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Coking Analysis Based on the Prediction of Coil Surface Temperature in Radiation Section of Ethylene Cracking Furnace

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Ethylene cracking furnace is the key equipment in petrochemical industry. Coking within coils in radiation section mainly affects the life span of ethylene cracking furnace. During industrial production, engineers periodically measure the radiant coil surface temperature which reflects the degree of coking, in order to decide time for decoking. Nowadays, some devices can be used for the online measurement of radiant coil surface temperature. However, high cost and unacceptable error limit their practical applications. Ethylene cracking process is a well-developed process with a high degree of instrumentation and control, in which a huge amount of operational data has been collected. It also makes it possible to predict the radiant coil surface temperature through the correlation among process data, and further to identify the influence factors of coking during the operation, which would provide a reference to improve the performance of ethylene cracking furnace.
In this work, an industrial ethylene cracking furnace is considered. The correlation between process variables and radiant coil surface temperatures are analysed according to the structural characteristics and the process information of ethylene cracking furnace, and the process variables with high correlation to the radiant coil surface temperatures are recognized. Based on Partial Least Squares (PLS), each group of radiant coil surface temperaturess was estimated by the obtained process variables with total error level below 1 %. Radiant coil surface temperature predicted by the regression model can be regarded as the indices of coking degree in the radiant coil, which can provide a reference for decoking plan. At the same time, the obtained regression model parameters can be used as a reference for the adjustment to reduce the rate of coking. Therefore, the process of coking within each radiant coil can be synchronized with others and the overall continuous operating time of ethylene cracking furnace can be increased.

1. Introduction

Ethylene is obtained by the steam cracking of hydrocarbon in the ethylene cracking furnace (Khor et al., 2014). This technology has been applied for about 70 y when the first commercial plant came into operation. Besides ethylene, there are also many other hydrocarbon products obtained in the cracking process, among which coke is the only solid component. Even though its amount is negligible in a short period, it can be deposited on the inner surface of the radiant coils (Cai et al., 2002), which will compromise the heat transfer efficiency of the radiant coils. In order to retain the same cracking temperature and conversion, the fuel flow rate needs to be further increased, or the flow rate of hydrocarbons needs to be reduced. As the cracking reaction continues, the coke layer is getting thicker and the coil surface temperature is increasing accordingly. The unit has to be shut down for coke removal (decoking) when the coil surface temperature reaches the limits of material. If decoking too early, it will result in shorter production cycle, therefore yields and profits will be affected. On the contrary, if decoking too late, coils inside the furnace could be broken, which could cause serious loss of

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facility and personnel. It is of great importance to measure surface temperature of the radiant coil in real time. In industry, the temperature can be manually measured by operator, or obtained by in situ infrared detector. Manual measurement is more reliable, but not available in real time, while the data obtained by infrared detector is limited by the inside geometry of furnace and suffers from low resolution.
Multivariate statistical process control (MSPC) method has widely applied in process industries. Huge amounts of data have been collected and stored in ethylene process, which provides a possibility to the application of statistical model. Although the surface temperature of the radiant coil is difficult to measure, it should be highly corrected with other process variables and can be somehow calculated based on its correlations with them. As a well developed multivariate statistical technique, Partial Least Square (PLS) has many applications in process monitoring and fault diagnosis area, such as estimation of the compounds concentration under nominal operating conditions (Taris et al., 2015), estimation of polymer quality parameters for a LDPE plant (Rumana et al., 2006) and its developed technique (Faisal et al., 2009). Tathagata (2005) has successfully predicted the silicon content in blast furnace hot metal by PLS. In the ethylene industrial process, few industrial applications of PLS have been reported.
In this paper, operating data collected from a petrochemical plant are analysed and a PLS is developed for predicting radiant coil surface temperature, in order to provide a reference for decoking scheduling.

2. Methodology

PLS is a technique based on latent variables LV for relating two data matrices (Michel et al., 2005), a set of predicted variables $Y \in R^{n \times p}$ and a set of predictor variables $X \in R^{n \times m}$, by a linear multivariate model. There are three steps to develop the PLS model, i.e. training, cross-validation and testing steps. In the training steps, data are normalized to zero mean and unit standard deviation. For each column x_i can be replaced by its scaled value x_i^{scaled} as below:

$$x_i = \frac{(x_i - \mu(x))}{\sigma(x)} \tag{1}$$

where $\mu(x)$ and $\sigma(x)$ are mean and standard deviation of X.
The matrix X can be decomposed as follows:

$$X = TP^T + E = \sum_{j=1}^{\alpha} t_j p_j^T + E \tag{2}$$

Where T is a score matrix, P is a loading matrix, α is the number of latent variables, E is residual matrix, t_j (the j^{th} column of T) is score vector and P_j (the j^{th} column of P) is loading vector. Similarly, Y can be decomposed as follows:

$$Y = UQ^T + F = \sum_{j=1}^{\alpha} u_j q_j^T + F \tag{3}$$

where U is a score matrix, Q is a loading matrix, F is a residual matrix, u_j (the j^{th} column of U) is a score vector and q_j (the j^{th} column of Q) is a loading vector. The inner relationship between t_j and u_j can be obtained through a univariate regression as follows:

$$u_j = b_j t_j \tag{4}$$

Where b_j is the regression coefficient. To maximize the covariance between X and Y, The optimal number of latent variables can be extracted by testing the models.
In the cross-validation step, different PLS models with different number of latent variables are tested by validation data. The PLS model with the minimum average error rate S gives the optimal number of latent variables, which is calculated as:

$$S = \frac{\sqrt{\sum(y - y^{preed})^2 / N}}{\mu(y)} \tag{5}$$

where y^{pred} is the prediction of model, N is the testing data number and $\mu(y)$ is the mean of Y.
In the testing step, the average error rate with the optimal number of latent variables can be obtained by testing the PLS model with the optimal number of latent variables using testing data.

3. The data set

The cracking furnace consists of convection section and radiation section. The convection section is mainly used for material preheating and heat recovery. In radiation section, the cracking reaction occurs in the preheated mixture of hydrocarbon and steam heated to about 800 °C. The heat required for the cracking reaction is from the external surface of the radiant coils by convective heat transfer. In the furnace, energy is translated from the furnace inside surface to the radiant coils by radiation heat transfer. Predicting variables are selected based on heat conservation of radiant coils inside and outside surfaces.

In the current study, the operating data are collected from an ethylene cracking furnace with naphtha as raw material. There are six groups of radiation coils in the ethylene cracking furnace, and sixteen coils in each group. There are about 871,379 operating data sts from November 2015 to November 2016, among which 206,597 are collected every minute and 5,802 are collected every hour, while only 70 manuals measured coil surface temperature data are available. There are 32 X-type variables and 12 Y-type variables. The X-type variables include total feed rate of naphtha, total feed rate of steam, naphtha and steam feed rate of six coil groups, feed temperature, feed pressure, coil outlet temperature, outlet pressure, furnace temperature on south and north, furnace pressure, furnace oxygen content and fuel gas flow rate. The Y-type variables include the south radiant coil surface temperature and the north radiant coil surface temperature of the six group coils. The X-type variables are measured continuously, while the Y-type variables are measured intermittently, and coil surface temperatures at both sides of radiant coil are rarely measured at the same time.70 groups of coil surface temperatures of the north radiant coil and 70 groups of coil surface temperature of the south radiant coil are recorded. Because the data from November 2015 to February 2016 is more coherent and complete than other time period, the initial 10 groups of the north and south radiant coil surface temperature are used as validation set, the next 12 groups of the north radiant coil surface temperature and 9 groups of the south radiant coil surface temperature are used as testing set and others are used as the training set.

4. Modelling and analysis

High dimensionality, collinearity and nonlinearity are involved in most chemical processes. When the predicted variable, radiant coil surface temperature, is within a relatively small range of variation from 980 to 1,100 °C, it is assumed that the non-linearity among variables can be ignored. PLS is a capable method on dealing with the process variables with high dimensionality and collinearity. In order to obtain accurate coil surface temperature prediction, PLS model is built based on the average coil surface temperature in each group radiant coil on both north and south sides. The error S is calculated based on cross-validation method for different number of latent variables. The results of first coil group modelling in north side are displayed in Figure 1. As shown, modelling error decreases with the number of latent variables increasing. Model error value can be achieved less than 0.01 with 0.0090 when the number of variables is 5. Minimum value of cross-validation S can be reached when the number of latent variables is 4. High value of S may be due to overfitting when the number of latent variables is over 6.

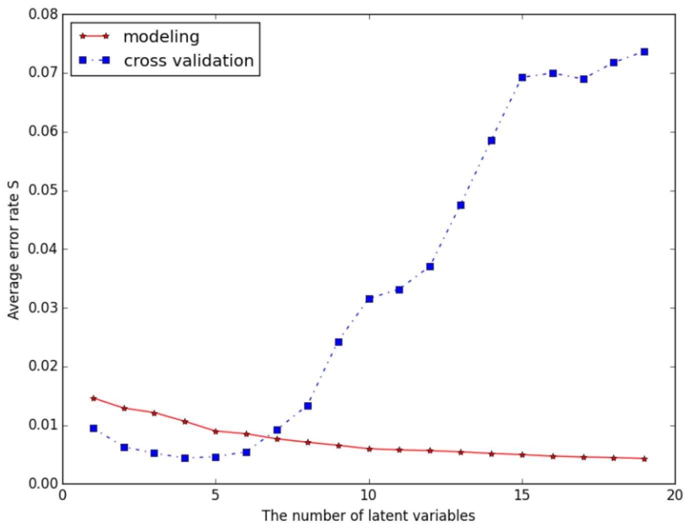

Figure 1: The cross-validation results of first group radiant coil in north side

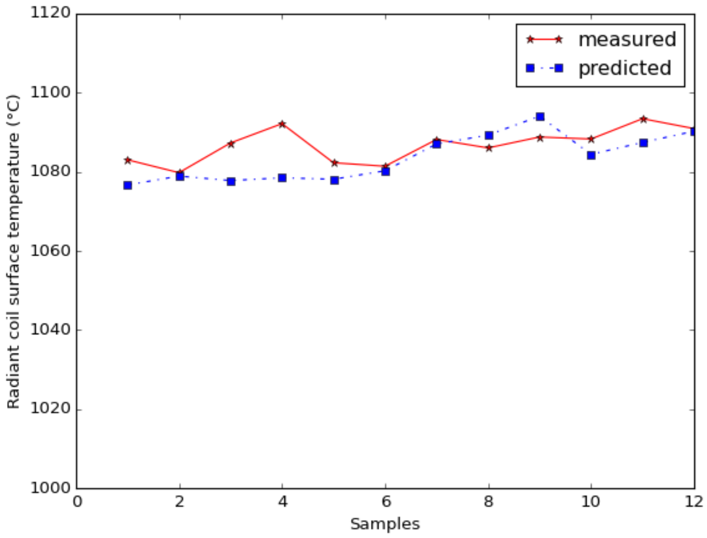

Figure 2: The coil surface temperatures of first group radiant coil in north side

The optimal number of latent variables can be selected as 5. The cross-validation S value is 0.0046 and the test S value is 0.0054 under 5 latent variables. The measured and predicted surface temperatures of the first radiant coil group in north side are displayed in Figure 2 with 5 latent variables. A good agreement can be observed between measured and predicted coil surface temperatures in most data points.

Figure 3 shows the cross-validation results of first group coils in south side.

Optimal prediction is obtained when the model S value is 0.0110 under 4 latent variables. Average error of PLS is 0.0097 which can be obtained by validation data and average error of PLS is 0.0094 which can be obtained by testing data. The measured and predicted data of first radiant coil group in south side are displayed in Figure 4 with 4 latent variables. Although small deviation exists in the measured and predicted values, their trends are similar.

Table 1 and Table 2 show the optimal number of latent variables and S based on PLS model for radiant coils surface temperature in both of north and south side. All values of S are within industrial acceptable range.

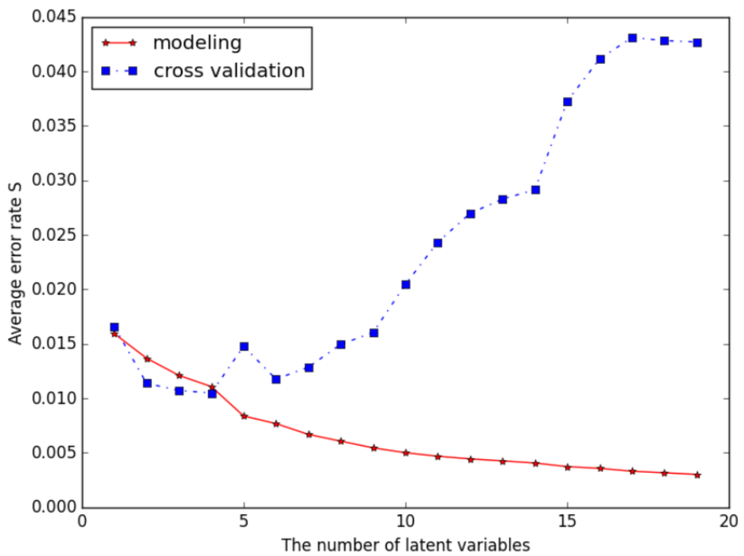

Figure 3: The cross-validation results of first group radiant coil in south side

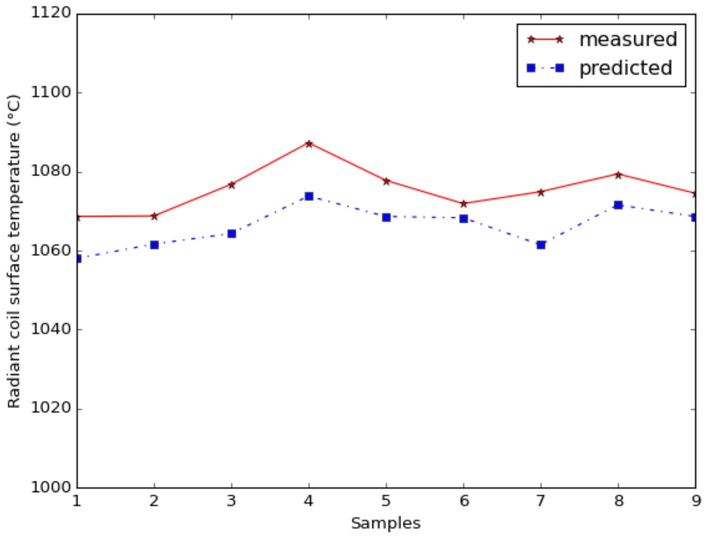

Figure 4: The coil surface temperatures of first group radiant coil in south side by measuring and predicting

Table 1: The optimal LV number and S of the first group of coils on north side

	Coils 1	Coils 2	Coils 3	Coils 4	Coils 5	Coils 6
LV	5	6	5	4	6	3
S	0.0090	0.0077	0.0083	0.0103	0.0080	0.0118

Table 2: The optimal LV number and S of the first group of coils on south side

	Coils 1	Coils 2	Coils 3	Coils 4	Coils 5	Coils 6
LV	4	4	4	4	4	7
S	0.0110	0.0134	0.0108	0.0084	0.0100	0.0114

Figure 5 and Figure 6 show the predicted results for first group coils in both of north and south side, which are analysed by using operating data from November 2015 to February 2016 (133,000 samples). It can be seen from Figure 5 and Figure 6 that the coil surface temperatures generally increase monotonically. At the beginning, the increase is relatively fast, and gets relatively slow later. In the last stage, the furnace surface temperature of the north side is close to 1,100 °C, which indicates decoking operation should start.

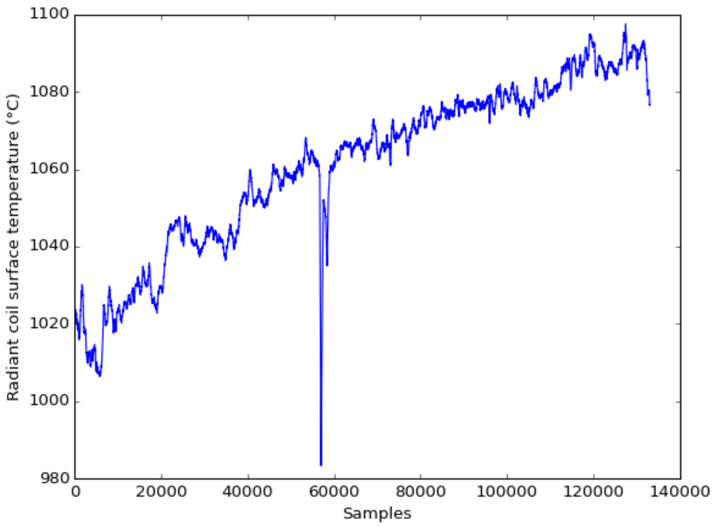

Figure 5: The predicted coil surface temperatures of the first group coils in north side

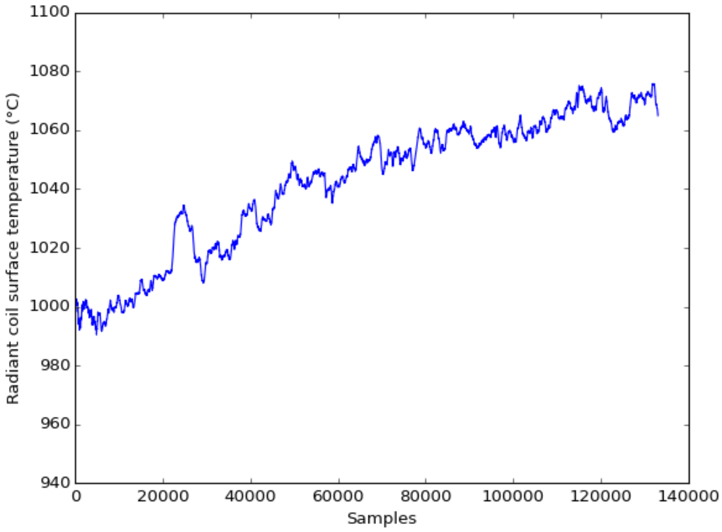

Figure 6: The predicted coil surface temperatures of the first group coils in south side

A sudden drop can be observed in north coil surface temperatures of first group, while no drop in south side. The same results can be observed in other five coils groups. This surface temperature drop occurred on December 15, 2015, which has no manual measurement as reference due to the limitations of manual measurement. Thus, analysis is conducted on the historical operational data. At that time, obvious decreasing can be found in naphtha feed, fuel gas flow and coil outlet temperature, and obvious increasing can be found in the furnace oxygen content and carbon monoxide content. Although the temperature on the south side of the furnace and the temperature on the north side of the furnace are both reduced, the temperature reduction on the north side of the furnace is bigger. This situation may be caused by fuel nozzle malfunction on the north side of the furnace.

5. Conclusions

In industry, coil coking trend can be analysed by furnace coil surface temperature when furnace is under normal operating condition. High coil temperature is always accompanied with heavy coke deposition. The whole system needs to be shut down for decoking even only one group coils surface temperatures reach 1,100 °C, which is a waste of resource. In this paper, a method for online coil surface temperature monitoring based on PLS method is proposed, which has a good performance. Operating parameters of each coil can be adjusted based on the estimation of coil surface temperature to make the coking degree synchronized across all coils, which can maximize each production cycle without risking process safety. If more detailed historical data of cracking process are collected, the prediction of PLS model can be further improved.

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