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A two-layer fuzzy synthetic strategy for operational performance assessment of an industrial hydrocracking process

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ABSTRACT

The operating performance may deteriorate from the optimal condition in industrial hydrocracking process due to changes in product requirements, equipment performance degradation, environmental noises, and random disturbances, etc. Therefore, it is necessary to carry out effective online operating performance assessment for it. In this paper, a two-layer fuzzy synthetic strategy is proposed for operating performance assessment of the hydrocracking process. First, an operating performance assessment index is constructed based on the concept of positive deviation of the quality variables. As there are many products in the process, an assessment system is further built based on the performance index. To calculate the indicators in the assessment index system in real-time, partial least squares is used for prediction. To solve the problem of limited labeled samples in the prediction, the process variables are classified into several subspace blocks according to their correlations with different key indicators. Then, a two-layer fuzzy synthetic evaluation strategy is designed to evaluate the actual operating performance of the hydrocracking process. The proposed strategy is finally illustrated with a series of cases on an industrial hydrocracking process in China.

1. Introduction

Oil refining process is an important part of modern industry. There are many kinds of refining processes, which mainly include atmospheric distillation, vacuum distillation, catalytic cracking, catalytic reforming, hydrocracking and delayed coking, etc. Among them, hydrocracking is one of the most widely used refining technique with two main advantages. First, the hydro-treatment in hydrocracking helps to remove harmful compounds such as sulfur, nitrogen, and oxygen. Hence, there is less coke generation in raw material conversion. Second, it has the flexibility to adjust the operation conditions based on product requirements. Thus, operating performance in hydrocracking process has particularly attracted much attention in the past decades in both academia and industrial fields due to its direct impact on productions, consumptions, efficiency and safety. However, many factors such as material fluctuation, product customization, environment changes and equipment aging, may cause the operating performance deviate from the optimal condition with the running of process. Hence, it is crucial to carry out online operating performance assessment for the hydrocracking process.

Usually, it is difficult to directly measure or estimate the operation performance of industrial processes. However, it is often reflected by the online process running data. Hence, data-driven techniques have been largely used in industrial processes for tasks like process monitoring, soft sensor, fault diagnosis, etc. (Wang, Pan, Yuan, Yang, & Gui, 2019; Yuan, Li & Wang, 2019; Yuan, Ou et al., 2019). Recently, some studies have also been conducted on operating optimality assessment for complex industrial processes. Ye, Liu, Fei, and Liang (2009) proposed a probabilistic framework for online operating safety and optimality assessment of multimode industrial processes, in which the Gaussian mixture model was used to approximate multiple operating modes. Then, the safety and optimality indices are defined and calculated for each operating mode by two successive nonlinear mappings. Finally, a hierarchical-level classification method was presented to divide these indices into different performance levels. Yu, Chang, Li, and Yang (2016) proposed an operational performance assessing approach to judge the process state for multimode processes. The method first established a Gaussian mixture model for the process state with multiple modes. Then, Bayesian inference was used as an online evaluation strategy to identify the current operating performance. In some previous research works (Liu, Wang, & Chang, 2016; Liu, Wang, Chang, & Ma, 2015a, 2015b; Yan, Wang, & Chang, 2013), the evaluation strategies were formulated for both steady and transitional modes on account of different process characteristics. In the steady mode, the optimality index was predicted by partial least squares (PLS) method based on a comprehensive economic index (CEI). In the transitional mode, the optimality index was calculated by the weighted average of the CEIs from the similar historical transitions. Sedghi and Huang (2017) proposed a systematic framework of optimality assessment for processes

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which typically have multi-mode and multi-region operations. In their work, kernel density approach and Mclust discriminant analysis approach were adopted for the operating mode detection. Then, mixture probabilistic principle component regression (Yuan, Zhou et al., 2019) method was used to tackle the multi-modal behavior of steady state modes. Moreover, dynamic principle component regression was used to investigate the transitions. In the aforementioned works, an optimality index is often first defined for the operating performance assessment. Then, mathematical prediction models are constructed between the optimality index and process measured variables with historical training dataset. Finally, the operating performance index can be further predicted by the trained models.

Generally, the optimality index can be defined on the basis of product quality, operation costs, economic profits and environmental benefits. Among them, most existing optimality indices are based on product quality or operation costs. However, they are process specific indices, which are not applicable to other processes. Hence, even if product quality is used as the optimality index, it is difficult to directly apply the above methods to evaluate the operating performance in the hydrocracking process. Different from other processes, there are many different products in the hydrocracking process, which include light naphtha, heavy naphtha, aviation kerosene and diesel oil, etc. Moreover, each product oil has a number of quality properties to be controlled and monitored. Thus, the optimality index is no longer just a single indicator but an index system with multiple indicators and multiple levels. Moreover, the operating performance assessment may be inaccurate if it is only judged by the prediction results of the optimality index. In addition to the operating performance assessment of industrial processes, many researchers also pay attention to the health condition of the industrial systems, like the aerospace propulsion system (Xu & Han, 2012), power transformer system (Ranga, Chandel, & Chandel, 2017; Zhao et al., 2013), and wind turbine generator system (Hu et al., 2016; Li et al., 2013; Li, Lei, Li, & Ran, 2014). These industrial systems are small-scale and relatively simple in health condition. Nevertheless, the operational characteristics of the large-scale hydrocracking process are much more complex than these systems due to the multi-product and multiple quality properties.

Different from the aforementioned researches, an operating performance assessment framework is proposed for the hydrocracking process in this paper. In the proposed framework, the concept of Positive Deviation of Quality Variables (PDQ) is first proposed based on the practical technical requirements of the hydrocracking process. Based on PDQ index, the operating performance assessment of the hydrocracking process is decomposed into two parts, i.e., index system construction and online assessment. In the index system, the indices are divided into four levels, which include the process variables, product properties, different products and operation performance from the fourth bottom level to the first top level. For the product properties, they are predicted with an ensemble strategy with prediction models on different variable sub-blocks based on partial least squares (PLS). Then, the online assessment framework uses a two-layer fuzzy synthetic evaluation strategy for multiple indices. The first layer assessment is about the indicators which are at the fourth-level and third-level, and the second layer assessment is about the indicators at the second-level and first-level. To facilitate the determination of the parameters of the fuzzy membership functions, a performance degradation index is defined.

The main contributions of this paper are as follows. First, a correlation-based variable division strategy is proposed to partition the auxiliary variables into subsets to build local soft sensor models for multi-product quality variables, which can effectively handle the problem of limited training samples. Then, an index system is carried out for operating performance assessment of different indicators, in which indicator weight is determined by their characteristics at each level. Third, a two-layer fuzzy synthetic evaluation strategy is proposed to carry out multi-index comprehensive evaluation, which can provide performance assessment for different layers.

Table 1
Sampling frequency of the main components of the raw oil and the products.

Object	Parameters	Unit	Analysis frequency
Raw oil	Initial boiling point	℃	Five times a week
Raw oil	Final boiling point	℃	Five times a week
Raw oil	Density	kg/m^3	Once a week
Raw oil	Content of sulfur	mg/kg	Five times a week
Light naphtha	Content of C4	m%	Twice a day
Light naphtha	Content of C5	m%	Twice a day
Light naphtha	n-pentane	m%	Twice a day
Heavy naphtha	Initial boiling point	℃	Twice a day
Heavy naphtha	Final boiling point	℃	Twice a day
Heavy naphtha	Content of sulfur	mg/kg	Three times a day
Aviation kerosene	Initial boiling point	℃	Once a day
Aviation kerosene	Final boiling point	℃	Once a day
Aviation kerosene	Flash point	℃	Three times a day
Aviation kerosene	Freezing point	℃	Three times a day
Diesel oil	Initial boiling point	℃	Three times a day
Diesel oil	95% distillation temperature	℃	Three times a day
Diesel oil	Content of sulfur	mg/kg	Three times a day
Diesel oil	Density	kg/m^3	Once a day
Diesel oil	Flash point	℃	Once a day

The rest of this paper is organized as follows. In Section 2, an analysis of the hydrocracking process is conducted. The problems arising in the operating performance assessment are pointed out. Operating performance assessment strategy is introduced in detail in Section 3. The effectiveness of the scheme is tested and discussed in Section 4. Finally, some conclusions are given in Section 5.

2. Process analysis

2.1. Process description

The flow chart of the hydrocracking process is shown in Fig. 1. It is composed of the hydrotreating (HT), hydrocracking (HC), high and low pressure separation (HPS/LPS) and fractionation parts. Heavy vacuum gas oil (HVGO) is the feed material, and the products are light ends (LE), light naphtha (LN), heavy naphtha (HN), kerosene (Krs), diesel (Dsl) and bottom oil (Btm). Hydrotreating is the first stage of hydrocracking process, which the preheated HVGO and hydrogen enter the stage at the same time. Sulfur and nitrogen compounds are converted to hydrogen sulfide and ammonia, which are subsequently removed in the hydrotreating stage. The liquid effluent from the hydrotreating is then transmitted to the hydrocracking reactor where most of the cracking reactions take place in the liquid phase. The HT and HC consist of three or four beds, where recycling H_2 is used to cool the reaction mixtures and control the reaction temperature. The reactor output is combined with water to reduce the corrosion of ammonia on the pipes. Meanwhile, the effluent is supplied to the HPS where it is separated into hydrogen-rich gas, liquid hydrocarbon and water. The hydrogen-rich gas is mixed with hydrogen make-up and recycled back to the reactor section. Then, the hydrocarbon liquid is sent to the LPS where H_2S and NH_3 are recovered. Finally, the liquid hydrocarbon product is fed into the fractionation section where it is separated into different products.

A number of sensors are installed in the hydrocracking process to obtain on-line information about the operating performance. Most of the process variables (e.g. temperature, pressure, flow, etc.) are measured and sampled online every one minute. As the raw oil and the product oil are all mixtures, their components are analyzed by offline laboratory test with different sampling frequencies. For example, the distillation points are measured once a day for each product. However, the sulfur content, nitrogen content and residual carbon are often measured five times a week. The process parameters are adjusted manually according to the measured information. Table 1 shows the sampling frequency of the main components of the raw oil and the products.

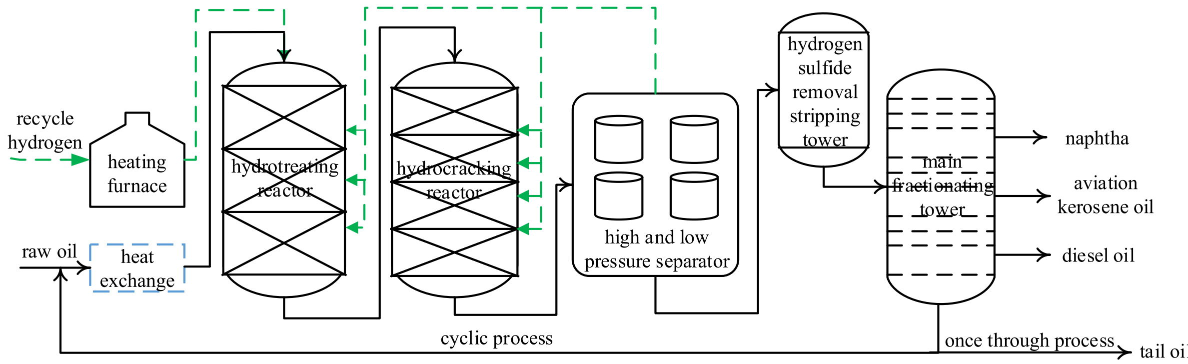

Fig. 1. Flow diagram of hydrocracking process.

2.2. The concept of positive deviation of quality variables

Before carrying out operating performance assessment, it is necessary to determine the objectives of the optimal operating performance for the hydrocracking process. Generally, the objectives for optimal operation include improving product quality and yields, reducing energy consumption and operation costs, as well as improving safety performance, etc. However, the cost of the catalysts is especially expensive in the actual production of refining industry. Compared to improving product quality and yields, refinery companies generally prefer to prolong the service life of catalyst as long as possible while production is guaranteed. Thus, it is regarded as the main objective to guarantee the product quality while prolong the service life of the catalyst for online operating performance assessment of the hydrocracking process in this paper. It is reported that the higher the operating temperature of the bed, the higher the carbon deposition of the catalyst (Cui et al., 2012; Hanaoka, Miyazawa, Shimura, & Hirata, 2015; Onishchenko, Kulikov, & Maksimov, 2017; Pereyma et al., 2015). Hence, it is necessary to largely control the reaction temperature in order to prolong the service life of the catalyst. However, if the yield of the light oil and product quality are to be improved, the reaction temperature must be raised to some extent, which may increase the deposition of the carbon and accelerate the deactivation of the catalyst. In order to extend the service life of the catalyst, the operation optimization of the hydrocracking process is to make sure that the product quality can be qualified without over pursuit of high product quality. Hence, the positive deviation of quality variables is first proposed in this part.

Concept 1: Consider the relationship between catalyst service life and product quality, positive deviation of quality variables (PDQ) is the positive deviation between the actual product quality and product quality production requirements, which is defined as

$$\Delta y_{i,j}(h)=\begin{cases} y_{i,j}(h)-y_{i,j,L_{MIN}} & y_{i,j}(h)\geq y_{i,j,L_{MIN}} \\ y_{i,j,L_{MAX}}-y_{i,j}(h) & y_{i,j}(h)\leq y_{i,j,L_{MAX}} \\ \min\{(y_{i,j}(h)-y_{i,j,L_{MIN}}),(y_{i,j,L_{MAX}}-y_{i,j}(h))\} & y_{i,j,L_{MIN}}\leq y_{i,j}(h)\leq y_{i,j,L_{MAX}} \end{cases},$$
$$h=1,2,\ldots,k, \tag{1}$$

where $\Delta y_{i,j}(h)$ is the positive deviation index for the jth quality property of the ith product; $y_{i,j,L_{MIN}}$ and $y_{i,j,L_{MAX}}$ are the corresponding lower bound and upper bound of production requirements, respectively; $y_{i,j}(h)$ is the actual quality value of the jth quality property of the ith product.

For nonnegative PDQ index, the smaller the value, the better the operating performance. If the PDQ index is negative, the product quality properties are unqualified and the operating performance is unhealthy. Table 2 shows the production requirements for the main quality properties of the product oil.

Table 2
Production requirements for the main quality properties of the product oil.

Object	Parameters	Unit	Production requirements
Light naphtha	Content of C4	m%	≯1.5
Light naphtha	Content of C5	m%	≮96
Heavy naphtha	Final boiling point	℃	≯185
Heavy naphtha	Content of sulfur	mg/kg	0.2 ∼ 0.5
Aviation kerosene	10% distillation temperature	℃	≯200
Aviation kerosene	Final boiling point	℃	210 ∼ 280
Aviation kerosene	Flash point	℃	38 ∼ 48
Aviation kerosene	Freezing point	℃	≯ − 48
Diesel oil	95% distillation temperature	℃	≯365
Diesel oil	Content of sulfur	mg/kg	≤ 10
Diesel oil	Density	kg/m^3	≯849
Diesel oil	Flash point	℃	≮57

2.3. The challenges of operating performance assessment in the hydrocracking process

(1). The operating performance cannot be quantitatively described. To realize the optimizing adjustment of the production process, the real-time operating performance should be quantitatively analyzed to determine whether the current state is optimal or not. However, the performance change from optimal to poor is a gradual transition process, which is difficult to use specific numerical representation.
(2). Assessment indicators cannot be calculated in real time. It is difficult to calculate some key performance indicators online due to the limitations of the measuring instruments and costs. At present, the measurement of these indicators mostly relies on off-line laboratory test, which has a large time lag.
(3). Multiple indicators are difficult to evaluate comprehensively. The products in the hydrocracking process are widely distributed, and each product has a variety of quality properties that need to be controlled. Therefore, it is necessary to comprehensive multiple product quality indicators at the same time when evaluating the process operating performance. However, it is difficult to conduct comprehensive evaluation of such multiple indicators, since there is a certain correlation or restriction relationship between these indicators.

The objective of operating performance assessment for hydrocracking process is to quantify the operating performance in real time. In order to handle the operating performance assessment difficulties and achieve the assessment objective, a two-layer fuzzy synthetic evaluation strategy is proposed in this paper, which is introduced in detail in the next section.

3. Two-layer fuzzy synthetic evaluation strategy

In this section, based on the positive deviation of quality variables, a two-layer fuzzy synthetic evaluation strategy is developed. The operating performance assessment framework aims to calculate

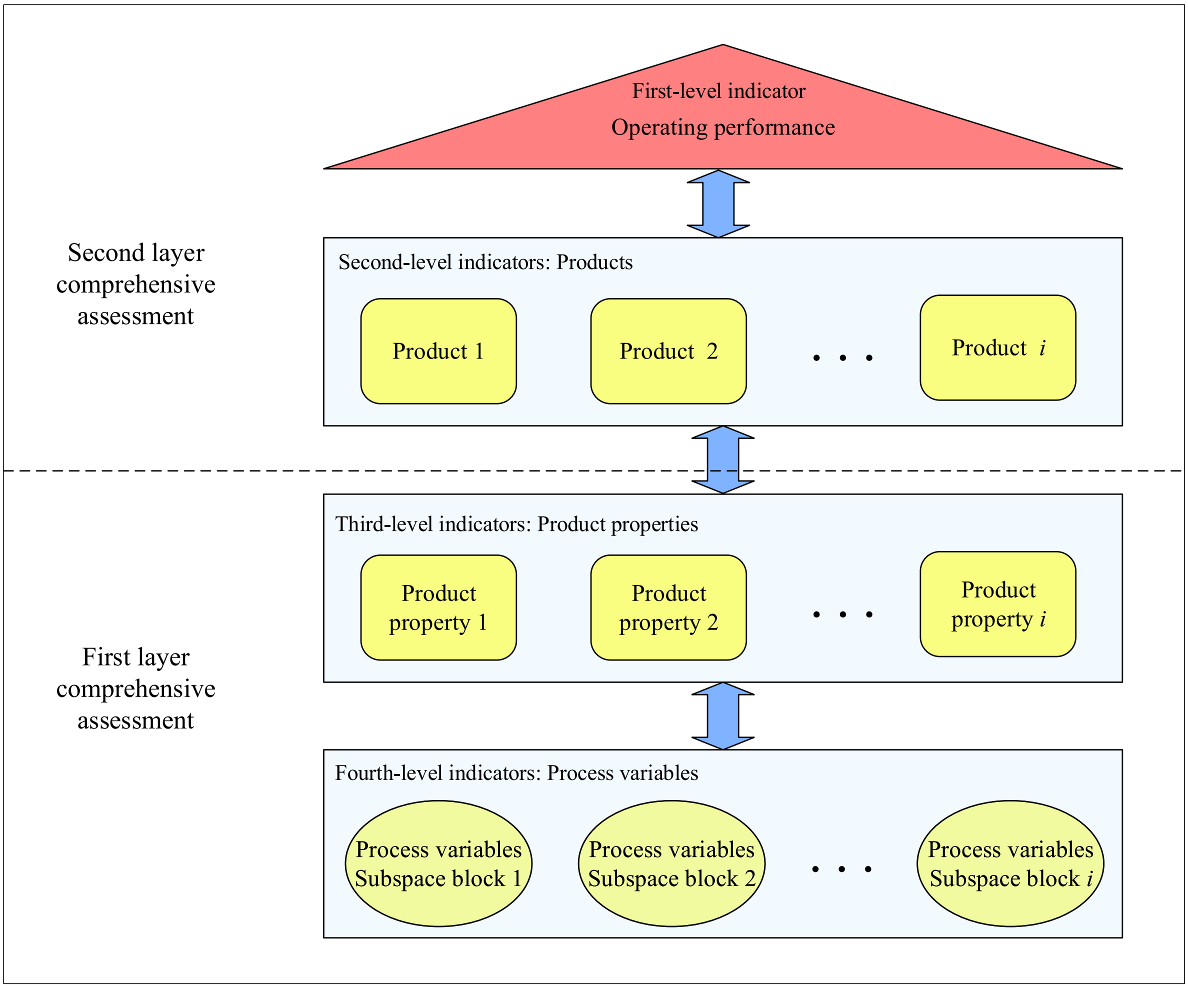

Fig. 2. The structure chart of the two-layer fuzzy synthetic evaluation scheme.

different assessment indicators in real time and handle comprehensive evaluation of multiple indicators.

3.1. Structure of two-layer fuzzy synthetic evaluation scheme

For the hydrocracking process with the characteristic of multi-product and multi-product properties, a two-layer fuzzy synthetic evaluation scheme is established, which is illustrated in Fig. 2.

Due to the multi-product and multi-property, the two-layer fuzzy synthetic evaluation scheme is built based on a four-level assessment index system. The fourth-level indicators are composed of the process variables, the third-level indicators are composed of the product properties and the second-level indicators are composed of the four kinds of products. Then, the scheme contains two-layer assessment stages vertically, namely the first layer comprehensive assessment with multi-properties and the second layer comprehensive assessment with multiple products. The first layer comprehensive assessment is about the indicators which located in the fourth and third levels. The second layer comprehensive assessment is about the indicators which located in the second-level and the first-level. As stated in the previous section, the operating performance assessment is based on the positive deviation of quality variables. Thus, once the result of the first layer evaluation is unqualified, the final result is directly identified as "Unqualified", which means the product property is unqualified at this time. Otherwise, it will proceed with the second layer assessment. Fig. 3 shows the detailed procedures for two-layer fuzzy synthetic evaluation flowchart for the operating performance assessment of the hydrocracking process, which is mainly composed of two steps:

Step 1: Data preprocessing and PDQ index prediction. For the assessment, it is necessary to first classify the operating performance into different grades according to the PDQ indicators. However, the PDQ indices cannot be calculated in real time since many of the product qualities are sampled in a very low frequency. Thus, a prediction model is required to be designed for each of the PDQ index, which is capable of calculating the index online. Since each product quality property corresponds to a PDQ index, an assessment index system is then established for the analysis of multiple products and multiple quality properties. These PDQ indicators are then used as the input variables for the proposed two-layer fuzzy synthetic assessment model.

Step 2: Assessment model. To handle the problem that the operating performance cannot be quantitatively described, the fuzzy synthetic assessment method is utilized in the proposed framework. For the fuzzy assessment, choose appropriate membership functions is the most important step. Nevertheless, due to the parameters of the memberships are usually set manually, the assessment results might be inaccuracy. Thus, a performance degradation index is designed, which can properly set the parameters of the membership functions. Finally, a complete assessment procedure of the hydrocracking process should include two layers to handle the comprehensive evaluation of multiple indicators. Once the result of the first layer evaluation is unqualified, the final assessment result is directly recognized as "Unqualified". Otherwise, it will proceed with the second layer assessment.

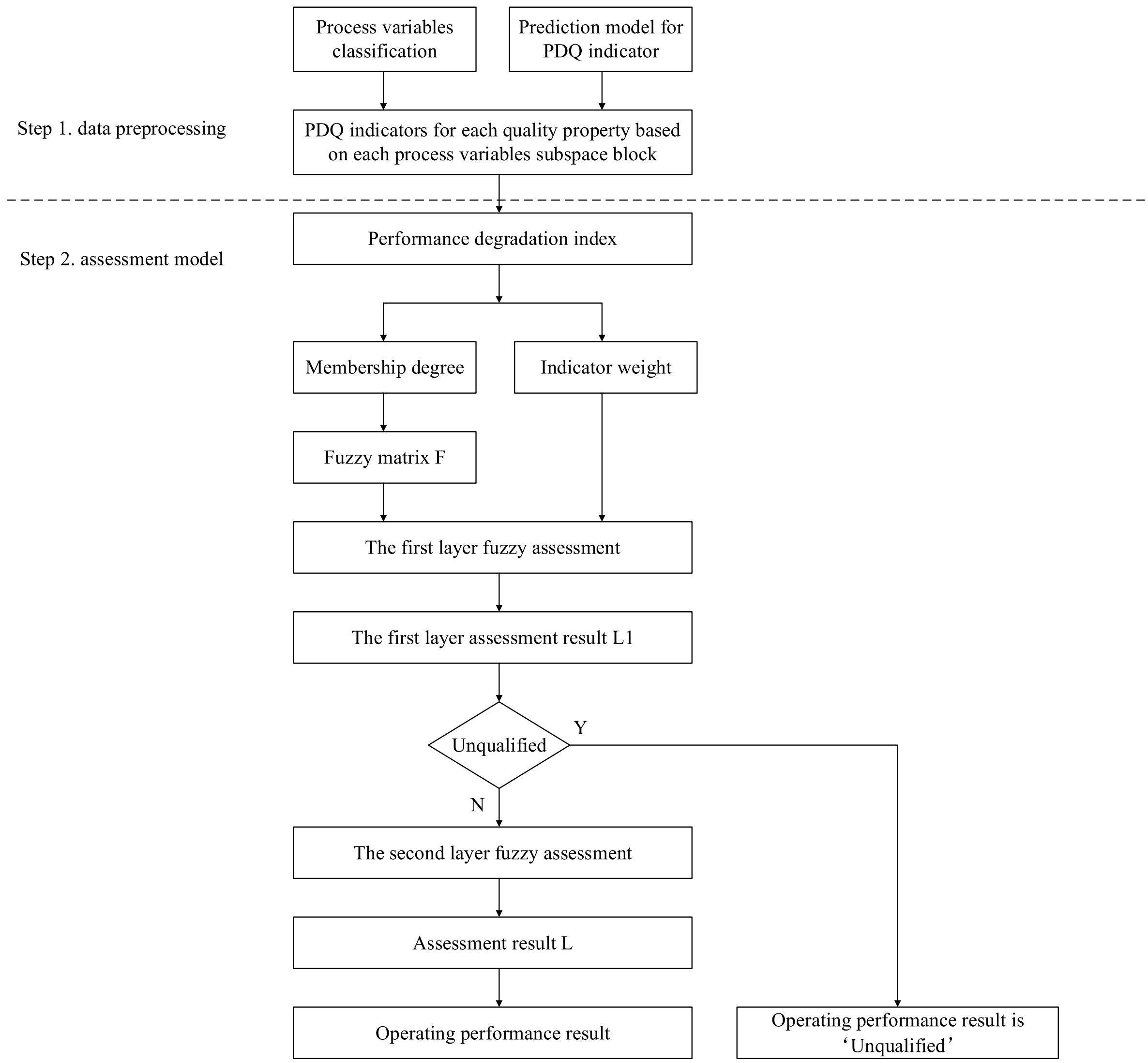

Fig. 3. Flowchart of the two-layer fuzzy synthetic assessment strategy.

3.2. Data preprocessing and PDQ index prediction

3.2.1. Operating performance grade classification

To assess the operating performance from optimal to unqualified, an operating performance objective function $f(i, j, P_{ij})(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m_i)$ should be established, where i represents the product; j represents the product quality properties; $P_{ij}(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m_i)$ represents the positive deviation for the jth quality property of the ith product. The exact solution of the function indicates the operating performance. However, the mathematical expression of the operating performance function might be very complicated, since there are multi-product and multiple quality properties. Therefore, it is more reasonable and feasible to classify the operating performance into a number of grades, such as optimal, good, poor and so on. Usually there is no clear boundary between adjacent grades, only with a vague transitional zone. In this paper, the operating performance is divided into five grades as optimal, good, general, poor and unqualified states. 'Optimal' represents that the operating performance is in optimal condition and the PDQ index is very small. 'Good' represents that the operating performance is in good condition and the PDQ index is small. 'General' represents that the operating performance is within a normal operating range, while the PDQ index is a little large. 'Poor' represents that the operating performance is beyond its normal operating range and the PDQ index is very large. 'Unqualified' represents that some product properties are unqualified, and the PDQ index is negative.

As the quality properties are measured with very low sampling frequencies and there are large time lags with the offline lab test, the PDQ index cannot be calculated in real time. Thus, it is necessary to develop soft sensor models to estimate these difficult-to-measure quality variables through those easy-to-measure process variables.

Moreover, the limited number of modeling data samples is another issue that needs to be considered in building the prediction models. Usually, the quality variables are measured with one sample per day. However, the dimension of process variables is comparable with the number of model samples. This can easily result in the underfitting problem of the prediction models. To deal with the limited data samples, the process variables are classified into several subspace blocks according to their correlations with the PDQ index. Then, prediction models are built between the PDQ index and the process variables in each subspace block.

3.2.2. Prediction model for the PDQ index

There are various kinds of methods for modeling, such as neural network (Han, Qiao, & Chen, 2012; Iliyas, Elshafei, Habib, & Adeniran, 2013; Yuan, Huang et al., 2018; Yuan, Li & Wang, 2019), support vector machine (SVM) (Bouhouche, Yazid, Hocine, & Bast, 2010; You, Gao, & Katayama, 2015; Zhang, Wang, He, & Jia, 2013), principal

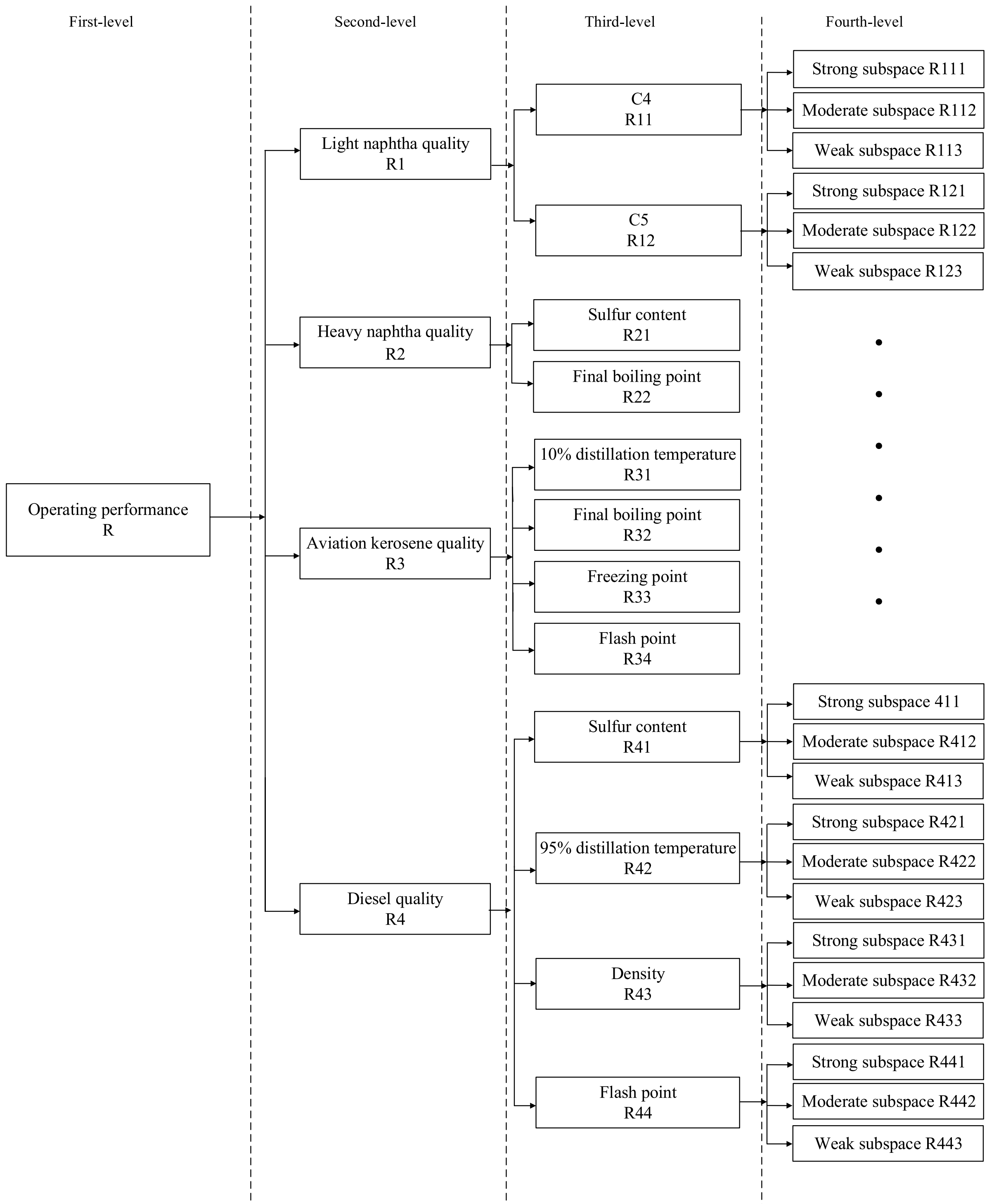

Fig. 4. Operating performance assessment index system of the hydrocracking process.

component regression (PCR) (Ge, 2014; Ge, Huang, & Song, 2015; Yuan, Wang et al., 2018) and so on. In this paper, partial least squares (PLS) (Liu, 2014; Matias, Souza, Rui, Gonçalves, & Barreto, 2015; Yuan, Zhou et al., 2018; Zamprogna, Barolo, & Seborg, 2004) is selected to estimate the PDQ index, which has been applied successfully in many engineering problems.

PLS has significant advantages in dealing with large numbers of highly correlated variables and reduce the dimension of data space. The input X and output Y can be linearly decomposed into the following forms:

$$X = TW^T + E_X \tag{2}$$

$$Y = UQ^T + E_Y \tag{3}$$

where T and U are the score matrixes of X and Y, W and Q are the loading vectors, respectively; E_X and E_Y are the residuals of X and Y, respectively.

The linear PLS regression model is composed of the decomposition models of X and Y and the regression expression. The regression coefficients can be obtained with a set of training samples. Then, the prediction model can be expressed as follow:

$$\hat{y}_c = X_c b_c \tag{4}$$

where $b_c = X_c^T U (T^T X_c X_c^T U)^{-1} T^T y_c = [b_{c,1}, b_{c,2}, \dots, b_{c,J}]^T \in R^{J\times 1}$ is the regression coefficient vector.

A detailed procedure of the prediction model for the PDQ index includes following steps:

Step1: Select the process variables χ. The process variables should be selected from both reaction stage and fractionation stage.

Step 2: Classify the process variables. The correlations between the process variables and the PDQ index have to be analyzed at first. Then, the process variables can be divided into three parts: strong correlation subspace block variables, moderate correlation subspace block variables and weak correlation subspace block variables. The Pearson's correlation coefficient is introduced in the paper to classify the process variables.

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{5}$$

where X_i denotes the process variables, Y_i denotes the PDQ index.

Step 3: Select the training data for each subspace block variables. The training data is selected from routinely collected production data of an oil refinery in China. The training data should cover as many production modes as possible. However, the training data must be selected carefully since the data from the cases with an accelerated deactivation of catalyst should be avoided.

Step 4: Develop the regression model. The concrete steps include principal components extraction, least squares regression model establishment and model evaluation. The detailed PLS algorithm has been given in many references (Ma et al., 2008; Vong, Geladi, Wold, & Esbensen, 1988).

3.2.3. Assessment index system

Since each product quality property corresponds to a PDQ index, it is necessary to develop an assessment index system for the operating performance assessment. The operating performance assessment index system of the hydrocracking process is shown in Fig. 4. The indicators are presented in a hierarchical structure, which are referred as the first-level, second-level, third-level and fourth-level indicators.

3.3. Development of assessment model

To solve the problem of operating performance cannot be quantitatively described, fuzzy synthetic assessment method is taken into account. Without loss of generality, fuzzy synthetic assessment primarily consists of fuzzification of input variables, weight vector construction, membership function selection, evaluation matrix calculation and defuzzification.

3.3.1. Fuzzification of assessment indicators

The PDQ indicators are the input variables of the fuzzy assessment model. Once these variables are prepared, these quantitative variables can be transformed into linguistic variables through fuzzification. Typical membership function types include trapezoidal, triangle, S-shaped, Z-shaped, bell-shaped, Gaussian distribution, etc. (Hussain, Gabbar, Bondarenko, Musharavati, & Pokharel, 2014; Jin, Ma, & Kosonen, 2017; Shaw, 2001). Although the trapezoidal and triangle shape functions are simple to calculate and widely used, the curve of the membership function is sharp and inapposite for the actual production condition. Hence, three more smooth membership functions are chosen in this paper, which are the S-shaped, Z-shaped, and bell-shaped membership functions. The S-shaped functions are represented as Eq. (6):

$$\varphi^j(x) = \begin{cases} 1, & x \le \alpha^j \\ 1 - 2\left(\dfrac{x-\alpha^j}{\beta^j - \alpha^j}\right)^2, & \alpha^j \le x \le \dfrac{\alpha^j + \beta^j}{2} \\ 2\left(\dfrac{x-\beta^j}{\beta^j - \alpha^j}\right)^2, & \dfrac{\alpha^j + \beta^j}{2} \le x \le \beta^j \\ 0, & x \ge \beta^j \end{cases} \tag{6}$$

where α^j and β^j are the parameters which determine the slope of the function curve. The Z-shaped functions are represented as Eq. (7):

$$\mu_i^j(x) = \frac{1}{1 + \left|\left(x - \sigma_i^j\right) \big/ w_i^j\right|^{2m}} \tag{7}$$

where σ_i^j and $w_i^j (i = -1, \dots, 1; j = 1, 2, 3)$ are the center and amplitude of the function curve, respectively, and m is a positive constant. The bell-shaped functions are represented as Eq. (8):

$$\psi^j(x) = \begin{cases} 0 & x \le c^j \\ 2\left(\dfrac{x-c^j}{d^j - c^j}\right)^2, & c^j \le x \le \dfrac{c^j + d^j}{2} \\ 1 - 2\left(\dfrac{x-d^j}{d^j - c^j}\right)^2, & \dfrac{c^j + d^j}{2} \le x \le d^j \\ 1, & x \ge d^j \end{cases} \tag{8}$$

where c^j and d^j are also the parameters which determine the slope of the function curve.

It can be seen that the parameters of the membership functions can directly affect the fuzzy set and the accuracy of the fuzzy synthetic assessment. To make the fuzzed value suitable for the hydrocracking process, a performance degradation index should be considered, which can be used to regulate the blurring of all PDQ indicators. Moreover, it can solve the problem that the PDQ index of different quality properties cannot be comprehensively evaluated due to different dimensions. The performance degradation index is between 0 and 1. In general, the smaller the index, the better the operating performance. As the negative deviation of quality is also be calculated, the performance degradation index is no longer the smaller the better, which only depends on the corresponding operating performance. The performance degradation index can be defined as

$$\eta(y(x)) = \begin{cases} 0, \Delta y_{i,j}(h) < \Delta y_{i,j,\min} \\ \dfrac{\Delta y_{i,j}(h) - \Delta y_{i,j,\min}}{\Delta y_{i,j,\max} - \Delta y_{i,j,\min}}, \Delta y_{i,j,\min} \le \Delta y_{i,j}(h) \le \Delta y_{i,j,\max} & h = 1, 2, \dots, k, \\ 1, \Delta y_{i,j}(h) > \Delta y_{i,j,\max} \end{cases} \tag{9}$$

where $\Delta y_{i,j}(h)$ is the PDQ index of the jth quality property of the ith product; $\Delta y_{i,j,\max}$ and $\Delta y_{i,j,\min}$ are the maximum and minimum values of the PDQ index for the jth quality property of the ith product, respectively. As can be seen from Eq. (9), each PDQ index has its own performance degradation value. Then, the parameters of the membership functions can be determined by the performance degradation index as shown in Table 3. Taking index R311 as an example, the calculated shapes of the memberships are shown in Fig. 5.

3.3.2. Calculation of indicator weight

The indicators in the fourth-level are the PDQ indicators which are predicted by the process variables from different subspace blocks. Hence, the weight needs to consider the correlation coefficient of

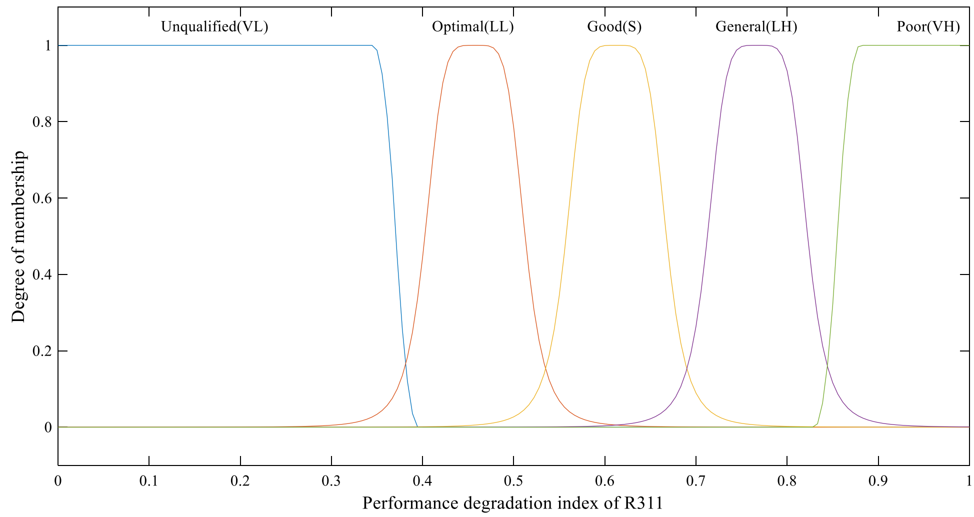

Fig. 5. The memberships of the index R311.

Table 3
Parameter calculation for the membership functions.

Label	PDQ	Function	Calculation of parameters
Unqualified (VL)	Negative	$\varphi^1(x)$	$\alpha^1=\omega_{VL1}\eta_{VL}, \beta^1=\alpha^1+\omega_{VL2}w_1^1$
Optimal (LL)	Very small	$\mu_1^1(x)$	$\sigma_1^1=\omega_{LL1}\frac{\eta_{VL}+\eta_{LL}}{2}, w_1^1=\omega_{LL2}(\sigma_2^1-\alpha^1), m=2$
Good (S)	Small	$\mu_1^2(x)$	$\sigma_2^1=\omega_{S1}\frac{\eta_{LL}+\eta_{S}}{2}, w_2^1=\omega_{S2}(\sigma_3^1-\sigma_2^1), m=2$
General (LH)	Large	$\mu_1^3(x)$	$\sigma_3^1=\omega_{LH1}\frac{\eta_{S}+\eta_{LH}}{2}, w_3^1=\omega_{LH2}(d^1-\sigma_3^1), m=2$
Poor (VH)	Very large	$\psi^1(x)$	$d^1=\omega_{VH1}\eta_{VH}, c^1=d^1-\omega_{VH2}w_3^1$

the process variables in the subspace blocks. The indicator weight is described as Eq. (10):

$$A_i = \sum_{s=1}^{n} |r_s| \Big/ \sum_{l=1}^{m} |r_l| \tag{10}$$

where $r_l,\ldots, r_s$ represent the correlation coefficient of the process variables in the subspace block; n and m are the numbers of the variables in the subspace block and all selected, respectively.

The weights of the indicators in the third-level is determined by the AHP (Analytic Hierarchy Process) method (Kokangul, Polat, & Dagsuyu, 2017). AHP method can get a more accurate weight for most assessment, and it can adjust the weight of each index according to the change trend. Therefore, it has a strong applicability and high real-time performance.

The indicators in the second-level are composed of the four kinds of product oil. The weights for these indicators are determined by the economic property. The indicator weight is described as Eq. (11):

$$A_j = S_i \Big/ \sum_{i=1}^{4} S_i \tag{11}$$

where S_i is the current market price of the ith product.

4. Case study

To validate the two-layer fuzzy synthetic evaluation strategy, it is evaluated with three cases on an industrial hydrocracking process from a refinery in China.

4.1. Hydrocracking process

Three cases of a real-time operating performance assessment are investigated by using the on-line monitoring data of an industrial hydrocracking process from a refinery in China in this section. In Case I, two groups of special data are selected to show the step-by-step evaluation procedure, and the key process variables of the hydrocracking process is shown in Table 4. Group 1 represents a good operating performance, and Group 2 represents an unqualified operating performance in which the content of C4 of light naphtha is unqualified. For example, the bottom temperature of the first bed of hydrotreating reactor in Group 1 is 392.556 °C, while it is 452.576 °C in Group 2. The outlet temperature values of fractionating heating furnace are 383.16 °C and 451.85 °C in Group 1 and Group 2, respectively. In Case II, continual monitoring data are used to validate the two-layer fuzzy synthetic evaluation strategy, and the assessment results are compared with a traditional fuzzy synthetic method. In Case III, monitoring data from September 15, 2016 to August 31, 2017 are selected to show the accuracy of the two-layer fuzzy synthetic evaluation strategy.

Table 4
Key process variables of the hydrocracking process.

No.	Parameters
1	Inlet temperature of the first bed of hydrotreating reactor (℃)
2	Outlet temperature of the first bed of hydrotreating reactor (℃)
3	Inlet temperature of the second bed of hydrotreating reactor (℃)
4	Outlet temperature of the second bed of hydrotreating reactor (℃)
5	Inlet temperature of the third bed of hydrotreating reactor (℃)
6	Outlet temperature of the third bed of hydrotreating reactor (℃)
7	Inlet temperature of the first bed of hydrocracking reactor (℃)
8	Outlet temperature of the first bed of hydrocracking reactor (℃)
9	Inlet temperature of the second bed of hydrocracking reactor (℃)
10	Outlet temperature of the second bed of hydrocracking reactor (℃)
11	Inlet temperature of the third bed of hydrocracking reactor (℃)
12	Outlet temperature of the third bed of hydrocracking reactor (℃)
13	Inlet temperature of the fourth bed of hydrocracking reactor (℃)
14	Outlet temperature of the fourth bed of hydrocracking reactor (℃)
15	Overhead pressure of desulfurization hydrogen stripper (MPa)
16	Overhead temperature of desulfurization hydrogen stripper (℃)
17	Bottom temperature of desulfurization hydrogen stripper (℃)
18	Stripping steam flow of desulfurization hydrogen stripper (t/h)
19	Overhead pressure of fractionating tower (MPa)
20	Overhead temperature of fractionating tower (℃)
21	Bottom temperature of fractionating tower (℃)
22	Stripping steam flow of fractionating tower (t/h)
23	Outlet temperature of fractionating heating furnace (℃)
24	Total flow rate of recycling hydrogen (t/h)
25	New hydrogen flow (t/h)
26	Waste hydrogen content (t/h)

4.1.1. Case I

(1) Validation of operating performance assessment by using data Group 1

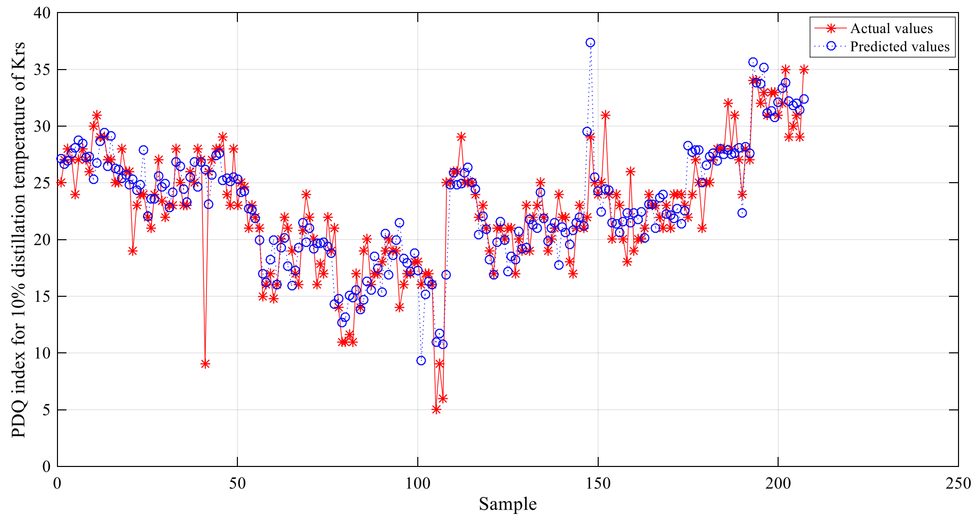

Fig. 6. Predicted PDQ index for 10% distillation temperature of aviation kerosene based on strong correlation subspace block variables.

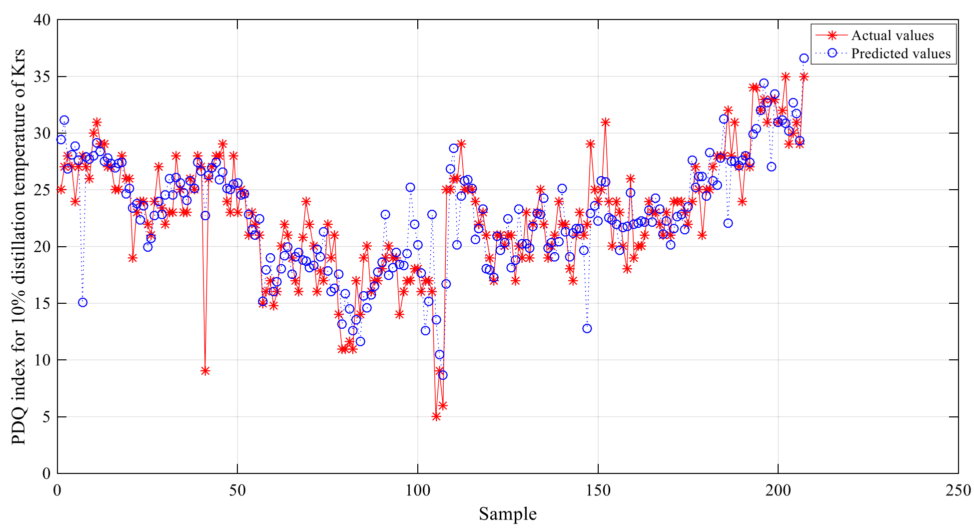

Fig. 7. Predicted PDQ index for 10% distillation temperature of aviation kerosene based on moderate correlation subspace block variables.

According to the flowchart of the two-layer fuzzy synthetic evaluation strategy, the first step is to predict the PDQ index. Take the PDQ index for 10% distillation temperature of aviation kerosene as an example, Figs. 6–9 show the comparisons of the actual and predicted values with models based on strong correlation subspace block variables, moderate correlation subspace block variables, weak correlation subspace block variables, and weighting ensemble approach, respectively. The red and blue lines represent the actual and predicted output trends, respectively. As can be seen, most of the samples can be well estimated for the PDQ index. Table 5 shows the calibration performance of the PDQ index for 10% distillation temperature of aviation kerosene, which indicates that both the root mean squared error (RMSE) and mean absolute error (MAE) are small enough and within the acceptable range for the real production. Moreover, the predicted result based on weighting ensemble method is obviously more accurate.

(a) Calculation of assessment indicators in the third-level

Based on the membership functions introduced in Section 3.3.1, the assessment matrix of the fourth-level indicators can be calculated as

$$V_{R11} = \begin{bmatrix} V_{R111} \\ V_{R112} \\ V_{R113} \end{bmatrix} = \begin{bmatrix} 0 & 0.0820 & 0.8970 & 0.0210 & 0 \\ 0.9440 & 0.0410 & 0.0150 & 0 & 0 \\ 0.9960 & 0.0014 & 0.0026 & 0 & 0 \end{bmatrix};$$

$$V_{R12} = \begin{bmatrix} V_{R121} \\ V_{R122} \\ V_{R123} \end{bmatrix} = \begin{bmatrix} 0 & 0.9968 & 0.0020 & 0.0012 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix};$$

By using Eq. (10), the corresponding weight of the indicators in the fourth-level can be calculated as

$$A_{R11} = \begin{bmatrix} 0.6068 & 0.2798 & 0.1134 \end{bmatrix};$$
$$A_{R12} = \begin{bmatrix} 0.498 & 0.366 & 0.136 \end{bmatrix};$$

The assessment result of the indicators in the third-level can be further calculated as

$$B_{R11} = A_{R11} * V_{R11} = \begin{bmatrix} 0.3770 & 0.0615 & 0.5488 & 0.0127 & 0 \end{bmatrix};$$
$$B_{R12} = A_{R12} * V_{R12} = \begin{bmatrix} 0 & 0.9984 & 0.0010 & 0.0006 & 0 \end{bmatrix};$$
$$V_{R11} = \begin{bmatrix} B_{R11} \\ B_{R12} \end{bmatrix} = \begin{bmatrix} 0.3770 & 0.0615 & 0.5488 & 0.0127 & 0 \\ 0 & 0.9984 & 0.001 & 0.0006 & 0 \end{bmatrix};$$

The evaluation matrix calculation of other indicators is similar.

(b) Calculation of assessment indicators in the second-level

By using the AHP method, the corresponding weight of the indicators in the third-level can be calculated as

$$A_{R1} = \begin{bmatrix} 0.5 & 0.5 \end{bmatrix};$$
$$A_{R2} = \begin{bmatrix} 0.4146 & 0.5854 \end{bmatrix};$$

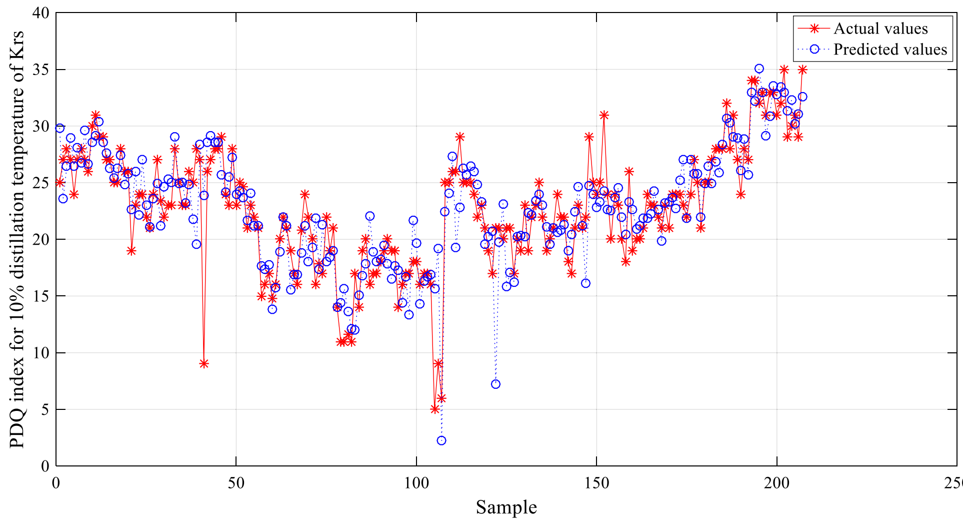

Fig. 8. Predicted PDQ index for 10% distillation temperature of aviation kerosene based on weak correlation subspace block variables.

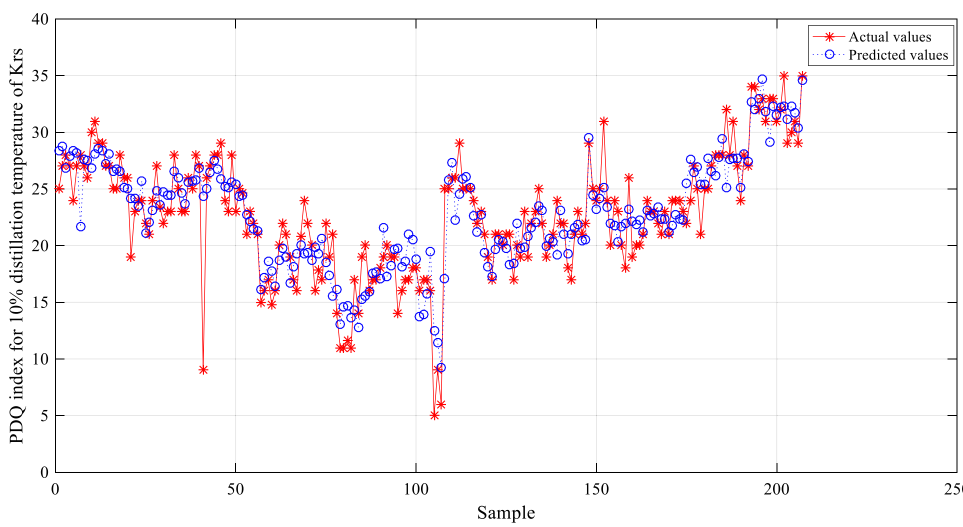

Fig. 9. Predicted PDQ index for 10% distillation temperature of aviation kerosene based on weighting.

Table 5
RMSE and MAE for the calibration data in the hydrocracking process.

Process variables	RMSE	MAE
Strong correlation subspace block variables	2.8033	1.9386
Moderate correlation subspace block variables	2.8884	2.0090
Weak correlation subspace block variables	3.0502	2.2058
Weighting	2.5363	1.8480

$A_{R3} = \begin{bmatrix} 0.2540 & 0.3212 & 0.2124 & 0.2124 \end{bmatrix};$

$A_{R4} = \begin{bmatrix} 0.2390 & 0.3464 & 0.2130 & 0.2016 \end{bmatrix};$

The assessment matrix of the indicators in the second-level can be calculated as

$$V_R = \begin{bmatrix} B_{R1} \\ B_{R2} \\ B_{R3} \\ B_{R4} \end{bmatrix} = \begin{bmatrix} A_{R1} * V_{R1} \\ A_{R2} * V_{R2} \\ A_{R3} * V_{R3} \\ A_{R4} * V_{R4} \end{bmatrix}$$
$$= \begin{bmatrix} 0.1965 & 0.3050 & 0.4185 & 0.0800 & 0 \\ 0 & 0 & 0.4146 & 0.2964 & 0.289 \\ 0 & 0.0080 & 0.5058 & 0.3447 & 0.1415 \\ 0 & 0.1369 & 0.3738 & 0.2892 & 0.2001 \end{bmatrix};$$

(c) Calculation of assessment indicators in the first-level

By using Eq. (11), the corresponding weight of indicators in the second-level can be calculated as

$A_R = \begin{bmatrix} 0.224 & 0.208 & 0.226 & 0.343 \end{bmatrix};$

The assessment matrix of the indicator in the first-level can be calculated as

$B_R = A_R * V_R = \begin{bmatrix} 0.0440 & 0.1171 & 0.4225 & 0.2567 & 0.1607 \end{bmatrix}.$

Because the maximal value appears in the third element of the matrix with the value of 0.4225, the operating performance can be evaluated as 'Good', which is in accordance with the result of the real-time monitoring data Group 1. The degree of membership is shown in Fig. 10 for each operating performance grade at this sampling point. It can be seen that the maximum membership value appears when the operating performance is 'Good'.

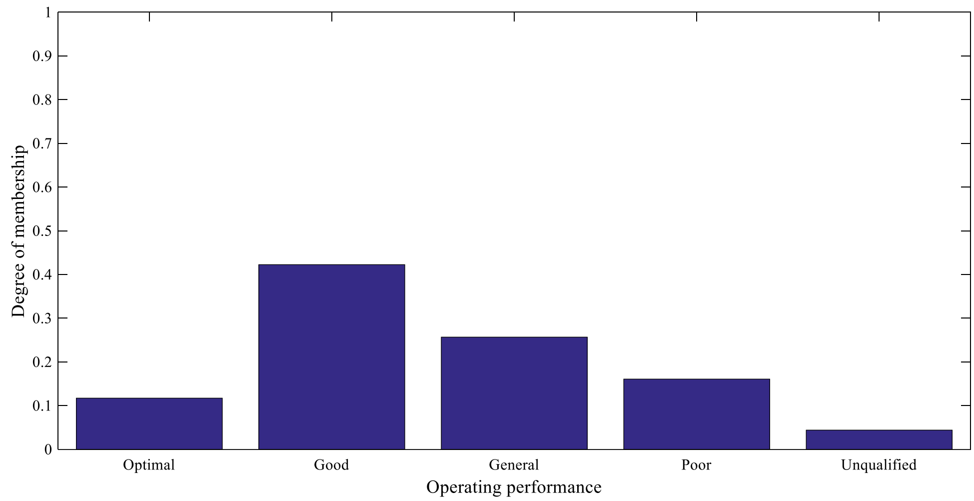

Fig. 10. The degree of membership for each operating performance grade with the data of Group 1.

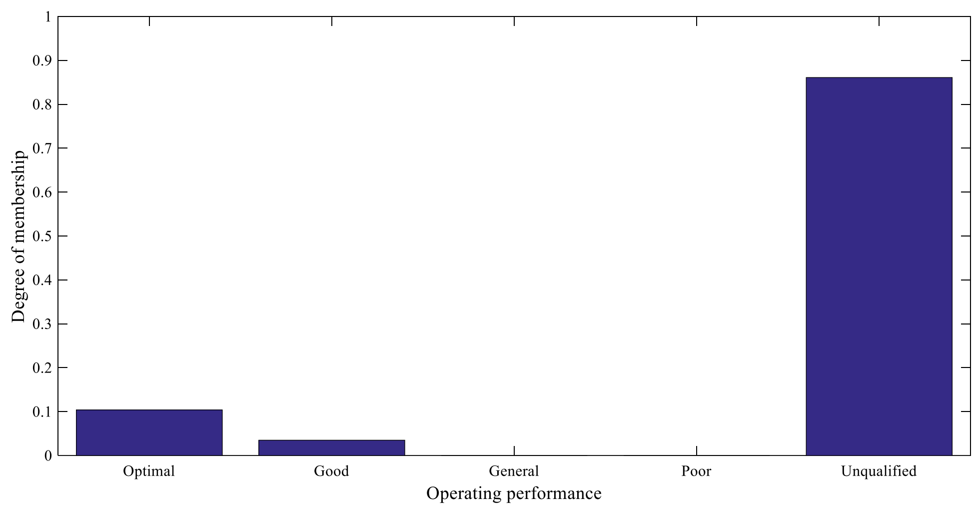

Fig. 11. The degree of membership for each operating performance grade with the data of Group 2.

(2) Validation of operating performance assessment by using data Group 2

By using data Group 2, the assessment matrix of the index R11 can be calculated as $B_{R11} = A_{R11} * V_{R11} = \begin{bmatrix} 0.861 & 0.104 & 0.035 & 0 & 0 \end{bmatrix}$, and the maximal value appears in the first column of the matrix. According to the principle of the two-layer fuzzy synthetic assessment strategy introduced in Section 3.1, the operating performance result can be considered as 'Unqualified', which agrees with the fact that the content of C4 of light naphtha is not up to standard. The degree of membership for each operating performance grade at this point is shown in Fig. 11. It can be seen that the maximum membership value appears when the operating performance is 'Unqualified'.

4.1.2. Case II

In this case, the monitoring data at 8 a.m. on October 25, 2016 and for the full day on July 31, 2017 are further used to validate the two-layer fuzzy synthetic method. The results show that the proposed method is more appropriate in reflecting the operating performance than the traditional fuzzy synthetic assessment. For example, the operating performance of 8 a.m. on October 25, 2016 should be evaluated as 'Unqualified', which is actually the data in Group 2 and has been demonstrated in Section 4.1.2. However, the traditional fuzzy method assesses the operating performance as 'Good', since the maximal value appears in the third element of the assessment matrix ($B_R = A_R * V_R = \begin{bmatrix} 0.2506 & 0.2836 & 0.3613 & 0.286 & 0 \end{bmatrix}$). The membership for each operating performance grade with the traditional fuzzy method is shown in Fig. 12.

Fig. 13 shows the continuous operating performance assessment results with two-layer fuzzy synthetic assessment method and the traditional fuzzy assessment method, which are highlighted in red line and the blue line, respectively. At the 53nd and 209th sampling points, the operating performance of the hydrocracking process can be evaluated by the offline lab test data of the product quality properties. The content of C4 of light naphtha is not up to standard at the 53nd sampling point. From the figure, the actual operating performance of the 53nd and 209th sampling points are consistent with the results of the two-layer fuzzy synthetic assessment, but not completely consistent with the traditional fuzzy method assessment results. Compared with the traditional fuzzy assessment method, the two-layer fuzzy synthetic assessment method can reflect the change of the real-time operating performance more accurately.

4.1.3. Case III

To illustrate the practicality of the two-layer fuzzy synthetic assessment strategy, the monitoring data from September 15, 2016 to August 31, 2017 are selected to assess the actual operating performance of the hydrocracking process in the plant within about a year. Fig. 14 shows the continuous estimation results for the operating performance.

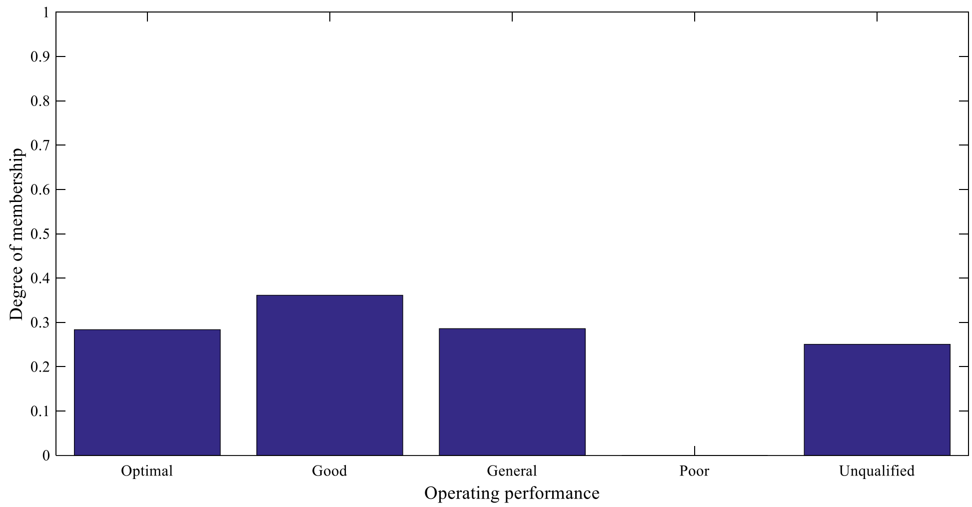

Fig. 12. The degree of membership for each operating performance grade with the traditional fuzzy method.

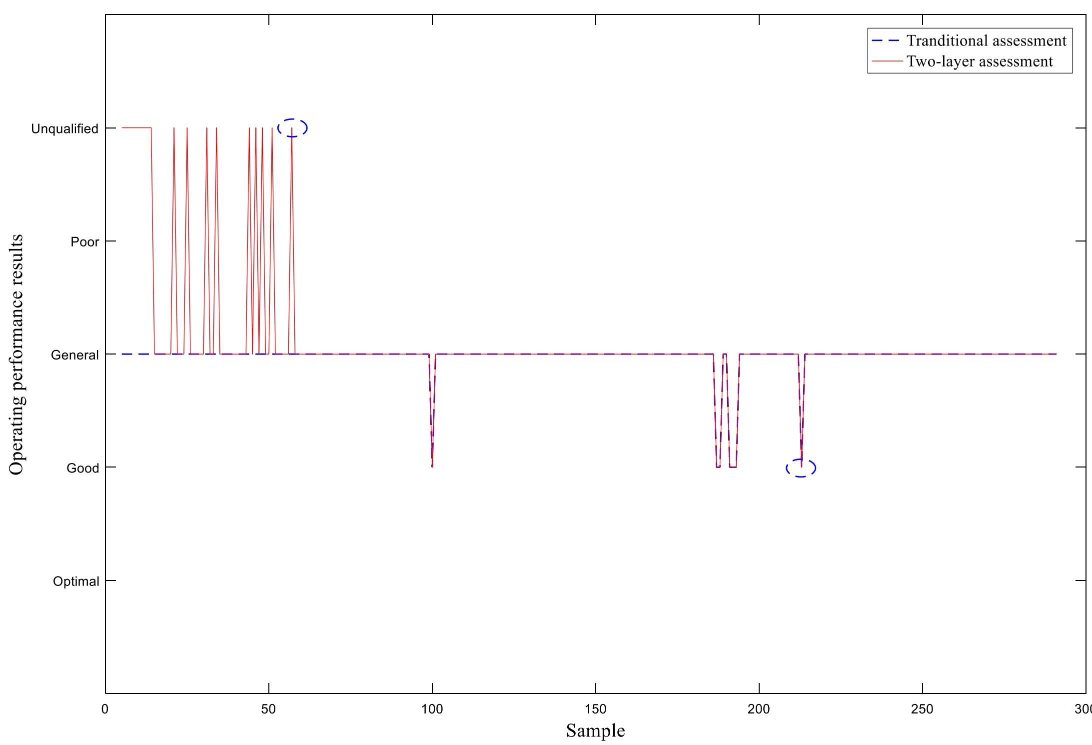

Fig. 13. Continuous operating performance assessment results of the hydrocracking process from 00:00 to 23:55 in July 31, 2017.

From this figure, it is clear that the operating performance may deviate from the optimal condition for a variety of reasons. Thus, the operating performance is diversified.

There are totally 299 data samples that containing variable values for all quality properties. The 299 data samples can be used to label the operating performance of the hydrocracking process. Because of the change of production requirements and other reasons, the content of C4 of light naphtha is difficult to control in the production. Thus, the process is mostly in an unqualified operating state. Fig. 15 shows the comparisons of the actual operating performance and the two-layer fuzzy synthetic assessment results within the year, where the blue line and the red line represent the two-layer fuzzy synthetic assessment results and the actual operating performance of the hydrocracking process, respectively. It can be seen that the actual operating performance and the point pairs of the two-layer synthetic assessment results basically coincide, which demonstrates accurate assessment results. The operating performance assessment is based on the predicted results of the PDQ indicators. However, the assessment results will also be biased since there are errors in the predicted results. Whereas, the two-layer fuzzy synthetic assessment can largely reduce the operating performance assessment errors caused by the deviation of the PDQ index predicted results. Table 6 shows the accuracy of the two-layer fuzzy synthetic assessment strategy, which is acceptable in practice. Hence, the two-layer fuzzy synthetic assessment method can be considered as an effective method for online operating performance assessment of the hydrocracking process.

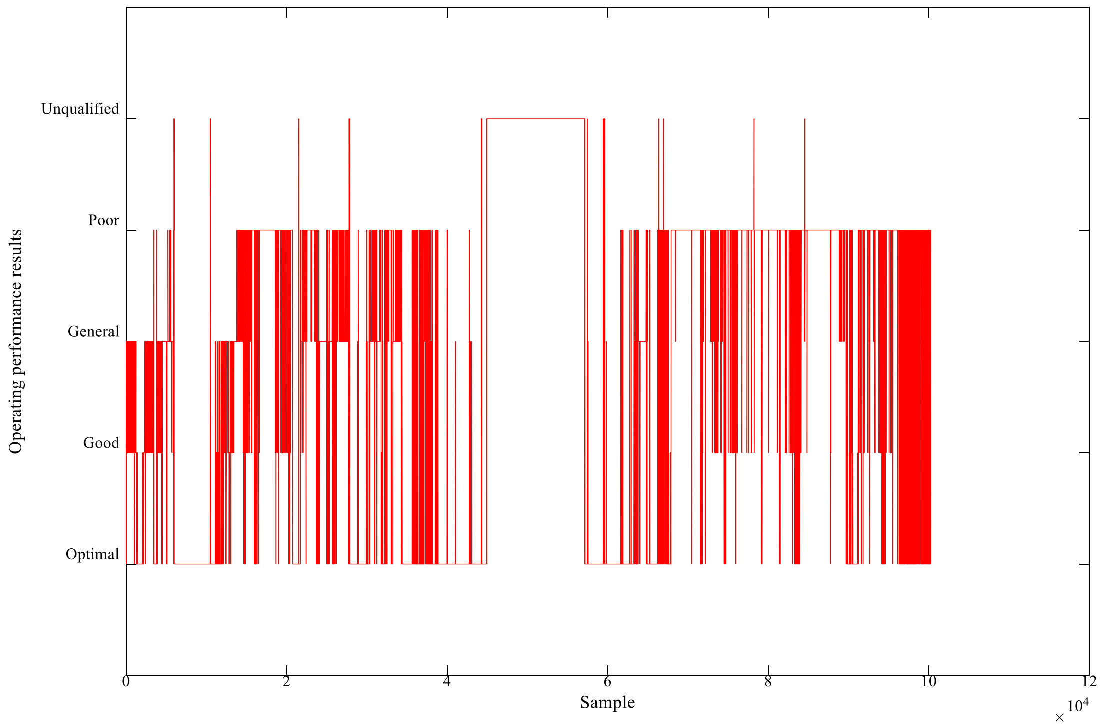

Fig. 14. Continuous operating performance assessment results of the hydrocracking process from September 15, 2016 to August 31, 2017.

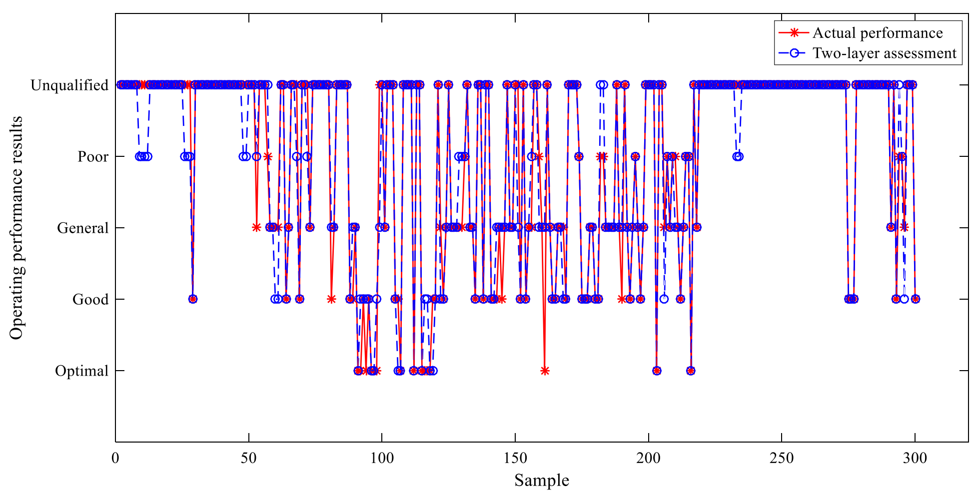

Fig. 15. Comparisons of the actual operating performance and the two-layer fuzzy synthetic assessment results.

Table 6
The accuracy of the two-layer fuzzy synthetic assessment strategy.

Operating performance grade	Actual performance	Assessment results	Accuracy
Optimal	15	9	0.6
Good	38	30	0.789
General	48	38	0.792
Poor	12	5	0.417
Unqualified	186	171	0.919
Summation	299	254	0.849

5. Conclusions

In this paper, a novel framework is established for operating performance assessment of the hydrocracking process. The operating performance assessment index system is constructed based on the concept of positive deviation of quality variables, which is derived from the actual requirement in the hydrocracking process. By classifying the process variables into different subspace blocks according to their correlation with the product quality properties, the indicators in the assessment index system can be calculated by PDQ prediction models. Then, a two-layer fuzzy synthetic evaluation strategy was used to achieve the online assessment. A series of cases were presented to illustrate the feasibility of the proposed framework on an industrial hydrocracking process.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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