values are recorded. The standard deviation of the residuals is 4.60, representing the degree of accuracy of the prediction. At the same time, another model reflecting all possible interactions among the independent variables is also tested. The results show that the standard deviation of the residuals for this model is 4.15, which is less than that of the model without interactions.

Here, we can interpret the standard deviation of the residuals. The actual upper and lower limits of the residuals are ±7°C, respectively, during the process of controlling the temperature. If the prediction model gives a residual of 4.15, then the hit ratio would be 90.84%, with the assumption that the residual follows a normal distribution. This means that 90.84% of the residuals fall within the range of -7°C ~ +7°C. Currently, the actual hit ratio of the field data reaches 80% on average and, using the prediction model, we can anticipate that the hit ratio will increase by 10%, in which case the productivity will increase by 1% on average.

3. Fuzzy regression model

The fuzzy model is made up of several *if-then* fuzzy rules. In general, the conclusive part of a fuzzy rule has three types of input and output: integers, fuzzy sets, and linear equations. Among them, the fuzzy model with the linear type of equation can represent more complicated, non-linear structures with higher precision, despite the small number of rules used for the numerical input and output data.

Since temperature prediction modeling of the steel-making process is very complicated, it is appropriate to represent it using fuzzy rules of the linear type. A model is therefore developed by sequentially determining and then evaluating the structure and coefficient of the antecedent part and consequent part.

There are no well-established methods of determining the structure of the antecedent part. In this paper, the trapezoid form is adopted to represent the structure as opposed to the triangular form. As shown in Fig. 2, the trapezoid form improves the accuracy of the solution when fuzzifying the arrival temperature. On the other hand, the coefficients of the fuzzy structure are determined using an extension of the simplex method to the constrained optimization problem [9].

As explained above, the structure and coefficients of the antecedent part are already known. As such, the identification of the consequent part becomes a problem that requires us to seek a solution to n linear simultaneous equations with m variables given n fuzzy rules. Therefore, if the structure of the consequent part is set, solving the simultaneous equations becomes the estimation of the population parameters with multiple linear regression modeling.

For the purpose of comparison, the same input variables are used for predicting the temperature decrease as in the regression analysis in Section 2.2. Moreover, the arrival temperature is fuzzified, as compared to the case where the same variable is divided into a piecewise linear function in the regression analysis.

The fuzzy model is set, and the experimental results are obtained using the identical data set. As a result, the fuzzification of the arrival temperature at 1500°C and 1550°C gives the smallest standard deviation of the residual. The fuzzified sections are found to be identical to those obtained using the regression model. The fuzzy models are derived through the fuzzy regression equations and the resulting standard deviation of the residuals is found to be 4.59. Moreover, the standard deviation decreases to 4.16 when the interactions between the input variables are included.

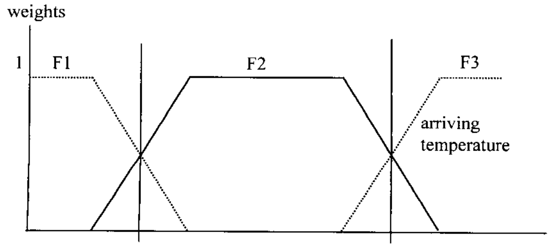


그림 2. 도착온도의 퍼지 구조.

Fig. 2. Fuzzy structure for the arrival temperature.

4. Neural network model

Neural networks are composed of simple parallel elements in a structure which is inspired by the nervous system. As in nature, the neural network function is determined largely by the connections between the elements. Usually, neural networks are adjusted or trained such that a particular input leads to a specific target output. Based on a comparison of the output and the target, the network is adjusted until the network output matches the target.

To predict the temperature decrease, the development of the neural network model is attempted based on the matlab environment [10]. As the most popular neural network architecture in use today, multilayer perceptrons are adopted to predict the temperature decrease during the continuous casting procedure.

The neural network model is develo Equation (3), in which the values, p_{old}, and p_{pre}, refer to the original and preprocessed values ped for the purpose of conducting a comparative analysis. The input layer is made up of twelve nodes which represent the independent variables, while the output layer consists of only one node, the dependent variable, which is the same as that used in other analysis methods. We adopt the back propagation algorithm as the training method, since multilayer perceptrons using propagation are known to have the capability of modeling the almost arbitrary complex functions between the input variable and the output, if there are enough hidden layers with the adequate number of neurons. The process of training can be summarized as follows:

- Filter the input pattern to the network.
- Calculate output values for each processing element within the network nodes.
- Calculate the error produced by the network.
- For the output layer, calculate the values of the weight changes.
- For the hidden layers, calculate the values of the weight changes.
- Update each weight according to its change in value.
- Repeat these steps until the error produced by the network is sufficiently low or the neural network fulfills the termination criteria.

As shown in Fig. 3, the log-sigmoid transfer function described in Equation (2) is selected as the activation function at each node, and with which the input value, n, falls in the range of [0, 1]. The back propagation algorithm is commonly used in the model due to its differentiability.

$$\text{logsig}(n)=1/(1+\exp\text{-}n) \tag{2}$$

where n is the net input of the hidden layer

To determine the complexity of the model, we divide the data

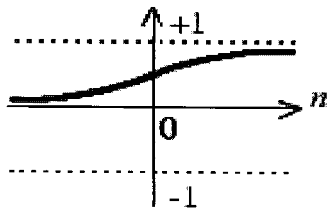


그림 3. 시그모이드 전이함수.

Fig. 3. The sigmoid transfer function.

into two sets: one for training and one for testing, and conduct a number of experiments with various network configurations. In each experiment, we trained the neural network model using the training data and then evaluated the model using the testing data. Through such experiments, we are able to select the network configuration which minimizes the testing error. The resulting model has two hidden layers and sixteen hidden neurons in each layer. To maximize the efficiency of the training process, we preprocess the data so that it falls within the range [-1,1], as described in of the variable p, respectively, and p_{min} and p_{max} refer to the maximum and minimum values of the variable p in the data set, respectively.

$$p_{pre}=2*(p_{old}-p_{min})/(p_{max}-p_{min})-1 \quad (3)$$

As the last step required to train the neural network, we decide the training period. Since using a long training period runs the risk of over fitting, a similar procedure is performed to determine the training period as that used to determine the complexity of the network model. Subsequently, we train the selected neural network model to learn the underlying function between the independent and dependent values.

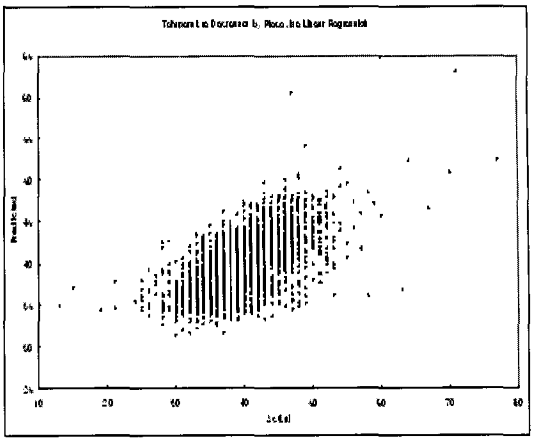
The temperature decrease is predicted using the neural network model developed in this paper. The standard deviations of the residuals are 4.53 and 4.19 for the cases without and with interactions, respectively.

III. Comparison of the results

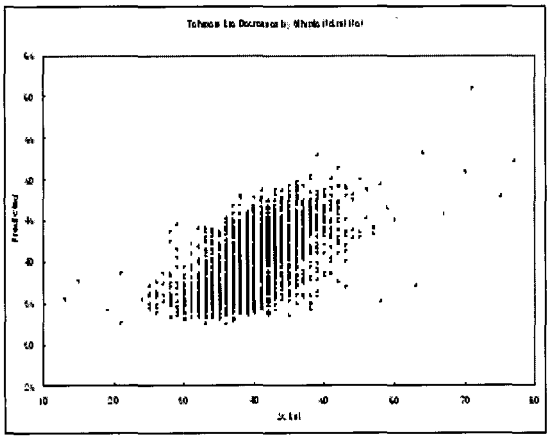
Considering the 12 variables as input, the coefficients of the model are estimated, and the prediction of the starting temperature is performed. First, when the interactions among the input variables are ignored, the scatter plots for the predicted versus the actual values of the starting temperature are plotted, as shown in Fig. 4. From this, it is found that all three methods give similar results. To compare the results statistically, the standard deviations of the residuals resulting from the different methods are shown in Table 2. The F-tests against the null hypotheses, in which the variances of the residuals are the same for the three methods, show that all of the p-values are very large, as shown in Table 3. This suggests that equivalent accuracies can be obtained for the three methods at a level of significance of 0.001.

The nodes of the hidden layer in the NN model can be considered to be a reflection of the interactions between all of the input variables. Reflecting the interactions in the multiple regression and fuzzy models requires the inclusion of all the interactions in the models. Including the interactions improves the accuracy of the temperature prediction. As a result, the standard deviation of the residuals drastically decreases, as shown in Table 2. Likewise, Table 3 shows the results of the F-test against the null hypothesis, in which the variances of the residuals are identical, showing that there is no difference in the prediction accuracy between the three methods.

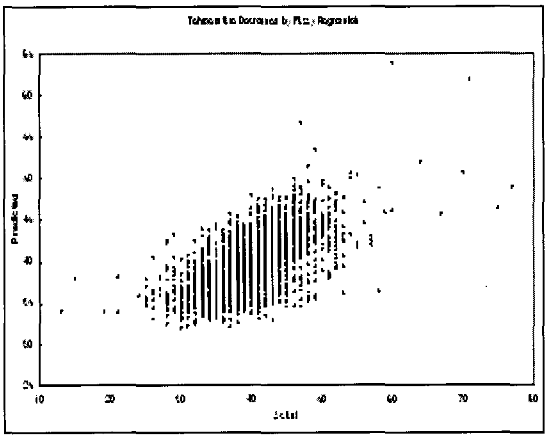
In comparing the temperature prediction models for the batch transferred from the secondary refining process to the continuous caster, the three different models give the same prediction accuracy when identical input variables are used for the multiple linear regression, fuzzy regression and neural network models. This identical accuracy comes from the assumption made about the linearity of the prediction model. On the other hand, the



(a) Regression



(b) Fuzzy regression



(c) Neural net

그림 4. 온도하락 비교-예측 대 실제.

Fig. 4. Plots of the decreases-predicted vs. actual values.

표 2. 모형별 잔차의 표준편차.

Table 2. Standard deviation of the residuals for each model.

	Model		
	Ordinary Regression	Fuzzy Regression	Neural Network
Without Interaction	4.60	4.59	4.53
With Interaction	4.15	4.16	4.19

표 3. 모집단 분산의 동일성에 대한 F 검정.
Table 3. F-test for equality of population variances.

	Null Hypothesis	F-statistic	p-value
Without Interaction	$H_0: \sigma_R^2 = \sigma_F^2$	0.996	0.919
	$H_0: \sigma_F^2 = \sigma_N^2$	0.974	0.537
	$H_0: \sigma_N^2 = \sigma_R^2$	1.031	0.472
With Interaction	$H_0: \sigma_R^2 = \sigma_F^2$	1.005	0.910
	$H_0: \sigma_F^2 = \sigma_N^2$	1.014	0.736
	$H_0: \sigma_N^2 = \sigma_R^2$	0.981	0.653

Note: σ_R^2, σ_F^2, and σ_N^2 represent the population variance of residuals by the ordinary regression, fuzzy regression, and neural network models, respectively.

accuracy of the temperature prediction model does not increase significantly, despite the assumption of linearity and the analysis of the non-linear model in the NN model.

Although no differences in accuracy are found between the three models, the NN model is recommended, because it is the most convenient. In the regression model, the possibility of multicollinearity should be considered, when the interactions between all of the input variables are reflected, since multicollinearity may lead to problems related to the robustness of the prediction results. Another advantage of the NN model is its adaptability to change. The characteristics of the input data change with passing time, and as new data are added to the database. Modifying the estimated parameters for this modified data requires the periodic re-evaluation of the model in the case of the multiple regression or fuzzy regression models. Likewise, parameter estimation should be performed carefully.

On the other hand, there is no need to consider multicollinearity in the NN model. When the characteristics of the data change, the NN model can fix the coefficients of the model through its own learning ability. Therefore, the NN model is recommended as an adequate tool for the prediction of the temperature decrease of the batch transferred from the secondary refining process to the continuous caster. Nonetheless, the drawback of the NN model is that it takes a long time to find a good solution during the initial stages of model development.

IV. Conclusion and further research

In this study, a prediction model is developed for the purpose of estimating the temperature decrease of the batch while it travels from the secondary refining process to the continuous caster in the steel-making process. Three different models are examined using the same data, namely the multiple regression, fuzzy regression, and NN models. To compare the accuracy of these three models, a limited number of input variables are selected from amongst those variables significantly affecting the decrease in temperature. In addition, actual data are gathered from steel works and processed using each model. The results show that the difference in accuracy between the three models is not statistically significant. Nonetheless, the NN model is recommended because of its adaptive ability and robustness.

To date, studies on temperature control in the steel-making process have been extremely limited and concentrated on processes or metallurgical properties. In fact, few studies have been conducted on the temperature control of the batch transferred between the converter and continuous caster. The model used in this paper allows the temperature decrease to be predicted using data gathered in the field, without any precise metallurgical knowledge being required. Developing a more precise model would require the construction of a mathematical model that includes such metallurgical knowledge.

References

[1] K. W. Park, "Determination of important factors for production planning of steel making plants," *Master Thesis*, POSTECH, 2000.

[2] J. J. Buckley, T. Feuring, "Linear and non-linear fuzzy regression: Evolutionary algorithm solutions," *Fuzzy Sets and Systems*, 112(3), pp. 381-394, 2000.

[3] T. Feuring, J. J. Buckley, and Y. Hayashi "Fuzzy regression: an evolutionary algorithm approach," *Proceedings of the 1998 IEEE International Conference on Fuzzy*, pp. 704-708, 1998.

[4] Li S, D. C. Wunsch, O'Hair E, and M. G Giesselmann, "Comparative analysis of regression and artificial neural network models for wind turbine power curve estimation," *J. of Solar Energy Engineering*, vol 123, pp 327-332, 2001.

[5] Y. O. Chang and B. M. Ayyub, "Fuzzy regression methods - a comparative assessment," *Fuzzy Sets and Systems,* vol. 119, pp. 187-203, 2001.

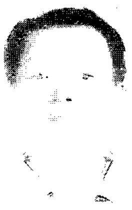
[6] F. Karlsruche, "Piecewise linear networks (PLN) for process control," *Proceedings of the 2001 IEEE Systems, Man, and Cybernetics Conference*, 2001.

[7] J. Finol, Y. K. Guo, and X. D. Jing, "A rule based fuzzy model for the prediction of petrophysical rock parameters," *J. of Petroleum Science and Engineering*, vol. 29, pp. 97-113, 2001.

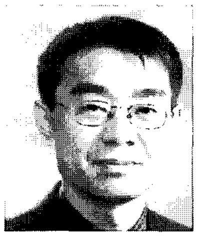
[8] J. Neter, W. Wasserman, and M. H. Kutner, *Applied Linear Statistical Models*, Richard D. Irwin, Inc, 1974.

[9] S. S. Rao, *Optimization, Theory and Applications*, 2nd ed. John Wiley & Sons, 1984.

[10] The MathWorks, Inc, *Neural Network Toolbox User's Guide*, The MathWorks, Inc., 2000.



Jonghan Kim is a general manager of 6 sigma laboratory at the Research Institute of Industrial Science and Technology in Korea. He received BS in statistics from Kyungpook National University, MS and Ph D degrees in industrial engineering from Seoul National University. His main research interest is in soft computing, 6 sigma and systems engineering.



Deokhyun Seong is a professor of business administration at the Pukyong National University in Korea. He received BS and MS degrees in industrial engineering from Seoul National University, and Ph D degree in industrial engineering from Pohang University of Technology (POSTECH) in 1993. His main research interest is in multivariate statistical analysis, process modeling, and scheduling.