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Research on State Evaluation of Petrochemical Plants Based on Improved TOPSIS Method and Combined Weight

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Abstract: Due to the involvement of hazardous materials and the potential serious accidents that may occur in petrochemical plants, it is of great significance to develop real-time state evaluation methods offering high performance. Data-driven methods have received widespread attention following the development of advanced condition-monitoring systems. However, scarce training samples evaluated under multiple operating conditions are available because of the high stability and reliability requirements of petrochemical plants. In this paper, a real-time state evaluation method based on the technique for order preference by similarity to ideal solution (TOPSIS) is proposed, which circumvents dependence on data samples. First, the positive and negative ideal solutions of TOPSIS are determined using expert experience and the process index control limits of process cards. Then, fixed-value and fixed-interval indices are proposed to address the interval-optimal parameters. Subsequently, a new combined weight is established using the entropy method and the subjective weight coefficient. Finally, the above steps are integrated into an improved TOPSIS for the state evaluation of petrochemical plants. Experiments conducted on a fluid catalytic cracking (FCC) unit show that the proposed method can quantify the real-time operating status of a petrochemical plant. Furthermore, compared with the equal weight method, the evaluation result of combined weights is more aligned with the actual operating status.

Keywords: technique for order preference by similarity to ideal solution (TOPSIS); petrochemical plants; state evaluation; health index

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1. Introduction

Petrochemical plants, as high-risk systems, mostly involve the processing and use of flammable, explosive, toxic, and other dangerous materials or operate under high-temperature, high-pressure, vacuum, and other extreme conditions [1]. The above characteristics necessitate the safe operation of petrochemical plants. Once an abnormality occurs, it will lead to non-smooth operation or the generation of inferior products if it is not handled properly. Furthermore, it may lead to an unplanned shutdown and even casualties. According to statistics, there were 974 chemical accidents from 2013 to 2018 in China, resulting in 1253 deaths [2]. Therefore, it is critical to carry out the state evaluation of petrochemical plants [3].

A technique based on monitoring data, state evaluation essentially consists of the construction of an indicator that can characterize the target operating status. According to their principles, state evaluation methods can be divided into three categories: model-driven methods, knowledge-driven methods, and data-driven methods [4,5]. Model-driven methods realize state evaluation through the establishment of a mechanistic model, whose results are relatively accurate [6]. However, it is difficult to apply such methods to complex objects. Although knowledge-driven methods do not require the establishment of precise mathematical models, they demand extensive expert experience and representative observations to depict system characteristics [7]. Data-driven methods rely heavily on the operation data of evaluation objects, requiring less expert knowledge and fewer operational mechanisms [8].

With the rapid development of Distributed Control Systems (DCSs), most petrochemical plants have achieved comprehensive real-time monitoring of key parameters and accumulated vast quantities of historical data. Coupled with the rise of computer technology, data-driven state evaluation methods have drawn considerable attention in the academic community in the last few decades [9,10]. Fezai et al. proposed an abnormal condition detection method via the kernel partial least squares (KPLS) method and a generalized likelihood ratio test (GLRT) for chemical systems. Validated by the Tennessee Eastman process, its computation efficiency and detection performance are superior to the conventional GLRT technique [11]. Aggoun and Chetouani explored a fault detection technique for chemical processes by employing the Nonlinear Auto-Regressive Moving Average with eXogenous input (NARMAX) model and Bhattacharyya distance (BD), the performance of which was demonstrated via a real fault in a separation unit [12]. Peng and Guo established a fault detection and quantitative scheme using a dimensionality reduction model and support vector data description (SVDD). In addition, an experiment on the Tennessee Eastman process was carried out to show the higher detection accuracy of the method compared to other traditional techniques [13]. However, these methods usually fail to achieve satisfactory performance without the provision of sufficient training samples under multiple operating conditions.

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a typical multi-attribute decision-making method [14,15]. For the object to be evaluated, two distances need to be calculated: one is the distance to the positive ideal solution (i.e., the optimal solution) and the other is the distance to the negative ideal solution (i.e., the worst solution). Then, the solutions can be ranked according to the closeness degree, which is calculated based on the above two distances [16]. Due to its good interpretability and implementability, TOPSIS has been applied in many fields [17], such as maintenance management [18], supply chain management [19], state evaluation [20], etc. Rao and Baral developed a model for the specification, comparison, and optimum selection of anaerobic digestion feedstock via TOPSIS and graphical methods [21]. Zhang and Cai proposed an evaluation approach based on fuzzy matter elements and TOPSIS for oil–paper insulation conditions [22]. Liu and Wang presented an improved TOPSIS to evaluate the safety of different driving behaviors by combining Mahalanobis distance and contact vector distance [23].

The determination of positive and negative ideal solutions is the most important process of TOPSIS [24]. In order to determine these positive and negative ideal solutions, the historic data used must contain the optimal and the worst operating statuses of an object when TOPSIS is used for state evaluation. However, it is difficult to accumulate data that meet the above requirements due to the high stability and reliability requirements of petrochemical plants. Furthermore, there are no unified criteria for determining positive and negative ideal solutions. On the other hand, each evaluation parameter must be numeric and increase or decrease monotonically in the traditional TOPSIS [25]. Unfortunately, there are many interval-optimal parameters associated with petrochemical plants, such as reaction temperature, reaction pressure, etc. Specifically, the ideal operating state for interval-optimal parameters is to be within the limits of a certain value or interval rather than corresponding to a maximum or minimum value.

Given the above problems, an improved TOPSIS is proposed for the state evaluation of petrochemical plants in this paper. This improvement consists of the following: (1) The positive and negative ideal solutions are determined using expert experience and the process index control limits of process cards. The primary advantage of this process consists of its independence from comprehensive historical data for the determination of positive and negative ideal solutions. (2) Fixed-value and fixed-interval indices are proposed to deal with interval-optimal parameters. Therefore, the implementation range of

TOPSIS can be extended to the state evaluation of petrochemical plants that are subject to interval-optimal parameters. (3) A new combined weight is established using the entropy method and subjective weight coefficient.

This paper is organized as follows. The entire process of the state evaluation approach based on improved TOPSIS and the combined weight is introduced in Section 2. Section 3 presents the results of experimental tests on a fluid catalytic cracking (FCC) unit to prove the effectiveness of the proposed approach. Finally, conclusions are presented in Section 4.

2. Methodology

2.1. TOPSIS

A system's positive and negative ideal solutions are the evaluative basis of TOPSIS [26]. The positive ideal solution is a set composed of the optimal value or interval of each parameter in the evaluation index system, while the negative ideal solution is a set consisting of the worst value or interval of each parameter in the evaluation index system. Therefore, the closeness degree can be obtained based on the Euclidean distance from the evaluative solution to the positive and negative ideal solutions in order to determine the ranking of all objects under evaluation [27]. If the result is closest to the positive ideal solution and farthest from the negative ideal solution, the evaluative solution is the best. Otherwise, the evaluative solution is the worst [28]. The main steps of TOPSIS can be summarized as follows:

(1) Establish an evaluation matrix A

$$A = \left(x_{ij}\right)_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

where m is the number of objects to be evaluated, while n refers to the number of evaluation indices. x_{ij} represents the value of the jth evaluation index of the ith evaluation object $(1 \le i \le m, 1 \le j \le n)$.

In order to avoid information inundation caused by the large differences in the magnitude of the evaluation indices, the evaluation matrix A is normalized using Equation (2).

$$\begin{cases} R = \left(r_{ij}\right)_{m\times n} \\ r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}} \end{cases} \tag{2}$$

(2) Calculate the value matrix V

$$V = RW = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \begin{bmatrix} \omega_1 & 0 & \cdots & 0 \\ 0 & \omega_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \cdots \\ 0 & 0 & \cdots & \omega_n \end{bmatrix} \tag{3}$$

where W is the weight matrix, which indicates the importance of each evaluation index to the evaluation result. It is generally obtained through empirical judgment and corresponds to $\sum_{j=1}^{n} \omega_j = 1$

(3) Determine the positive ideal solution S^+ and negative ideal solution S^-.

According to the value matrix V, the positive ideal solution S^+ and negative ideal solution S^- can also be determined.

$$\begin{cases} S^+ = \left\{s_1^+, s_2^+, \cdots, s_n^+\right\} \\ S^- = \left\{s_1^-, s_2^-, \cdots, s_n^-\right\} \end{cases} \tag{4}$$

The positive and negative ideal solutions are determined by the types of indices used, which are generally divided into a cost index and a benefit index in traditional TOPSIS. For cost indices, the smaller the better. For benefit indices, the larger the better.

i. Cost index

$$\begin{cases} s_j^+ = \min\left(v_{ij} \middle| 1 \le i \le m\right) \\ s_j^- = \max\left(v_{ij} \middle| 1 \le i \le m\right) \end{cases} \quad (5)$$

ii. Benefit index

$$\begin{cases} s_j^+ = \max\left(v_{ij} \middle| 1 \le i \le m\right) \\ s_j^- = \min\left(v_{ij} \middle| 1 \le i \le m\right) \end{cases} \quad (6)$$

(4) Solve the closeness degree D.

After determining the positive and negative ideal solutions, the Euclidean distances from the object under evaluation to the positive ideal solution and negative ideal solution, which are D^+ and D^-, respectively, are calculated.

$$\begin{cases} D^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - s_j^+\right)^2} \\ D^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - s_j^-\right)^2} \end{cases} \quad (7)$$

Therefore, the closeness degree D can be calculated based on D^+ and D^-. The maximum closeness degree is 1, indicating that the object being evaluated is the best.

$$D = \frac{D^-}{D^+ + D^-} \quad (8)$$

2.2. Improved TOPSIS for State Evaluation of Petrochemical Plants

2.2.1. Improved Methods for Determining Positive Ideal Solution and Negative Ideal Solution

In traditional TOPSIS, the positive and negative ideal solutions are determined using historical data. Specifically, the positive ideal solution is composed of the optimal values of all evaluation indices in the historical data, while the negative ideal solution is composed of the worst values [29]. Therefore, historical data should cover the optimal and worst conditions as much as possible. On the other hand, traditional TOPSIS only provides the methods of determining positive and negative ideal solutions for the benefit index and cost index. Unfortunately, the above two conditions are generally not satisfied in the state evaluation of petrochemical plants. This is due to two reasons. First, it is difficult to provide sufficient historical data to cover the operating states of different pros and cons due to the high stability and reliability requirements of petrochemical plants. Second, there are many interval-optimal parameters in petrochemical plants, such as reaction temperature, reaction pressure, etc. Given the above problems, the methods for determining the positive and negative ideal solutions are improved as follows.

(1) The determination of positive ideal solution

The positive ideal solution in the context of petrochemical plants is determined by integrating expert experience and historical data. In detail, the experts select the optimal operation period of petrochemical plants according to fluctuation, product quality, and other information. The operation data during this period can be used to develop the positive ideal solution. In addition to the benefit index and cost index considered in traditional TOPSIS, there are two other considerations for the monitoring parameters of petrochemical plants: First, a plant's operating state is optimal when the parameter is a certain value. The closer to this value, the better the operating state of the parameter. In this paper, these parameters are defined as a fixed-value index. Second, a plant's operating state is optimal when the parameter is in a certain interval. The closer to this interval, the better the operating state of the parameter. Similarly, these parameters are defined as fixed-interval indices in this paper. The optimal values of the fixed-value or fixed-interval index can be determined using Equations (8) and (9), respectively

i. Fixed-value index

$$s_j^+ = q_j \tag{9}$$

where q_j is the optimal value of the jth parameter in the evaluation index system.

ii. Fixed-interval index

$$s_j^+ = \left[q_j^l, q_j^u\right] \tag{10}$$

where q_j^u and q_j^l are the upper and lower bounds of the optimal interval of the jth parameter, respectively.

(2) The determination of negative ideal solution

The process card of a petrochemical plant constitutes important technical data for ensuring operational safety. The process control indices and their control limits listed on the process card are important parameters for judging the operational status of a petrochemical plant. The control limit of each index refers to the normal operational status of the parameter. When a parameter exceeds the control limit, it can be regarded as an abnormal operation of the parameter. If it is not adjusted for a long time, it is likely to induce an abnormal state of the petrochemical plant. Therefore, the control limit is taken as the worst value of each parameter in the evaluation index system. Then, the negative ideal solution can be composed of the worst values of all the parameters in the evaluation index system. Since the control limit is a fixed interval, the determined negative ideal solution consists of two values, including the upper and lower control limits.

2.2.2. Combined Weight of Evaluation Index System

Due to the different influences on the operation state, each parameter in the evaluation index system is assigned a weight according to its importance [30]. The weight can be determined by fusing the subjective weight and objective weight, which is called combined weight in this paper. The subjective weight is determined according to the importance level of parameters in the process card, while the objective weight of parameters can be calculated using the entropy weight method based on historical data. Finally, the combined weight of each parameter is determined by combining the subjective weights and objective weights. The specific steps of this process are as follows:

i. The subjective weight coefficient α based on importance levels

The operating procedures classify the importance of key process control indicators. Accordingly, this paper assigns a subjective weight coefficient α to each parameter according to the parameter importance level. For example, an oil refinery divides the importance of the key process control indicators of the catalytic cracking unit into three levels: urgent, important, and general, and the corresponding subjective weight coefficients can be set to 1.5, 1.2, and 1.0.

ii. The objective weight based on the entropy weight method

The core of the entropy weight method is to calculate the information entropy based on the historical data of the parameters to characterize the discrete degree of each parameter. The larger the level of information entropy, the smaller the discrete degree of the sequence, and the smaller the influence of the parameter on the evaluation result, that is, the smaller the weight. The evaluation matrix $A_{m\times n}$, contains m samples, and each sample is described by n characteristic parameters. First, it is normalized to obtain $R_{m\times n}$. The information entropy calculation equations of each characteristic parameter are as follows:

$$\begin{cases} E_j = -\frac{\sum_{i=1}^{m} p_{ij}\ln\left(p_{ij}\right)}{\ln(m)} \\ p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \end{cases} \tag{11}$$

where r_{ij} refers to the normalized value of the jth parameter of the ith evaluation object. Specifically, $\lim\limits_{p_{ij}\to 0}\left(p_{ij}\ln(p_{ij})\right) = 0$.

After obtaining the information entropy of each parameter, the difference coefficient H_j is calculated according to the following equation.

$$H_j = 1 - E_j \tag{12}$$

where E_j is the information entropy of the jth parameter.

Furthermore, the objective weight ω'_j of each parameter can be calculated according to the following Equation.

$$\omega'_j = \frac{H_j}{\sum_{j=1}^{n} H_j} \tag{13}$$

iii. The combined weight ω_j

After determining the subjective weight and the objective weight, in order to fully integrate the advantages of the two weights, a calculation method for determining the combined weight is proposed. First, the fusion weight ω''_j of each parameter is calculated using the following equation

$$\omega''_j = \alpha_j \cdot \omega'_j \tag{14}$$

where α_j and ω'_j are the subjective weight coefficient and objective weight of the jth parameter, respectively. ω''_j is the calculated fusion weight, which is normalized using the following equation to obtain the combined weight of each parameter.

$$\omega_j = \frac{\omega''_j}{\sum_{j=1}^{n} \omega''_j} \tag{15}$$

2.2.3. Health Index

The above positive and negative ideal solutions may be intervals, thus differing from the positive and negative ideal solutions of traditional TOPSIS, and the original relative closeness solution method is no longer applicable. Therefore, the solution method for determining relative closeness is optimized, and the solution for the interval index is added. In order to conform to the process of evaluating the operating state of the plant, this paper defines the relative closeness D as the health index HI, whose calculation equation is as follows

$$\begin{cases} HI = \frac{D^-}{D^+ + D^-} \\ D^+ = \sqrt{\sum_{j=1}^{n} \omega_j \left(DS_j^+\right)^2} \\ D^- = \sqrt{\sum_{j=1}^{n} \omega_j \left(DS_j^-\right)^2} \end{cases} \tag{16}$$

where DS_j^+ and DS_j^- are the distance between the actual value of the jth parameter and its optimal and worst value or interval, and ω_j is the combined weight of each parameter.

The larger the health index (HI), the better the operating state of the device. When HI is 1, this indicates that the device is in the optimal operating state; on the contrary, when

HI is 0, this indicates that the device is in the worst operating state and must be adjusted immediately.

i. DS_j^+

Positive ideal solutions include cost type, benefit type, fixed value type, and fixed interval type. Among them, the positive ideal solutions corresponding to cost type, benefit type, and fixed value type are all numerical values, which can be calculated using the following equation:

$$DS_j^+ = x_j - s_j^+ \tag{17}$$

where x_j is the actual value of the jth parameter, and s_j^+ is the optimal value of the jth parameter.

When the parameter is an interval, the following equation is used to calculate DS_j^+.

$$DS_j^+ = \begin{cases} 0, & x \in \left[q_j^l, q_j^u\right] \\ \min\left(\left|x_j - q_j^l\right|, \left|x_j - q_j^u\right|\right), & x \notin \left[q_j^l, q_j^u\right] \end{cases} \tag{18}$$

where q_j^u, q_j^l are the upper and lower bounds of the optimal interval of the jth parameter, respectively.

ii. DS_j^-

In this paper, the control limit of each parameter in the evaluation index system is used as the negative ideal solution. The control limit consists of two values: the upper limit and the lower limit. The corresponding calculation equation is as follows.

$$DS_j^- = \begin{cases} \min\left(\left|x_j - p_j^l\right|, \left|x_j - p_j^u\right|\right), & x \in \left[p_j^l, p_j^u\right] \\ 0, & x \notin \left[p_j^l, p_j^u\right] \end{cases} \tag{19}$$

Finally, the above steps are integrated, and a real-time state assessment method for petrochemical plants based on improved TOPSIS is proposed. The specific process is shown in Figure 1.

The procedures are summarized in detail as follows.

Step 1: Establish the evaluation index system according to the process control indicators and the results of the correlation analysis of different monitoring parameters.

Step 2: Determine the control limit of each parameter in the evaluation index system.

Step 3: Determine the optimal interval of each parameter in the evaluation index system.

Step 4: Determine the positive and negative ideal solutions based on control limits and optimal intervals of each parameter in the evaluation index system.

Step 5: Calculate the objective weight of each parameter in the evaluation index system using information entropy and history data.

Step 6: Define the subjective weight coefficient according to the importance of each parameter in the evaluation index system.

Step 7: Calculate the combined weight of each parameter in the evaluation index system using the entropy method and subjective weight coefficient.

Step 8: Calculate the health index according to the positive ideal solution, the negative ideal solution, combined weight, and real-time data.

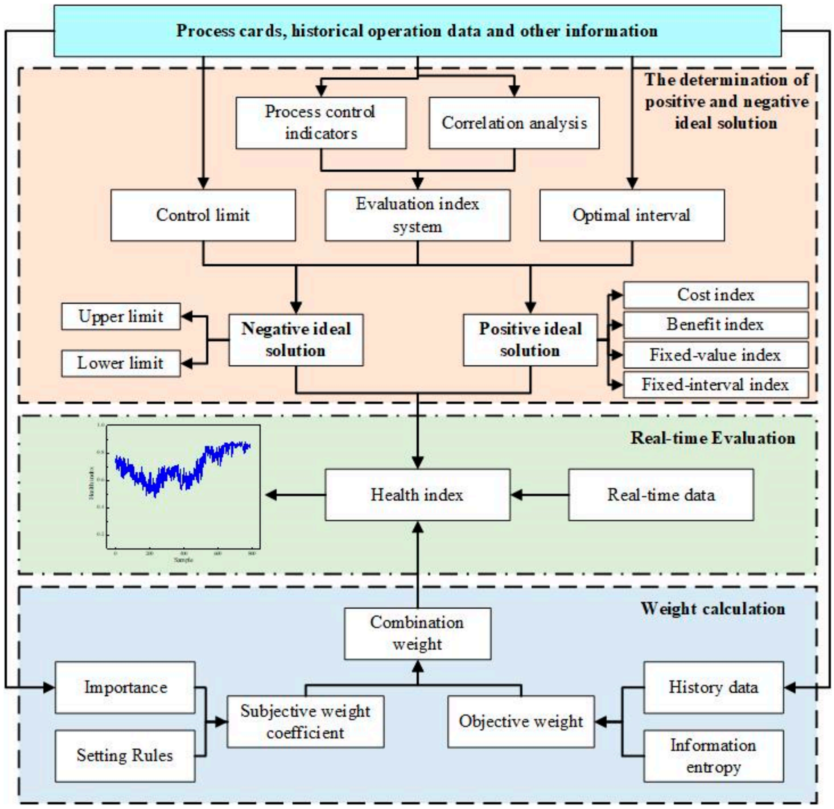

Figure 1. Real-time state evaluation process of petrochemical plant based on improved TOPSIS.

3. Application

3.1. Background

The FCC unit is the most critical secondary processing unit in an oil-refining unit, and it is also the most common unit for the production of gasoline, diesel, liquefied gas, and other light oil products [31]. In order to verify the effectiveness of the method proposed in this paper, the improved TOPSIS is employed to evaluate the status of a Reaction and Regeneration System in an FCC unit.

The data used were taken from a 2.6-million-ton catalytic cracking unit from a refining company in North China, which adopted the maximizing iso-paraffins (MIP) process. The feedstock is 37% tail oil of vacuum residue desulfurizer (VRDS) and 63% hydrogenated gas oil. The DCS employs the Experion PKS300 produced by Honeywell, and its measurement points for the Reaction and Regeneration System exceed 270, as shown in Figure 2.

Taking this abnormal case of a 2.6-million-ton catalytic cracking unit examined in November 2020 as an example for analysis, abnormal operating conditions were defined as yellow smoke and oil leakage from the E201A head of a raw oil slurry heat exchanger. The amount of oil slurry circulation fluctuated greatly. The specific disposal process is as follows: reduce raw materials with water in the tank farm; operate the plant at a low load; contact the tank farm for dehydration; change the regeneration slide valve to manual control; and resume normal production after the abnormality is eliminated.

In this case, the trends of the monitoring parameters are significantly different due to different correlations with the anomalous source, i.e., E201A. The trends of four important monitoring parameters are shown in Figure 3. PIC1001 and PIC1055 show significant fluctuations, while TIC1001 and TIC1005 are relatively stable. On the other hand, a timely intervention to maintain stability must occur when TIC1001 and TIC1005 fluctuate; otherwise, this may lead to unacceptable product quality.

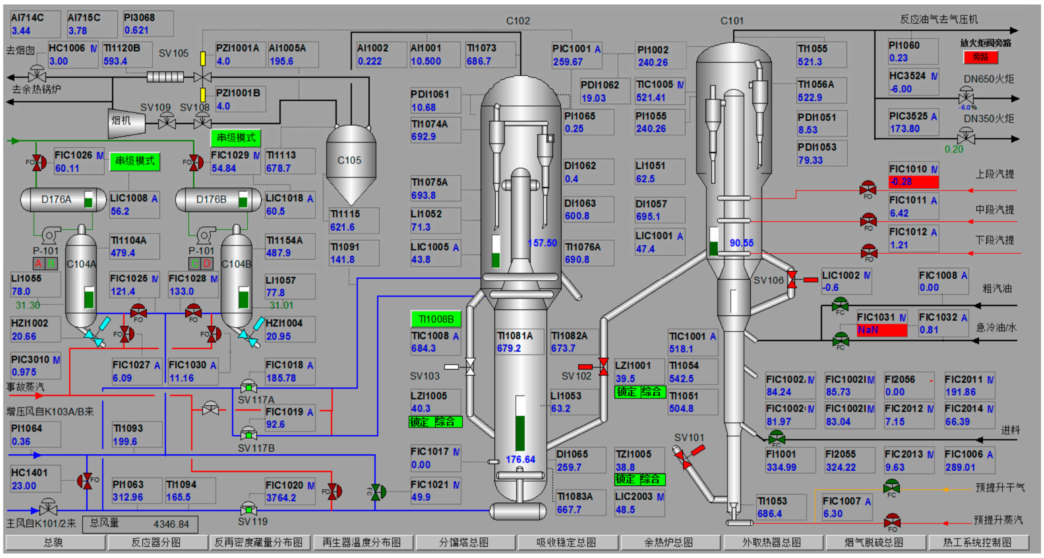

Figure 2. Distribution of DCS measuring points in the Reaction and Regeneration System of an FCC unit.

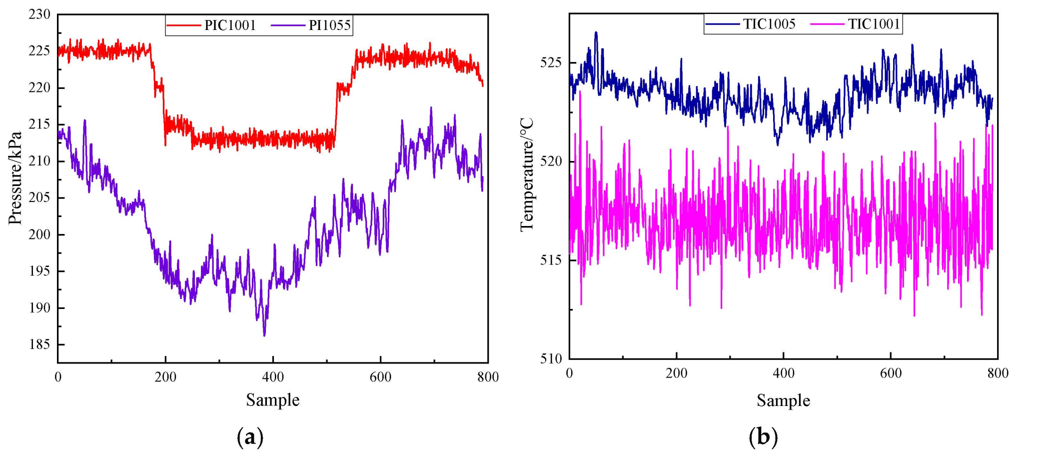

Figure 3. The trends of some important monitoring parameters. (**a**) The trends of PIC1001 and PI1055. (**b**) The trends of TIC1001 and TIC1005.

3.2. Results and Discussion

There are a total of 14 process control indicators in the process card of the Reaction and Regeneration System, and it involves five categories, including oxygen content (1), loose air flow (2), catalyst storage (2), pressure (2), and temperature (7). Meanwhile, seven experts, including three operators, two maintenance technicians, and two site supervisors, were invited to determine the optimal operation intervals of the monitoring parameters. The seven experts had worked with the catalytic cracking unit for more than 8 years. Then, the optimal operation intervals and operation control limits of the above 14 indicators were determined based on the process card and expert experience. Important information on the 14 process control indicators in the process card of the Reaction and Regeneration System, including tag number, unit, etc., is shown in Table 1. Furthermore, the positive and negative ideal solutions can be observed in Table 1.

Table 1. Important information on the 14 process control indicators in the process card of the Reaction and Regeneration System.

No.	Tag Number	Unit	Control Limit	Optimal Interval	Type
1	AI1001	%	1~7	2–4	Fixed-interval index
2	FIC1018	m^3/min	100~200	180	Fixed-value index
3	FIC1019	m^3/min	30~100	80	Fixed-value index
4	LIC1001	t	40~110	85	Fixed-value index
5	LIC1005	t	120~200	150	Fixed-value index
6	PI1055	kPa	190~270	210–250	Fixed-interval index
7	PIC1001	kPa	220~285	230–270	Fixed-interval index
8	TI1079A	°C	660~720	695–700	Fixed-interval index
9	TI1079B	°C	660~720	695–700	Fixed-interval index
10	TI1079C	°C	660~720	695–700	Fixed-interval index
11	TI1079D	°C	660~720	695–700	Fixed-interval index
12	TIC1001	°C	500~530	518	Fixed-value index
13	TIC1005	°C	500~530	526	Fixed-value index
14	TIC1008	°C	660~720	685	Fixed-value index

According to the distribution of the DCS measurement points, the four temperature-monitoring parameters (TI1079A, TI1079B, TI1079C, and TI1079D) are the same temperature at different measuring points of the second dense bed. Moreover, the Pearson correlation coefficients between the four parameters all exceed 0.99, indicating that they have strong correlations. Therefore, only one temperature-monitoring parameter of the second dense bed (TI1079A) was reserved in the state evaluation index system, which contains a total of eleven monitoring parameters.

Then, the objective and subjective weights were calculated. A total of 1000 historical datapoints were inversely transformed to calculate the information entropy of each parameter, and the objective weight of each parameter can be obtained by referencing Equation (13). For subjective weight, the process card has divided the monitoring parameters' importance into three levels: general, important, and emergency. Among them, four parameters, including AI1001, FIC1018, FIC1019, and TI1079A, correspond to the general level; four parameters, including LIC1001, LIC1005, TIC1005, and TIC1008, correspond to the important level; and three parameters, including PI1055, PIC1001, and TIC1001, correspond to the emergency level. Then, the subjective weight coefficients of the three levels of emergency, important, and general were set to 1.5, 1.2, and 1.0. In summary, the combined weight of each parameter can be calculated as shown in Equation (15), as shown in Figure 4.

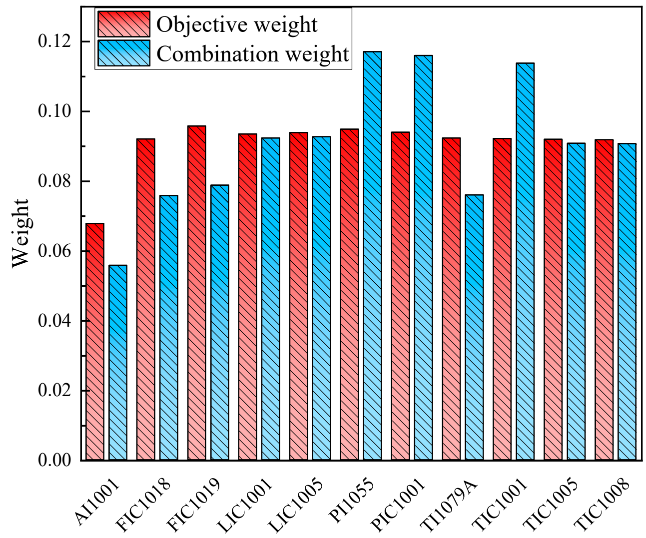

Figure 4. A comparison of objective weight and combined weight.

According to the positive and negative ideal solutions and parameter types in Table 1 combined with the distance calculation equations of the fixed-value type and fixed-interval type given in Section 2.2, the health index of the Reaction and Regeneration System can be obtained by inputting monitoring data. The health indices in two cases of equal weight and combined weight were calculated, respectively. The equal weight is determined by dividing the weights of the 11 monitoring parameters equally; that is, their weights are all taken to be 0.091. Figure 5 shows the trend of the health index under the two weights.

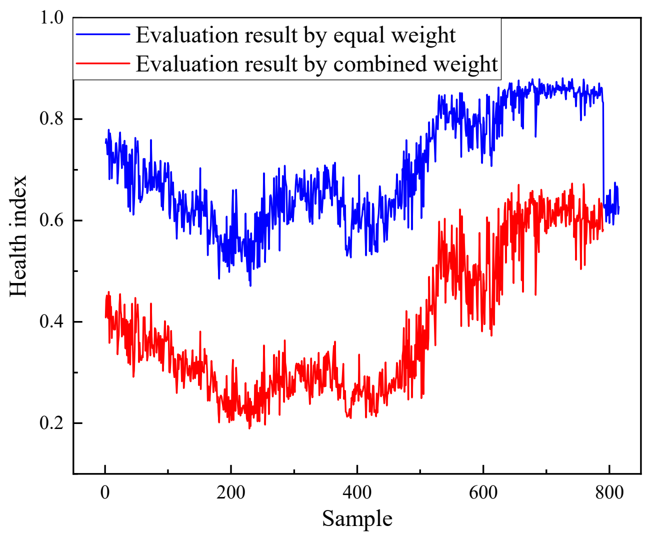

Figure 5. The health index determined according to equal weight and combined weight.

It can be seen from Figure 5 that the trends of the health index obtained using equal weight evaluation and combined weight evaluation are consistent. In addition, in combination with Figure 3, the trends in the health index and key parameter PI1055 are the same. In the initial stage of the anomaly, no disposal measures were taken, as an anomaly was not detected. So, the parameters that were strongly correlated with anomaly sources continued to deteriorate, such as PI1055 and PIC1001. Specifically, the first 210 pieces of PI1055 continued to decline, and the health index obtained using the two weights also declined. Then, field operators reduced the load to avoid a worse situation before eliminating the anomaly. During this period, the unit operated in a stable state with slight abnormalities. In addition, the monitoring parameters, i.e., the health indices under two weights, also showed a stable trend. Once the 400th datapoint had been obtained, the anomaly gradually began to weaken after measurements were taken, while PI1055 and the health indices gradually began to improve. When the 620th datapoint was obtained, the anomaly disappeared, while the monitoring parameters and health indices returned to normal. The above process is consistent with the status record of this anomaly, proving that the evaluation results can reflect the operating trends of petrochemical plants.

Furthermore, in the equal weight evaluation, since the 11 evaluation parameters had the same weights, the larger fluctuations in PI1055 and PIC1001 were masked by normal fluctuations of the other parameters. In the combined weight evaluation, PI1055 and PIC1001 were given greater weights, which caused their larger fluctuations to have a greater impact on the health index than the normal fluctuations of the other parameters. Therefore, the health index obtained through equal weight evaluation was larger than that from the combined weight evaluation, and its variation range was relatively small. Moreover, after field operators reduced the load to avoid a worse situation, the health index calculated using the equal weight evaluation method dropped to around 0.6, while the health index calculated using the combined weight evaluation method fell to around 0.3. However, the low load is an emergency measure for abnormal working conditions, which should correspond to an abnormal operating state. Clearly, the result of the combined weight evaluation is more accurate with respect to reflecting the actual status of the Reaction and Regeneration System.

4. Conclusions

The long-term stable operation of petrochemical plants has resulted in limited information contained in historical data, which has posed more challenges for data-driven state evaluation methods. Therefore, this paper proposes a real-time state evaluation method for applications to petrochemical plants based on TOPSIS, which can be used to construct a state evaluation model without historical data. Compared with previous methods, the advantages of this method are as follows: (1) The positive and negative ideal solutions are determined using expert experience and the process index control limits of the process card. Historical data on the optimal and worst operating states are no longer required. (2) The method offers fixed-value and fixed-interval indices, which can be used to deal with the interval-optimal parameters of petrochemical plants, such as reaction temperature, reaction pressure, etc. (3) This method provides a new combined weight using the entropy method and subjective weight coefficient. Finally, the above steps are integrated to form a state evaluation method based on an improved version of TOPSIS. In addition, a state evaluation study was conducted in an actual abnormal case of an FCC unit. The results show that the method proposed in the paper can accurately quantify the operating status of the FCC unit, which is consistent with the trend of the crucial parameters. Although this paper presents a method for the state evaluation of petrochemical plants, there is a lack of research on abnormal causes. In future work, efforts will be focused on proposing diagnosis methods to identify the source of anomalies. This can help operators handle anomalies on time by providing causes.

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