Prediction of SCR Catalysts Performance in Coal-Fired Power Plants Based on Fusion of Multi-source Information

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Abstract. In this paper, an integrated algorithm was proposed to evaluate the DeNOx ability of SCR reactor using the operational data of power plant, including the identification of steady state based on R-statistic, the detection of the wrong points and the classification of working conditions by CNN-clustering algorithm. Then the performance profiles of the SCR reactor were extracted from the mass and mixed raw data. Furthermore, the catalyst samples after 0 days, 540 days and 1246 days of operation were collected from the first catalyst layer, and the degradation of the catalyst activity and the micro geometrical characteristic were obtained by the laboratory test. Finally, the FCM fuzzy clustering algorithm was used to fuse the health characteristics of the SCR catalyst layer from multi-source information, such as DeNOx ability of the SCR reactor, catalyst activity, the service of catalyst, and the health evaluation system of the catalyst layer in a full lifecycle was obtained.

Introduction

For SCR system in coal-fired power plants, the catalyst cost is highest and the performance reduce continuously. The traditional life prediction of the catalyst are based on laboratory detection, the catalyst manufacturers place the test samples in catalyst layer, and the samples were taken to the laboratory to test the activity at a certain intervals. However, the activity of the catalyst sample cannot be equal to the health of the catalyst layer in the SCR reactor, and the times for the catalyst tests is little because the sampling of the catalyst is performed only when the unit is shutdown, which limits the accuracy of the catalyst activity degradation curve.

In recent years, Song et al. [1] proposed a method for evaluating the potential of SCR reactor based on the field performance tests. This method solves the problem of sample representation in laboratory testing methods. However, the field test needs to be conducted under unit full-load conditions, which will impose additional burden on the thermal power unit that bears the task of peaking. Strege [2] installed a portable gas bypass in the SCR reactor, and ensured the same flue gas environment and catalyst in the two flue ducts, then evaluated the catalyst activity in the mainstream flue by detecting the activity of the bypass catalyst. This method makes the activity detection more flexible. However, due to the restriction of the unit transformation space, it cannot be effectively promoted in China.

Currently, the power plant in China has achieved distributed control, which makes it efficient to monitor unit state and store operating data containing massive information of the SCR catalyst health. In this paper, a steady-state operating condition database of SCR system was established firstly. Then the historical data of similar operating conditions were obtained by clustering SCR inlet gas parameters, and the degradation information of SCR reactor was extracted. Furthermore, fuzzy method [3] was used to combine all SCR deactivation information from different sources, and the new life evaluation system for plant SCR catalysts is proved to be robust.
Feature Extraction of SCR Performance Degradation Based on Operational Data

Research Object

The SCR reactor in a 660 MW supercritical coal-fired boiler is studied. It is arranged between the economizer and the air preheater, and the urea pyrolysis method is used to prepare the reducing agent.

Data Analysis and Mining Method

In this study, about 1.56 million historical operational data were collected and analyzed, the sampling frequency was one minute. According to the SCR mechanism, under the same gas environment and DeNOx efficiency, the more urea consumed, the worse the reactor performance. But as shown in Fig. 1, it cannot observe the trend that the urea consumption goes up or the SCR efficiency declines as the catalyst operation time increases. The reason is that the operating conditions change frequently in power stations, which make it difficult to maintain the gas environment same. On the other hand, SCR is a heavy delay process, the real relationship between urea flow rate and SCR efficiency is not clearly reflected by the raw data.

To extract the degradation trend of SCR reactor, a data mining method for SCR system is presented. As shown in Fig. 2, the process is divided into five steps. (a) The R-statistic algorithm [4] is used to calculate the steady-state factor for each sample, and when the steady-state factor is less than the steady-state threshold, this sample is marked as steady-state data. (b) Threshold is set to each parameter based on the statistics of probability distribution, and the data that exceed the limit or stay unchanged are marked as abnormal data. (c) Apart from the non-steady-state data and the abnormal data, the left are stored in the database of steady-state conditions. (d) CNN algorithm [5] is used to classify the steady-state samples so that the flue gas in the same working condition is obtained. (e) Under the same working conditions, the variation of the urea flow rate that achieves the same denitration efficiency is exploited as a characteristic of the SCR reactor performance.

Figure 1. Historical process curves of urea flow rate and denitration efficiency.

Figure 2. Data mining process of deterioration information in SCR reactor.
Steady-State Data Screening of Denitrification System

R-statistic algorithm is widely used in the steady state judgment of industrial process data. Taking a certain time data \( x_i \) for example, the variances calculated by two filtering methods are used to build a steady-state test index. In the R-statistic algorithm, the first variance \( s_{1,i}^2 \) is calculated as follows:

\[
x_{f,i} = \lambda_1 x_i + (1-\lambda_1) x_{f,i-1}
\]

\[
\nu_{f,i}^2 = \lambda_2 (x_i - x_{f,i-1})^2 + (1-\lambda_2) \nu_{f,i-1}^2
\]

\[
s_{1,i}^2 = \frac{2-\lambda_1}{2} \nu_{f,i}^2
\]

where \( x_{f,i} \) stands for first-order filtered data and \( \nu_{f,i}^2 \) is mean square error. Besides, filter coefficient \( \lambda_1 \) and \( \lambda_2 \) select the recommended value 0.2 and 0.1 respectively.

The second variance \( s_{2,i}^2 \) is calculated as shown in Eqs. (4)-(6):

\[
\delta_{f,i}^2 = \lambda_3 (x_i - x_{f,i-1})^2 + (1-\lambda_3) \delta_{f,i-1}^2
\]

\[
s_{2,i}^2 = \frac{2-\lambda_3}{2} \delta_{f,i}^2
\]

where \( \lambda_3 \) is set to 0.1. The steady factor \( R_i \) corresponding to \( x_i \) is defined as the ratio of \( s_{1,i}^2 \) and \( s_{2,i}^2 \). The bigger the steady factor, the more unstable the data is. Whether the data \( x_i \) achieve stability is judged by comparing steady state threshold \( R_{crt} \) with \( R_i \). For example, \( x_i \) is regarded as steady state when \( R_i < R_{crt} \).

The steady factors of unit load, NO\(_x\) concentration in the inlet and outlet, urea flow rate and gas temperature are calculated. SCR system is stable when all of the steady factors are less than the corresponding thresholds. Figure 3(a) shows that the stability of the data deteriorates with the increase of steady factor. Figure 3(b) gives the samples whose steady-state factor is less than 1.2. The relationships among the main parameters are clear. In this paper, data with a steady-state threshold of 1.2 are chosen for the following analysis. The number of samples is reduced to 150,577 after steady-state screening and wrong point removal.

Figure 3. The data distribution under various steady-state threshold.

Clustering of Flue Gas Conditions in SCR Inlet and Feature Extraction of Health Status

In fact, the actual load needs to follow the grid dispatching instructions so that the operating conditions change frequently, resulting in continuously change of flue gas conditions in SCR inlet.
Thus, CNN algorithm is used to cluster the three parameters that reflect the SCR inlet flue gas conditions such as load, NO\(_x\) concentration and flue gas temperature, as shown in Fig. 4.

![Image](image-url)

**Figure 4. Clustering and correlation analysis of SCR system.**

Fig. 4(a) presents the clustering result where steady state samples are divided into 5738 classes with the cluster radius of 0.05. Every point in Fig. 4(a) stands for a type working condition, whose quantity can be adjusted by changing cluster radius. Fig 4(b) shows a class with 243 samples, in which condition load, inlet NO\(_x\) concentration and flue gas temperature are controlled within 510MW~520MW, 290mg/m\(^3\)~305mg/m\(^3\) and 323 °C~326 °C respectively. Fig 4(c) describes relationships among denitrification efficiency, urea flow rate and time according to data in Fig. 4(b). The data set marked with 1 to 3 represents three different time scales. It demonstrates that denitrification efficiency goes up with increase of urea flow when there is small change in time. By comparing three marked data sets, it displays catalyst activity decreases with the increase of operation time and performance profile move towards the direction where urea flow rate rises and denitrification efficiency declines. Thence, 76 samples with the denitrification efficiency ranging from 85% to 88% are screened to extract deterioration characteristics of SCR reactor, which reflected by the trend of urea flow rate when the denitrification efficiency is definite.

**Degradation Characteristics of the Catalyst Samples**

**Catalyst Samples in the Power Plant**

Considering the DeNO\(_x\) ability of the SCR reactor was obtained by operational data mining, the health condition of the catalyst layer was further studied. From the installation of the catalyst layer, the catalyst samples were taken from the same place of the first catalyst layer 3 times, seperately after 0 days, 540 days and 1246 days of operation. Then the material parameters and the activity were test in the laboratory environment.

**The Material Parameters of the Catalyst Samples**

The micro specific surface area and the content of the active component V\(_2\)O\(_5\) were detected for the catalyst samples. In the laboratory, the micro specific surface area and V\(_2\)O\(_5\) content were test by using...
BET and XRF methods, respectively.

The Activity of the Catalyst Samples

In order to test the catalyst activity, a micro scale reactor was established with 5 catalyst plates. The experiments were conducted in 370 °C with 12.4 L/min synthetic gas, including 135 ppm NO\textsubscript{x}, 175 ppm NH\textsubscript{3}, 3.6 % O\textsubscript{2} and the balance gas N\textsubscript{2}. The activity of the catalyst samples can be calculated by Eq. 6:

\[
k = \frac{Q_F}{V_{cat}} \times A_{spec} \times \ln \left(1 - \frac{NO_{in}^{out} - NO_{out}^{in}}{NO_{in}^{out}}\right)
\]

where, NO\textsubscript{in} is the inlet NO\textsubscript{x} concentration, ppm, NO\textsubscript{out} is the outlet NO\textsubscript{x} concentration, ppm, k is the activity of the catalyst samples, m/h, Q\textsubscript{F} is the gas flow rate in standard condition, m\textsuperscript{3}/h, V\textsubscript{cat} is the catalyst volume, m\textsuperscript{3}; A\textsubscript{spec} is the macroscopic specific surface area of the catalyst, m\textsuperscript{2}/m\textsuperscript{3}.

The Evaluation of SCR Catalyst Layer Based on Multi-information Fusion

Expert Knowledge System

The health characteristics of SCR catalyst layer not only include the DeNO\textsubscript{x} ability of SCR reactor, but also contain the activity and the micro parameters of the samples in the catalyst layer. Besides, the design service life of the first catalyst layer is 24000 hours. Thus, 6 parameters were chosen to evaluate the health condition of the first catalyst layer: S1 is the specific surface area of the catalyst samples, S2 is the V\textsubscript{2}O\textsubscript{5} content in catalyst samples, S3 is the catalyst activity, S4 is the service time of the catalyst, S5 is the DeNO\textsubscript{x} ability of SCR reactor based on operational data mining. According to the expert knowledge, the erosion, sintering and ash deposition can reduce the specific surface area of the catalyst, so when S1 decreases, the catalyst health condition become weaker. V\textsubscript{2}O\textsubscript{5} content decides the number of active sites on the catalyst surface, when S2 decreases, the catalytic performance decline. The activity of the catalyst samples and the performance of the SCR reactor both have strong correlation with the health of the first catalyst layer, so the life of the catalyst layer reduces with the decreasement of S3 and S5. Since the catalyst is placed at the high ash environment, so the catalyst health condition will decrease when the service time S4 increases. Fig. 5 shows the trend of S1 to S6 with the time.
Performance Evaluation of SCR Catalyst Layer

S1 to S5 were discretized with the time step of 1 hour, thus the training set was obtained with 29904 data in the full lifecycle of the first catalyst layer. Then, FCM cluster algorithm was used to divided the samples into 10 subset, the cluster centers of each subset can represent 10 stage of the catalyst layer. As shown in Fig. 6, from Stage 1 to 10, the catalyst health condition continues to decrease. In the dimension of S3, S4 and S5, it can be seen that the catalyst service time increases and the activity of catalyst sample and the reactor performance decrease. After the first catalyst replacement, the health condition of the new catalyst layer can be deduced by comparing the distances beween the new data sample and the 10 cluster centers.

![Figure 6. The stages of the health condition for the first SCR catalyst layer.](image)

Conclusion

In this work, an integrated method were first presented to evaluate the SCR performance in a 660 MW coal-fired boiler based on the plant operational data, including the detection of error data, the identification of steady state and the clustering of SCR inlet gas condition, and the performance profile of SCR reactor was dug out from the noisy raw data. Then the catalyst samples after 0 days, 540 days and 1246 days of operation were collected for the laboratory testing, and the degradation of the catalyst activity and the micro geometrical characteristic was obtained. Finally, FCM algorithm was used to combine all SCR deactivation information from different sources, and the new life evaluation system for plant SCR catalysts is proved to be robuster.

References


