Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 8497299, 15 pages
https://doi.org/10.1155/2022/8497299

Research Article

Fault Diagnosis Method and Application of ESP Well Based on SPC Rules and Real-Time Data Fusion

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Received 9 January 2022; Revised 24 May 2022; Accepted 15 June 2022; Published 6 July 2022

Academic Editor: Jiafu Su

Aiming at the popularization and application of a real-time monitoring parameter acquisition system of the electric submersible pump (ESP) well, this paper proposes a fault diagnosis method of ESP well operation based on the SPC rule and prior knowledge fusion. Based on the study of parameter variation rules of ESP well, the SPC expansion rule model is established; by analyzing the variation of some typical characteristic parameters of ESP well, combined with SPC expansion rules and expert experience, a priori knowledge of fault diagnosis of ESP well is formed, that is, multiparameter fault analysis table and weight factor; the SPC extended rule model and prior knowledge are fused to establish the fault probability model of ESP well, form the fault diagnosis method of ESP well, develop the online fault diagnosis software of ESP well, and deploy it in 425 ESP wells in a block. Taking five types of tubing leakage, pump wear, shaft breakage, gas influence, and pump plugging as examples, the application process of fault diagnosis method is analyzed. The research and application show that compared with other fault diagnosis methods, this method needs a smaller time window and higher diagnosis accuracy. By setting multiple time windows, this diagnosis method is applied to calculate the fault probability of ESP well in real time, solve the real time and accurate identification of 14 sudden faults and gradual faults, and significantly improve the intelligent diagnosis level of production faults of ESP well.

1. Introduction

Artificial lift is used in 95% of oil wells worldwide. Among them, there are about 130,000 ESP lifting wells, second only to pumping unit rod pump wells. ESP oil wells lift the most liquid volume, and their annual crude oil output accounts for about 60% of the world's total oil volume, and ESP accounts for 43% of the global annual artificial lifting costs [1, 2]. The performance and service life of ESP in service in oilfields are affected by many problems, such as complex wellbore, high temperature, high pressure, high viscosity fluids, high gas-liquid ratio fluids, sand production, and waxing, which lead to shaft breakage in ESP well, tubing leakage, pump plugging, pump wear, gas influence, pump reverse, and tubing plugged. The fault of the ESP not only increases the maintenance cost of the oil well inspection pump operation but also indirectly affects the oil well production due to factors such as the shutdown of the operation and the reduction in the recovery period after the operation, and the loss of economic benefits increases. In order to ensure the smooth operation of ESP well, it is necessary to select a scientific and reasonable method for early fault diagnosis of ESP well.

At present, the fault diagnosis methods of ESP wells are divided into single-parameter diagnosis and multiparameter diagnosis. Among them, single-parameter diagnosis refers to monitoring the change law of a single parameter for fault diagnosis, mainly including the current card diagnosis method and holding pressure diagnosis method. The current card method was first proposed by Powers [3]. The paper analyzes the reasons for the formation of the typical characteristics of the current card in detail and provides a theoretical basis for the fault diagnosis of the current card. Initially, engineers and managers used manual identification of current cards to diagnose the faults of ESP wells, but the real time and accuracy were poor [4]. With the continuous development of neural networks, a large number of experts and scholars have begun to study the use of neural networks for current card recognition [5, 6]. It avoids the different interpretation results of the same ammeter card due to differences in personal knowledge and experience during manual identification. The pressure holding diagnosis method is based on the pressure holding by quickly closing the wellhead back pressure valve under the normal operation and shutdown state of the ESP well, recording the relationship between the wellhead tubing pressure and time during the entire holding pressure process, and drawing the holding pressure curve. And then, the fault of the ESP is analyzed according to the form and characteristic value reflected by the curve. For example, Zheng et al. [7] conducted a theoretical analysis of the relationship between the holding pressure value and time of the ESP well based on the working principle of the ESP and the theory of seepage mechanics, established a mathematical model of the holding pressure curve of ESP wells, and drawn typical holding pressure characteristic curves under different working conditions. Gu et al. [8] established the theoretical pressure holding curve model by analyzing the gas-liquid flow state in the wellbore before holding pressure, combined the characteristic curve of the ESP and the inflow performance curve of the oil well, and determined the extraction method of the characteristic parameters of the curve. Judge the fault type by comparing it with the characteristic parameters of the actual pressure holding curve. Single-parameter diagnosis only uses one parameter of pressure or current, which can diagnose fewer types of faults, and the accuracy of the diagnosis results is poor.

Multiparameter diagnosis refers to the simultaneous monitoring of the changing laws of multiple parameters to perform fault diagnosis together. In recent years, with the widespread application of the Internet of Things in oilfields, more and more real-time data from wellhead and downhole of ESP wells can be collected on the oilfield site, providing a data basis for the multiparameter diagnosis of ESP. Multiparameter diagnosis mainly includes threshold diagnosis method, comprehensive parameter diagnosis method, and expert system diagnosis method. The threshold diagnosis method is to diagnose the fault by setting the variation range of multiple parameters under different fault conditions and judging whether the variation range of the parameter exceeds the set threshold. There are two common threshold diagnosis methods: direct threshold method, which sets different thresholds for production parameters [9]; the indirect threshold method extracts the characteristic values of production parameters and sets different thresholds for them, such as expected value, average value, variance, and other characteristics [10-11]. The comprehensive parameter diagnosis method uses artificial intelligence algorithms to analyze multiple real-time monitoring parameters and obtain the diagnosis results. For example, Al-Jasmi et al. and Bermudez et al. [12, 13] established fault diagnosis models for ESP wells based on fuzzy logic algorithms, fault trend tables, and weighting factors. They realized the diagnosis of five types of faults for ESP wells. Patri et al. [14] used the time series shapelets method to analyze the shape changes of the collected historical data according to the pump intake pressure, current value, and voltage value measured by the multisensor measurement of the ESP well and judge whether a fault occurred. Barrios et al. [15] selected pump intake pressure, pump discharge pressure, flow, torque, pump intake temperature, and pump discharge temperature as characteristic values and used two decision tree classification algorithms to establish a fault diagnosis model. Diagnose the fault of oil nozzle closure, pump intake pressure increase, fluid viscosity increase, and gas influence during the operation of the multistage centrifugal pump. The expert system is an intelligent computer program system that contains a large amount of knowledge and experience at the level of experts in a certain field; that is, it can use the knowledge and expert experience of the oil and gas industry to deal with complex problems in the field of artificial lift fault diagnosis [16]. There are some expert systems for fault diagnosis of ESP, such as the ForeSite system of Weatherford, Schlumberger's Avocet system, and Halliburton's Voice of the Oilfield™ system, and an ESP fuzzy expert diagnosis system based on membership functions and fuzzy rules developed by Grassian et al. [17]. Although multiparameter diagnosis improves the accuracy of diagnosis, there are still some problems: the threshold diagnosis method is difficult to set a unified threshold for different faults to satisfy all oil wells in the same oil field. In addition, the thresholds of production parameters under different faults are different in different production stages of the same oil well; the comprehensive parameter diagnosis method can diagnose fewer types of faults; the expert system diagnosis method lacks self-learning ability for knowledge and examples, and it is difficult to realize the effective update iteration of the diagnosis model [18].

Statistical process control (SPC) technology refers to the analysis and real-time monitoring of products based on statistical analysis technology and control chart, early warning of abnormal trends in the production process, and scientifically distinguishing the change trend of real-time operation parameters [19]. In recent years, with the continuous rise of intersection, integration, and penetration between different disciplines [20], SPC technology has been gradually applied to fault diagnosis in the oil and gas industry. Mejía and Gutiérrez [21] proposed an architecture of online monitoring, acquisition, transmission, storage, and data processing based on SPC technology, which can detect and diagnose the ESP lift well in real time and accurately. Zheng et al. [22] carried out the research on the production fault diagnosis technology of water injection wells based on SPC rules and real-time data fusion. Based on the established SPC expansion rules, multiparameter rule fault chart, and weight factor table, the fault diagnosis model of water injection wells was established, and the real time and accurate diagnosis of 13 working conditions of water injection wells were realized. To sum up, the fault diagnosis based on SPC technology can solve the problems of real time and accuracy in the fault process and provides a new research idea for the fault diagnosis of ESP well.

In view of the above problems, this paper proposes a production fault diagnosis method of ESP well based on SPC expansion rules and real-time data fusion, establishes the fault diagnosis model of ESP well, and establishes the fault diagnosis system of ESP well. The field application shows that the diagnosis system can diagnose the fault of ESP well in real time and accurately. It has important practical significance for guiding field production, reducing the number of faults, prolonging the pump inspection cycle, reducing oil production cost, and improving the economic benefits of oilfield development. It also provides a new reference for fault diagnosis of other lifting wells.

2. Models and Methods

The production monitoring system for ESP wells includes two parts, the surface and the underground, as shown in Figure 1. Sensors, flow meters, and power supply systems are installed on the ground, which can measure parameters such as frequency (Fr), voltage (V), motor current (MC), wellhead temperature (WT), and flow (F). In the underground part, the multifunction sensor is installed under the motor and is in line with the completion tool. Different sensors can be selected to obtain different parameters, which can measure the pump discharge pressure (POP), pump intake pressure (PIP), pump intake temperature (PIT), motor temperature (MT), tubing pressure (TP), pressure difference (PD), and other parameters. The ESP production monitoring system can monitor the dynamics of downhole motors, pumps, and wells in real time and provide a data basis for fault diagnosis by obtaining accurate data in real time.

At present, the fault diagnosis based on SPC has made great progress, but the fault diagnosis method of SPC is only data to data, and the accuracy of diagnosis results is low. Therefore, this study proposes a fault diagnosis method based on the fusion of prior knowledge and SPC; that is, the multiparameter rule chart and weight factor of the electric pump well are used as prior knowledge to improve the accuracy of the diagnosis model.

The fault diagnosis process of ESP well in this study is shown in Figure 2 (in the figure, i represents the monitoring parameter, and j represents the fault type), which is mainly divided into four processes: (1) input the monitoring parameters into the established SPC expansion rule model, and output the monitoring parameter change rate a_i; (2) establish a priori knowledge model, that is, multiparameter fault analysis table B_{ij} and weight factor C_{ij} of ESP well; (3) use multiparameter analysis table, monitoring parameter change rate, and weighting factor to establish fault diagnosis model; (4) input the parameter change rate into the fault diagnosis model, and output the probability W_j of each working condition. The greater the probability value, the greater the possibility of such a working condition.

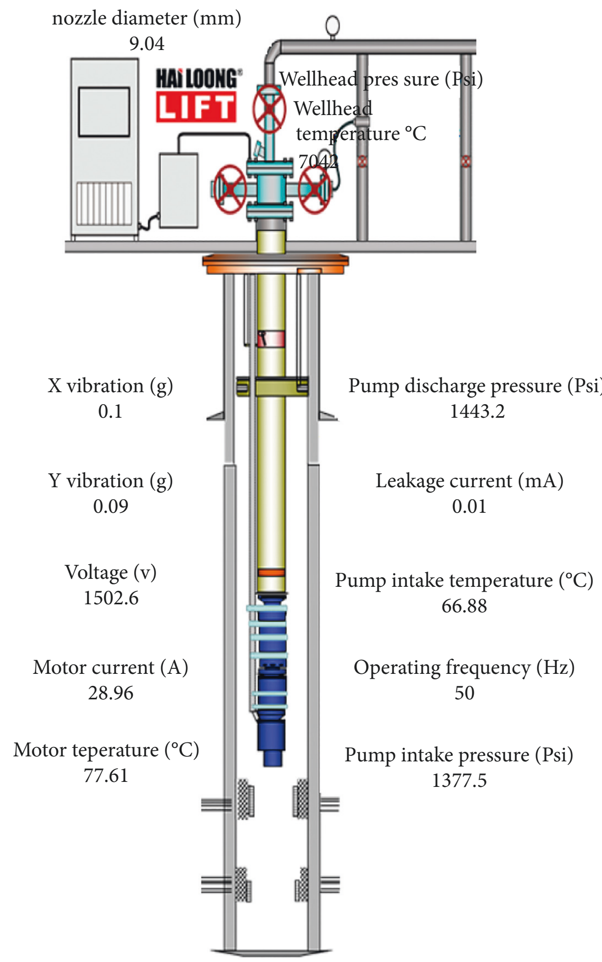

Figure 1: ESP well monitoring system.

2.1. SPC Extended Rule Model. The traditional SPC technology is based on the assumption that the process quality characteristics obey the normal distribution and are constructed according to the 3 σ principle to record the quality of the production process. The sampling interval (h) and sampling interval (n) in the monitoring process are fixed, and the control limit coefficient is set to constant 3. It is assumed that a process quality characteristic X follows a normal distribution; that is,

$$X \sim N\left(\mu_0, \sigma^2\right), \tag{1}$$

where μ is the mean of X and σ^2 is the variance of X.

Under the condition of equal sample size n, according to the principle of 3 σ, there are

$$P\left(\mu_0 - \frac{3\sigma}{\sqrt{n}} < \overline{x} < \mu_0 + \frac{3\sigma}{\sqrt{n}}\right) = 0.9973. \tag{2}$$

Under the condition of the reasonable control of process mean, the probability of sample mean falling into $(\mu_0 - (3\sigma/\sqrt{n}), \mu_0 + (3\sigma/\sqrt{n}))$ is 99.73%. Therefore, the traditional measurement mean control chart divides it into the controlled area and out of control area by control upper limit (UCL), control lower limit (LCL), and control center limit (CL), in which

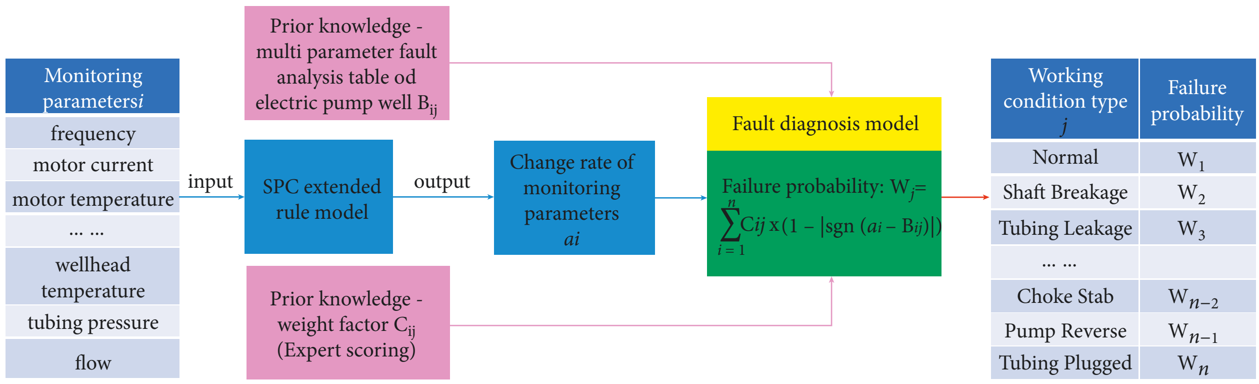

Figure 2: Working condition diagnosis process based on the fusion of prior knowledge and SPC.

$$\begin{cases} LCL = \mu_0 - \dfrac{3\sigma}{\sqrt{n}}, \\ CL = \mu_0, \\ UCL = \mu_0 + \dfrac{3\sigma}{\sqrt{n}}. \end{cases} \tag{3}$$

The control limit coefficient of the traditional measurement mean control chart is completely determined according to practical experience, so it is difficult to ensure the scientificity of decision-making. Therefore, scholars take the control limit coefficient K as the decision variable to optimize the economy and statistics of the control chart. The control upper limit (UCL), control lower limit (LCL), and control center limit (CL) of the control chart are set as follows:

$$\begin{cases} LCL = \mu_0 - \dfrac{k\sigma}{\sqrt{n}}, \\ CL = \mu_0, \\ UCL = \mu_0 + \dfrac{k\sigma}{\sqrt{n}}. \end{cases} \tag{4}$$

The conventional SPC control diagram in the national standard is shown in Figure 3, making $k = \sqrt{n}$. In the figure, the center line CL $= u_i$; the value range of area A above the center line CL: $u_i \sim u_i + \sigma_i$; the value range of area B above the center line CL: $u_i + \sigma_i \sim u_i + 2\sigma_i$; the numerical range of C zone above the center line CL: $u_i + 2\sigma_i \sim u_i + 3\sigma_i$; the numerical range of A area under the center line CL: $u_i \sim u_i - \sigma_i$; the numerical range of zone B under the center line CL: $u_i - \sigma_i \sim u_i - 2\sigma_i$; the numerical range of C zone under the center line CL: $u_i - 2\sigma_i \sim u_i - 3\sigma_i$. Among them, i is a certain real-time monitoring parameter collected by the ESP well; u_i is the mean value of the real-time monitoring parameter i of the ESP well; σ_i is the standard deviation of the real-time monitoring parameter i of the ESP well.

The standard SPC criterion is the eight commonly used discrimination criteria in the national standard GB/T4901-2001 conventional control chart, see Table 1 for details.

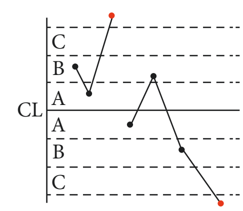

Figure 3: Conventional SPC control diagram.

When the SPC criterion is applied to the fault diagnosis of ESP well, it is hoped that it cannot only distinguish the abnormalities of monitoring parameters but also describe the change trend of parameters. Therefore, the standard SPC is expanded into 13 criteria and 5 types of trend characteristics (fluctuation, rise, sudden increase, drop, and sudden drop), forming extended SPC rules, see Table 2 for details. The meaning of each area in the table is the same as that in Table 1.

According to the extended SPC rule table, 15 data points are specified for each diagnosis.

2.2. Prior Knowledge—Multiparameter Fault Analysis Table. Through the analysis of the characteristic parameter changes of some typical working conditions of ESP wells, combined with the fault diagnosis investigation of domestic and foreign oil fields and oil companies, the trend of wellhead and downhole monitoring parameters of 14 typical working conditions of ESP wells is analyzed and counted. We have constructed a multiparameter fault analysis table for ESP well faults, as shown in Table 3.

Among them, 0 means fluctuation; 1 means rise; 2 means sudden increase; −1 means decline; −2 means sudden decline.

2.3. Working Condition Diagnosis Method. The working condition diagnosis process of ESP well is as follows.

2.3.1. Standardization of Time Window Monitoring Data. It is known from Table 3 that 15 points of the constructed SPC expansion rule model are used for a trend judgment. In practical applications, the number of data points in the

Table 1: Standard SPC eight different criteria.

SPC guidelines	Specific rules
Guideline 1	1 point falls outside of zone *A*
Guideline 2	9 consecutive points fall on the same side of the center line CL
Guideline 3	6 consecutive points have the same change trend
Guideline 4	Adjacent points in consecutive 14 points alternate up and down
Guideline 5	2 out of 3 consecutive points fall outside of zone *B* on the same side of the center line CL
Guideline 6	4 out of 5 consecutive points fall outside the *C* zone on the same side of the center line CL
Guideline 7	15 consecutive points fall within the *C* area on both sides of the center line CL
Guideline 8	8 consecutive points fall on both sides of the center line *C*, and none of them are in the *C* zone

Table 2: Extended SPC rules.

Serial number	SPC guidelines	Trend characteristics	Specific rule
1	Guideline 1	Sudden increase	A point falls on the center line CL and outside of zone *A*
2	Guideline 2	Sudden drop	A point falls below the center line CL and outside of zone *A*
3	Guideline 3	Rise	9 consecutive points fall outside of zone *B* above the center line CL
4	Guideline 4	Decline	9 consecutive points fall outside of zone *B* below the center line CL
5	Guideline 5	Rise	6 consecutive points increase, and the last point is outside of zone *A*
6	Guideline 6	Decline	6 consecutive points decrease, and the last point is outside zone *A*
7	Guideline 7	Fluctuation	Adjacent points in consecutive 14 points alternate up and down, and the difference between the maximum value and the minimum value is greater than 3 times the standard deviation
8	Guideline 8	Fluctuation	2 out of 3 consecutive points fall outside of zone *B* above the center line CL
9	Guideline 9	Fluctuation	2 out of 3 consecutive points fall outside of zone *B* below the center line CL
10	Guideline10	Rise	4 out of 5 consecutive points fall outside the *C* area above the center line CL
11	Guideline11	Decline	4 out of 5 consecutive points fall outside the *C* area below the center line CL
12	Guideline12	Fluctuation	15 consecutive points fall within the *C* area on both sides of the center line CL
13	Guideline13	Fluctuation	8 consecutive points fall on both sides of the center line CL and are not in the *C* zone

Table 3: Multiparameter fault analysis table of ESP well.

Working condition type	Fr	MC	MT	V	PIP	POP	PD	PIT	WT	TP	F
Normal	0	0	0	0	0	0	0	0	0	0	0
Shaft breakage	0	−2	1	0	1	−1	−2	1	−1	−1	−1
Tubing leakage	0	0	1	−1	1	−1	−1	1	−1	−1	−1
Pump plugging	0	−1	1	0	1	−1	−1	1	0	−1	−1
Perforation plugging	0	−1	1	0	−1	−1	1	1	0	−1	−1
Water-cut rise	0	1	0	0	1	1	1	1	0	−1	−1
Wellhead shut-in	0	−2	1	0	2	2	2	1	−1	2	−2
Reservoir pressure increase	0	0	0	0	1	1	−1	1	1	1	1
Gas influence	0	−1	0	−1	1	−1	−1	1	−1	−1	−1
Pump wear	0	−1	1	0	1	−1	−1	1	0	−1	−1
Frequency increase	1	2	2	1	−2	2	2	1	1	2	2
Choke stab	0	0	0	0	−2	−2	−2	−1	0	−2	2
Pump reverse	−1	−1	1	0	1	−1	−1	1	0	−1	−1
Tubing plugged	0	−1	1	0	1	1	−1	1	−1	−1	−1

diagnostic time window may not be equal to 15, and the data must be standardized to 15 points. Therefore, in order to ensure that the number of data points in the time window is equal to 15, this paper proposes the data analysis granularity S formula:

$$\mathrm{S} = \frac{\mathrm{T}}{15t} \times 60, \tag{5}$$

where T—diagnosis time window, min; t—ESP monitoring system parameter collection time interval, s.

Table 4: Trend values a_i of monitoring parameters in the diagnostic time window of ESP wells.

Monitoring parameters i	Parameter 1	Parameter 2	……	Parameter n
Trend a_i	a_1	a_2	……	a_n

2.3.2. Monitoring Parameter Change Rate a_i Calculation. Select the fault diagnosis time window, determine the data analysis granularity S, and calculate the average value of each

Table 5: Weighting factor C_{ij} of 14 working condition types.

Working condition type	Fr	MC	MT	V	PIP	POP	PD	PIT	WT	TP	F
Normal	0	0	0.1	0.1	0.1	0.1	0.1	0	0.1	0.1	0.2
Shaft breakage	0.1	0.05	0.2	0	0.1	0.05	0.05	0.05	0.05	0.2	0.15
Tubing leakage	0.1	0.15	0.1	0.1	0.05	0.05	0.05	0.05	0.05	0.15	0.15
Pump plugging	0.1	0.2	0.05	0.1	0.1	0.05	0.05	0.05	0.1	0.15	0.05
Perforation plugging	0.05	0.1	0.05	0.05	0.15	0.15	0.1	0.1	0.1	0.05	0.1
Water-cut rise	0.05	0.2	0.05	0.05	0.05	0.15	0.05	0.1	0.05	0.1	0.15
Wellhead shut-in	0	0.05	0.05	0.05	0.15	0.2	0.15	0.05	0.15	0.05	0.1
Reservoir pressure increase	0.05	0.05	0.1	0.05	0.15	0.01	0.05	0.15	0.15	0.1	0.05
Gas influence	0.1	0.05	0.1	0.05	0.15	0.15	0.2	0.15	0	0	0.05
Pump wear	0.1	0.2	0.1	0.1	0.05	0.05	0.05	0.1	0.15	0.05	0.05
Frequency increase	0.3	0.05	0.05	0.05	0.1	0.1	0.1	0.05	0	0.1	0.1
Choke stab	0	0.05	0.05	0.05	0.2	0.15	0.2	0.05	0	0.15	0.1
Pump reverse	0.05	0.1	0.15	0.1	0.05	0.15	0.1	0.1	0.05	0.05	0.1
Tubing plugged	0	0.05	0.1	0.05	0.15	0.15	0.1	0.1	0.1	0.1	0.1

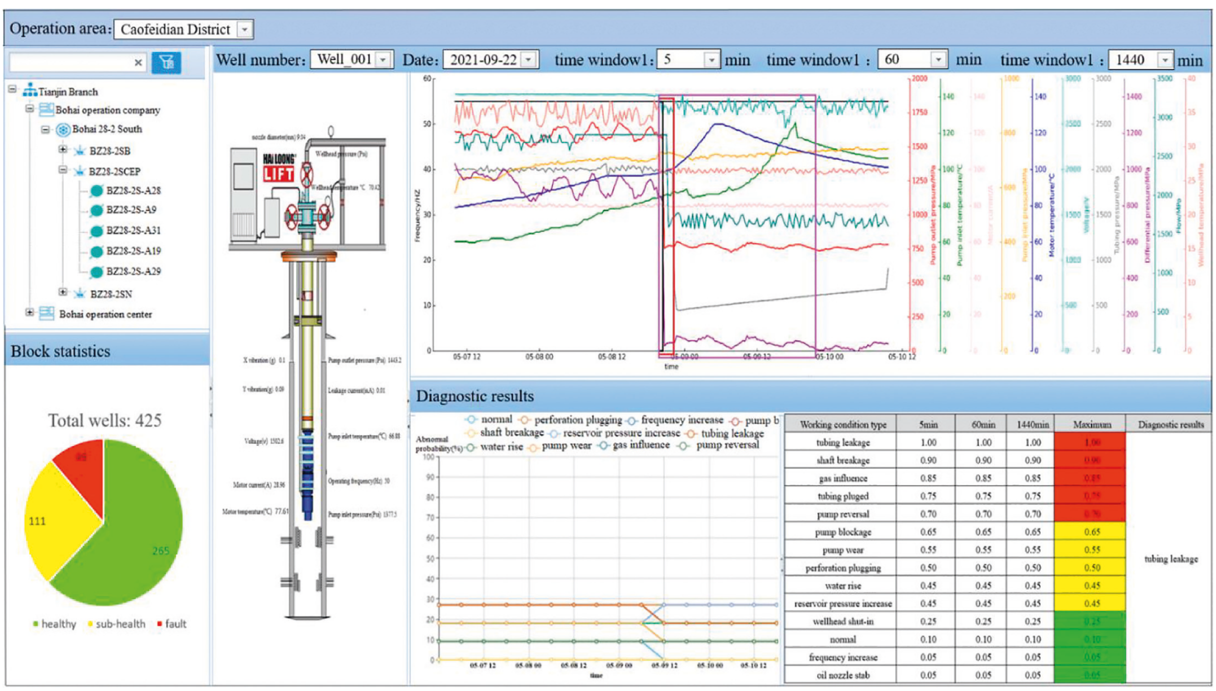

Figure 4: Monitoring interface of ESP well diagnosis system.

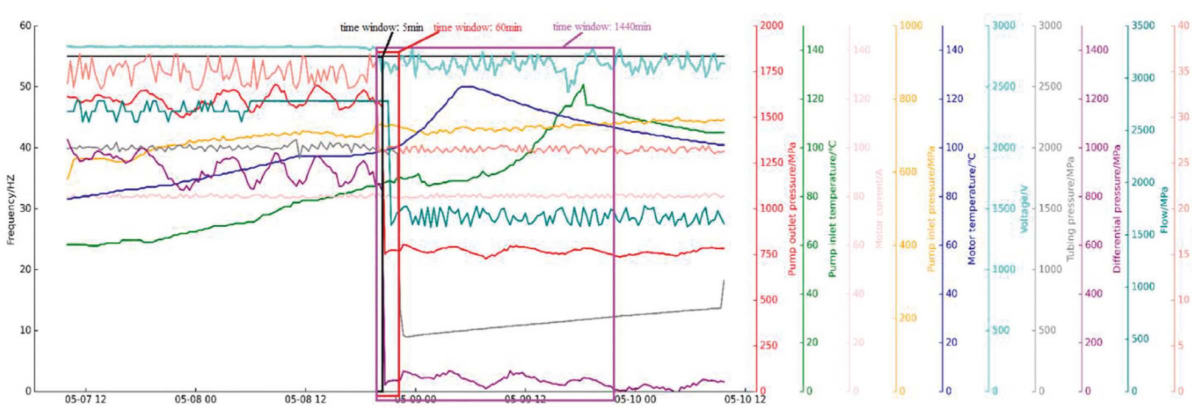

Figure 5: Monitoring parameters of well_001 well.

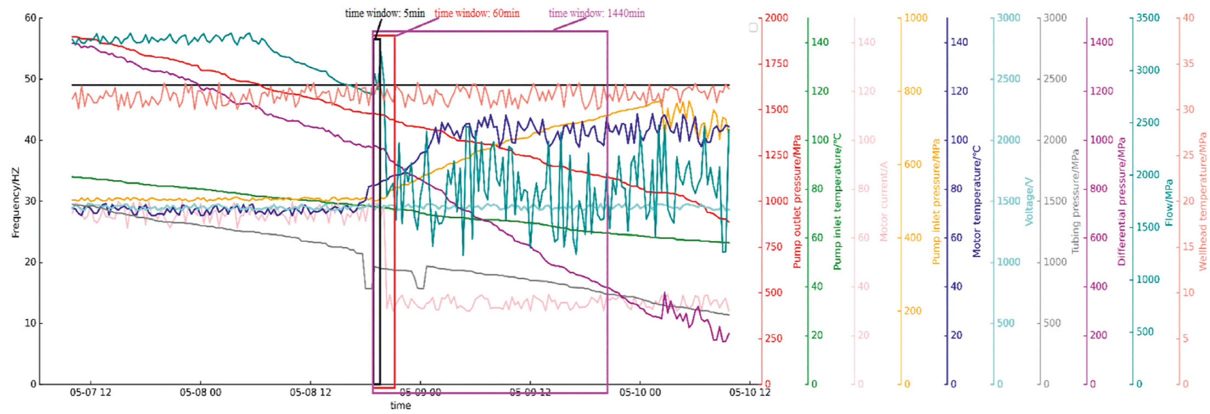

Figure 6: Monitoring parameters of well_002 well.

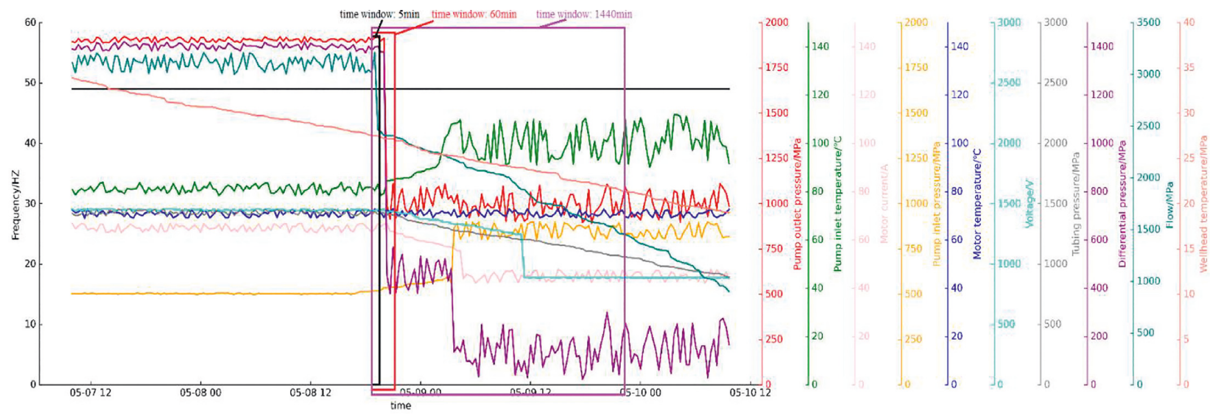

Figure 7: Monitoring parameters of well_003 well.

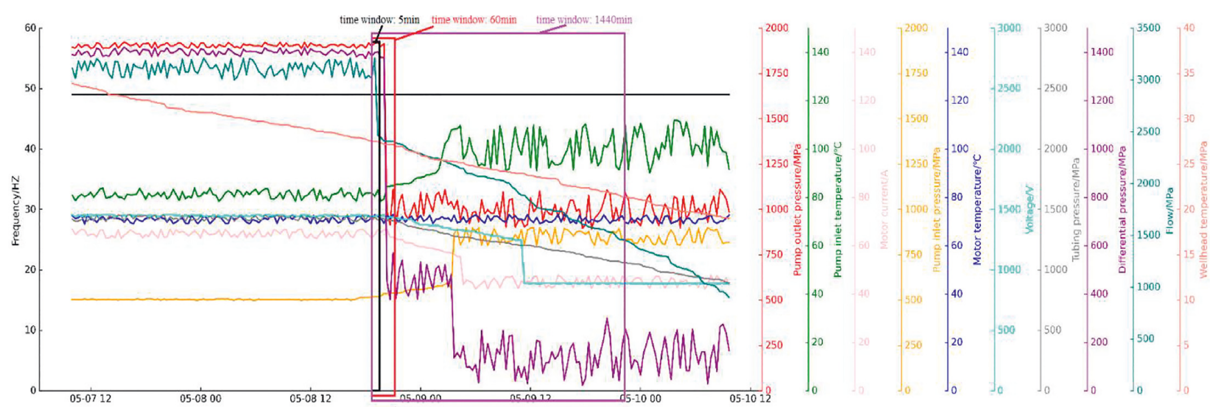

Figure 8: Monitoring parameters of well_004 well.

consecutive S data point as one data point. Use the established SPC expansion rule model to calculate the change trend of each parameter in this time period, and make the change trend of its parameter i a_i (−2, −1, 0, 1, 2). Suppose the change trend of each parameter is shown in Table 4.

2.3.3. Standard Change Trend B_{ij} Calculation. The standard change trend B_{ij} refers to the standard change trend of the parameter when a certain fault occurs, that is, the change trend value of the parameter i corresponding to the fault i in Table 1.

2.3.4. Calculation of Weighting Factor C_{ij}. The weighting factor C_{ij} refers to the contribution value of each parameter to this kind of fault when a certain kind of fault occurs. The cumulative sum of the weighting factors C_{ij} of all parameters under each type of fault is 1. The value of the weight factor C_{ij} is the weight value of the parameter i corresponding to

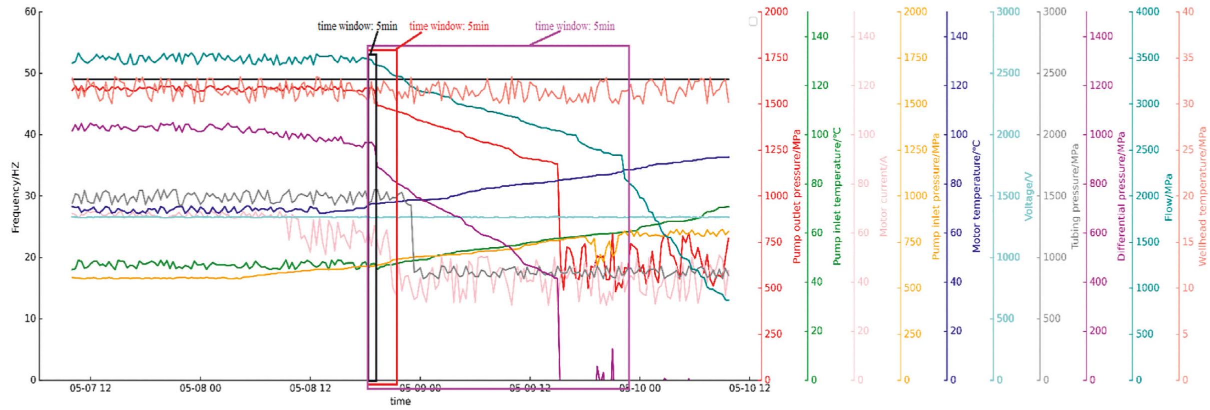

Figure 9: Monitoring parameters of well_005 well.

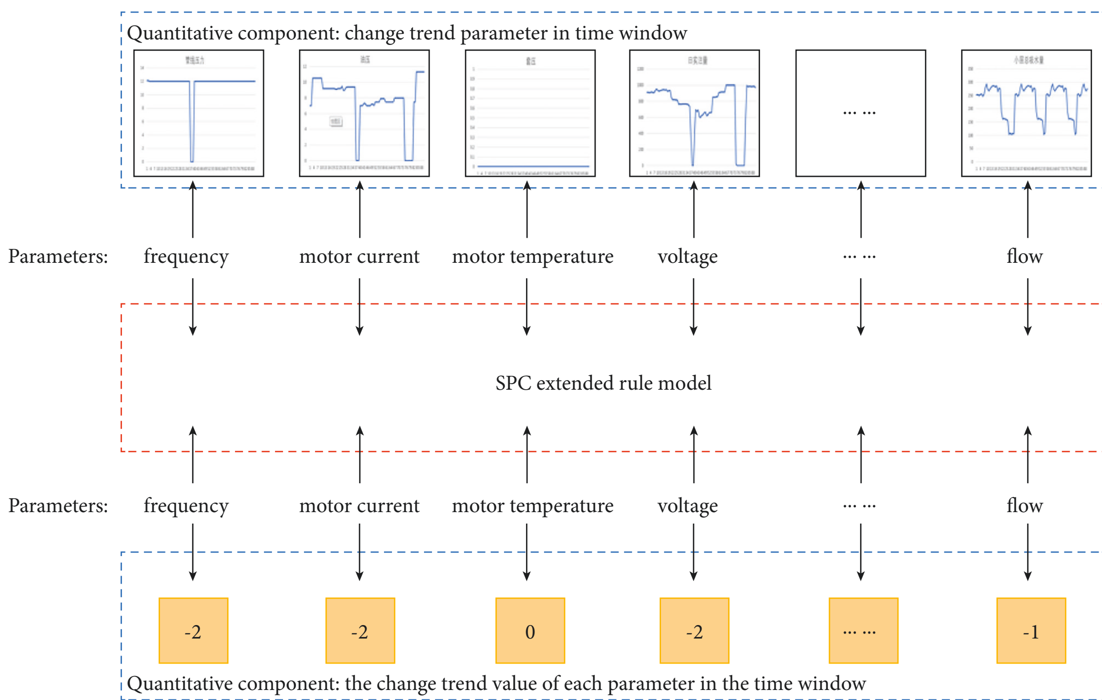

Figure 10: Calculation process of monitoring parameter change rate a_i.

Table 6: Trend changes of different oil wells in different time windows.

Well name	Fr	MC	MT	V	PIP	PDP	PD	PIT	WT	TP	F
Time window: 5 minutes											
well_001	0	−1	1	1	1	1	−1	−1	−1	−1	−1
well_002	0	0	−1	0	0	1	0	−1	0	−1	0
well_003	0	−1	0	−1	−2	1	−1	−2	0	−1	−1
well_004	0	2	1	−2	1	0	1	−1	1	−2	−1
well_005	0	−1	−1	0	0	1	0	−1	1	−1	0
Time window: 60 minutes											
well_001	0	−1	1	0	1	1	−1	−1	−1	−1	−1
well_002	0	0	0	−1	0	1	0	0	−1	0	0
well_003	0	−1	1	−2	1	1	−1	1	−1	−1	−1
well_004	0	−1	1	−1	1	0	−1	−2	−1	−1	−1
well_005	0	1	1	−1	1	1	0	−1	−1	−1	0
Time window: 1440 minutes											
well_001	0	−1	1	0	1	1	−1	−1	−1	−1	−1
well_002	0	−1	−1	−1	1	1	0	−1	−1	−1	0
well_003	0	−1	1	−1	1	1	−1	−1	−1	−1	−1
well_004	0	−1	1	−1	1	0	−1	−1	−1	−1	−1
well_005	0	−1	1	−1	1	1	0	−1	−1	−1	0

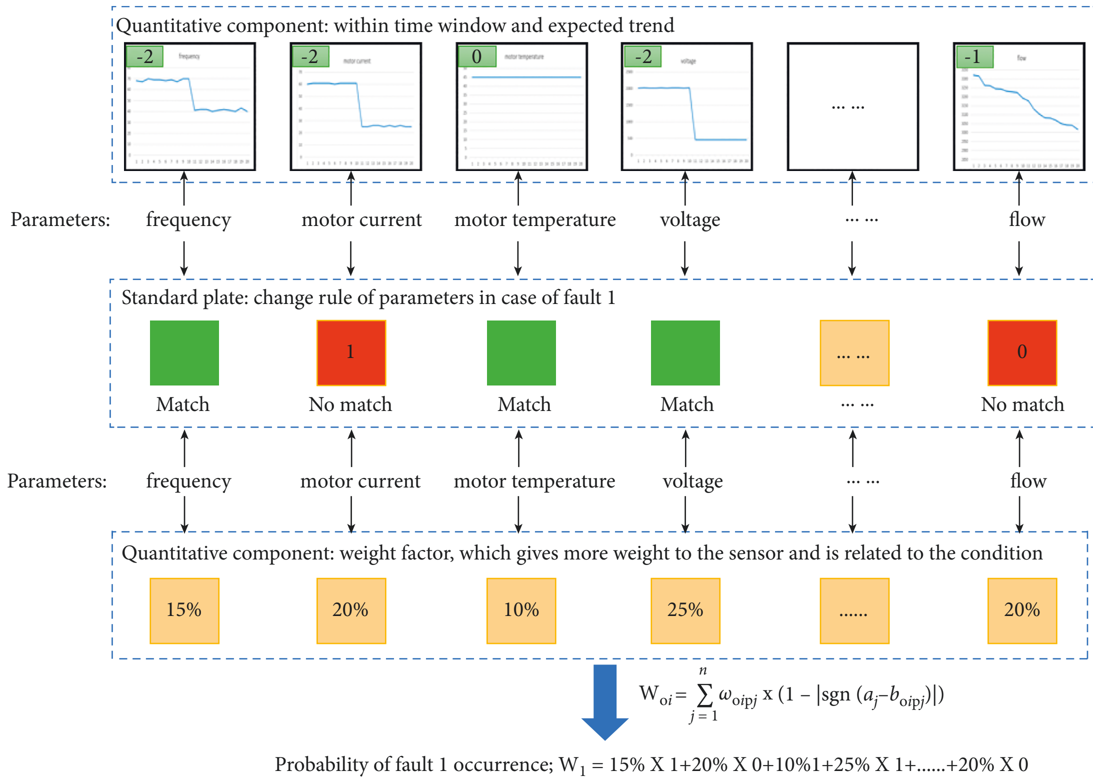

Figure 11: Calculation process of fault probability.

the fault j in Table 5. Table 5 shows the fault weight factors of ESP wells obtained according to expert scores and actual conditions on-site. These factors should be calibrated regularly according to the actual operating conditions of ESP wells.

2.3.5. Calculation of ESP Fault Probability W_j. The probability of fault refers to the probability of a certain fault. That is, to compare a_i with B_{ij} and add the weighting factor C_{ij} in the corresponding Table 5 under equal conditions, its value is the probability of occurrence of working condition j. The calculation formula is as follows:

$$W_j = \sum_{i=1}^{n} C_{ij} \times \left(1 - \left|\mathrm{sgn}\left(a_j - B_{ij}\right)\right|\right), \tag{6}$$

where W_j is the probability of occurrence of fault j, and the larger W_j, the greater the probability of occurrence of fault j; $\mathrm{sgn}\,(x)$ is a symbolic function, and its function expression is as follows:

$$\mathrm{sgn}\,(x) = \begin{cases} = 1 & x > 0 \\ = 0 & x = 0. \\ = -1 & x < 0 \end{cases} \tag{7}$$

3. Case Analysis

Based on the above fault diagnosis methods, the ESP well fault diagnosis system is developed, which has the functions of ESP operation monitoring, working condition diagnosis, fault type statistics, system management, and so on. The software is deployed in 425 wells in a certain block for practical application. The software monitoring interface is shown in Figure 4.

This paper selects the data of five wells from May 7, 2021, to May 10, 2021, as the research object. The data density is collected every 20 seconds. The working conditions of each well are tubing leakage, pump wear, shaft breakage, gas influence, and pump plugging. These five faults will be analyzed in detail as follows.

① Tubing leakage

Tubing leakage is usually caused by a fault of the sealing device, disconnection of the oil drain pin, or serious erosion. Generally, the tubing pressure, flow, and motor current will decrease, which may be accompanied by a decrease in voltage, pump discharge pressure, and wellhead temperature. The parameter changes are shown in Figure 5.

② Pump wear

When the sand content in the oil well is high, the pump wear condition will occur, and generally, the impeller of the pump will be worn. When the impeller is worn, the pump discharge pressure and flow will decrease, which may be accompanied by underload shutdown. The motor temperature, pump inlet pressure, and pump inlet temperature may rise, and the parameter changes are shown in Figure 6.

Table 7: Probability calculation results of working conditions.

Time window (mins)	Working condition type	Probability
Well name: well_001		
5	Normal	0.65
	Shaft breakage	0.70
	Tubing leakage	0.85
	Pump plugging	0.75
	Perforation plugging	0.60
	Water-cut rise	0.25
	Wellhead shut-in	0.10
	Reservoir pressure increase	0.40
	Gas influence	0.35
	Pump wear	0.75
	Frequency increase	0.05
	Choke stab	0.00
	Pump reverse	0.50
	Tubing plugged	0.75
60	Normal	0.50
	Shaft breakage	0.55
	Tubing leakage	0.55
	Pump plugging	0.40
	Perforation plugging	0.40
	Water-cut rise	0.15
	Wellhead shut-in	0.15
	Reservoir pressure increase	0.45
	Gas influence	025
	Pump wear	0.55
	Frequency increase	0.05
	Choke stab	0.05
	Pump reverse	0.70
	Tubing plugged	0.65
1440	Normal	0.60
	Shaft breakage	0.90
	Tubing leakage	1.00
	Pump plugging	0.65
	Perforation plugging	0.50
	Water-cut rise	0.25
	Wellhead shut-in	0.20
	Reservoir pressure increase	0.45
	Gas influence	0.85
	Pump wear	0.55
	Frequency increase	0.05
	Choke stab	0.05
	Pump reverse	0.70
	Tubing plugged	0.75
Well name: well_002		
5	Normal	0.60
	Shaft breakage	0.35
	Tubing leakage	0.55
	Pump plugging	0.50
	Perforation plugging	0.25
	Water-cut rise	0.45
	Wellhead shut-in	0.10
	Reservoir pressure increase	0.30
	Gas influence	0.20
	Pump wear	0.65
	Frequency increase	0.10
	Choke stab	0.10
	Pump reverse	0.55
	Tubing plugged	0.35

Table 7: Continued.

Time window (mins)	Working condition type	Probability
60	Normal	0.40
	Shaft breakage	0.55
	Tubing leakage	0.85
	Pump plugging	0.70
	Perforation plugging	0.35
	Water-cut rise	0.45
	Wellhead shut-in	0.10
	Reservoir pressure increase	0.45
	Gas influence	0.50
	Pump wear	0.80
	Frequency increase	0.00
	Choke stab	0.10
	Pump reverse	0.65
	Tubing plugged	0.65
1440	Normal	0.20
	Shaft breakage	0.75
	Tubing leakage	0.65
	Pump plugging	0.90
	Perforation plugging	0.65
	Water-cut rise	0.45
	Wellhead shut-in	0.10
	Reservoir pressure increase	0.30
	Gas influence	0.70
	Pump wear	0.80
	Frequency increase	0.00
	Choke stab	0.10
	Pump reverse	0.75
	Tubing plugged	0.65
Well name: well_003		
5	Normal	0.70
	Shaft breakage	0.90
	Tubing leakage	0.65
	Pump plugging	0.85
	Perforation plugging	0.50
	Water-cut rise	0.55
	Wellhead shut-in	0.35
	Reservoir pressure increase	0.50
	Gas influence	0.80
	Pump wear	0.65
	Frequency increase	0.15
	Choke stab	0.10
	Pump reverse	0.40
	Tubing plugged	0.50
60	Normal	0.50
	Shaft breakage	0.90
	Tubing leakage	0.75
	Pump plugging	0.65
	Perforation plugging	0.40
	Water-cut rise	0.40
	Wellhead shut-in	0.15
	Reservoir pressure increase	0.35
	Gas influence	0.75
	Pump wear	0.55
	Frequency increase	0.05
	Choke stab	0.00
	Pump reverse	0.50
	Tubing plugged	0.55

Table 7: Continued.

Time window (mins)	Working condition type	Probability
1440	Normal	0.25
	Shaft breakage	0.90
	Tubing leakage	0.85
	Pump plugging	0.80
	Perforation plugging	0.60
	Water-cut rise	0.45
	Wellhead shut-in	0.35
	Reservoir pressure increase	0.40
	Gas influence	0.80
	Pump wear	0.75
	Frequency increase	0.05
	Choke stab	0.00
	Pump reverse	0.80
	Tubing plugged	0.80
Well name: well_004		
5	Normal	0.70
	Shaft breakage	0.45
	Tubing leakage	0.30
	Pump plugging	0.85
	Perforation plugging	0.25
	Water-cut rise	0.30
	Wellhead shut-in	0.20
	Reservoir pressure increase	0.55
	Gas influence	0.70
	Pump wear	0.35
	Frequency increase	0.05
	Choke stab	0.05
	Pump reverse	0.75
	Tubing plugged	0.70
60	Normal	0.60
	Shaft breakage	0.55
	Tubing leakage	0.40
	Pump plugging	0.70
	Perforation plugging	0.65
	Water-cut rise	0.60
	Wellhead shut-in	0.20
	Reservoir pressure increase	0.50
	Gas influence	1.00
	Pump wear	0.75
	Frequency increase	0.05
	Choke stab	0.35
	Pump reverse	0.25
	Tubing plugged	0.70
1440	Normal	0.10
	Shaft breakage	0.70
	Tubing leakage	0.75
	Pump plugging	0.75
	Perforation plugging	0.55
	Water-cut rise	0.50
	Wellhead shut-in	0.20
	Reservoir pressure increase	0.50
	Gas influence	1.00
	Pump wear	0.65
	Frequency increase	0.05
	Choke stab	0.05
	Pump reverse	0.65
	Tubing plugged	0.70
Well name: well_005		

Table 7: Continued.

Time window (mins)	Working condition type	Probability
5	Normal	0.20
	Shaft breakage	0.55
	Tubing leakage	0.80
	Pump plugging	0.75
	Perforation plugging	0.75
	Water-cut rise	0.45
	Wellhead shut-in	0.15
	Reservoir pressure increase	0.45
	Gas influence	0.75
	Pump wear	0.95
	Frequency increase	0.25
	Choke stab	0.15
	Pump reverse	0.55
	Tubing plugged	0.35
60	Normal	0.30
	Shaft breakage	0.55
	Tubing leakage	0.45
	Pump plugging	0.65
	Perforation plugging	0.75
	Water-cut rise	0.55
	Wellhead shut-in	0.25
	Reservoir pressure increase	0.50
	Gas influence	0.15
	Pump wear	0.95
	Frequency increase	0.25
	Choke stab	0.05
	Pump reverse	0.60
	Tubing plugged	0.65
1440	Normal	0.20
	Shaft breakage	0.85
	Tubing leakage	0.70
	Pump plugging	1.00
	Perforation plugging	0.75
	Water-cut rise	0.55
	Wellhead shut-in	0.15
	Reservoir pressure increase	0.45
	Gas influence	0.85
	Pump wear	1.00
	Frequency increase	0.05
	Choke stab	0.05
	Pump reverse	0.95
	Tubing plugged	0.75

③ Shaft breakage

Shaft breakage is a sudden fault, which is easy to occur when the oil well has heavy oil, serious sand production or shutdown, and restart. At this time, the motor current suddenly decreases. Due to the decrease of tubing pressure, the oil well flow also decreases, the pump discharge pressure decreases, and the motor temperature will rise after stabilizing for a period of time. The parameter changes are shown in Figure 7.

④ Gas influence

Gas influence is a gradual fault, which is caused by high gas content in the fluid, low pump hanging

Table 8: Comparison of diagnostic results.

Well name	Working condition type	5 minutes	60 minutes	1440 minutes	Max	Diagnostic result
Fault diagnosis model based on SPC						
well_002	Normal	0.60	0.40	0.20	0.60	Pump plugging Pump wear
	Shaft breakage	0.35	0.55	0.75	0.75	
	Tubing leakage	0.55	0.85	0.65	0.85	
	Pump plugging	0.50	0.70	0.90	0.90	
	Perforation plugging	0.25	0.35	0.65	0.65	
	Water-cut rise	0.45	0.45	0.45	0.45	
	Wellhead shut-in	0.10	0.10	0.10	0.10	
	Reservoir pressure increase	0.30	0.45	0.30	0.45	
	Gas influence	0.20	0.50	0.70	0.70	
	Pump wear	0.65	0.80	0.90	0.90	
	Frequency increase	0.10	0.00	0.00	0.10	
	Choke stab	0.10	0.10	0.10	0.10	
	Pump reverse	0.55	0.65	0.75	0.75	
	Tubing plugged	0.35	0.65	0.65	0.65	
The fault diagnosis model of this study						
well_002	Normal	0.60	0.40	0.20	0.60	Pump plugging
	Shaft breakage	0.35	0.55	0.75	0.75	
	Tubing leakage	0.55	0.75	0.65	0.85	
	Pump plugging	0.50	0.85	0.90	0.90	
	Perforation plugging	0.25	0.35	0.65	0.65	
	Water-cut rise	0.45	0.45	0.45	0.45	
	Wellhead shut-in	0.10	0.10	0.10	0.10	
	Reservoir pressure increase	0.30	0.45	0.30	0.45	
	Gas influence	0.20	0.50	0.70	0.70	
	Pump wear	0.65	0.80	0.80	0.80	
	Frequency increase	0.10	0.00	0.00	0.10	
	Choke stab	0.10	0.10	0.10	0.10	
	Pump reverse	0.55	0.65	0.75	0.75	
	Tubing plugged	0.35	0.65	0.65	0.65	

depth, or insufficient liquid supply. At this time, the motor current, voltage, pump discharge pressure, wellhead temperature, tubing pressure, and flow will decrease, and the pump inlet pressure and pump inlet temperature will increase due to the increase of gas. In severe cases, airlock will occur, and the parameter changes are shown in Figure 8.

⑤ Pump plugging

In the production process, the pump impeller or suction inlet will be blocked due to wax deposition and sand production in the oil well. When the pump plugging, the frequency, voltage, and wellhead temperature remain unchanged; the motor current, pump discharge pressure, pressure difference, and flow decreased; motor temperature, pump inlet pressure, and pump inlet temperature all rise. The parameter changes are shown in Figure 9.

Next, these five wells are used to analyze the fault diagnosis process in detail.

3.1. Standardization of Time Window Monitoring Data. In the ESP well, the speed of different faults is different. For example, the shaft breakage off belongs to a sudden fault, which takes only a few minutes from the beginning of the fault to the complete fault; the pump wear belongs to a gradual fault, which takes more than 20 hours or even longer from the beginning of the fault to the complete fault. If a small time window is selected, some abrupt faults can be accurately and correctly diagnosed, but some gradual faults are difficult to be accurately diagnosed; on the contrary, if a longer time window is selected, the gradual fault can be accurately diagnosed, but the characteristics of some sudden faults will be weakened. Therefore, in order to enable the diagnosis system to capture all types of faults at the same time, the diagnosis time windows are selected as 5 minutes, 60 minutes, and 1440 minutes, respectively, for analysis, and the data density is $t = 20$ s. According to formula (5), the data analysis granularity is 1, 12, and 288, respectively. That is, take the average value of the values of 1, 12, and 288 consecutive points as a point, so as to ensure that the number of data points in a specific time window is equal to 15, so that SPC can expand the application of rules.

3.2. Calculation of Monitoring Parameter Change Rate $\mathbf{a}_\mathbf{i}$. The calculation process of monitoring parameter change rate a_i is shown in Figure 10. Input the parameters of the diagnosis time window into the SPC expansion rule model, that is, output the change trend of each parameter.

Based on the calculation process of monitoring parameter change rate in Figure 10, the SPC expansion rule model is used to calculate the change trend of parameters

Table 9: Diagnosis results of working conditions.

Well name	Working condition type	5 minutes	60 minutes	1440 minutes	Max	Diagnostic result
well_001	Normal	0.65	0.50	0.60	0.65	Tubing leakage
	Shaft breakage	0.70	0.55	0.90	0.90	
	Tubing leakage	0.85	0.55	1.00	1.00	
	Pump plugging	0.75	0.40	0.65	0.75	
	Perforation plugging	0.60	0.40	0.50	0.60	
	Water-cut rise	0.25	0.15	0.25	0.25	
	Wellhead shut-in	0.10	0.15	0.20	0.15	
	Reservoir pressure increase	0.40	0.45	0.45	0.45	
	Gas influence	0.35	025	0.85	0.85	
	Pump wear	0.75	0.55	0.55	0.75	
	Frequency increase	0.05	0.05	0.05	0.05	
	Choke stab	0.00	0.05	0.05	0.05	
	Pump reverse	0.50	0.70	0.70	0.70	
	Tubing plugged	0.75	0.65	0.75	0.75	
well_003	Normal	0.70	0.50	0.25	0.70	Shaft breakage
	Shaft breakage	0.90	0.90	0.90	0.90	
	Tubing leakage	0.65	0.75	0.85	0.85	
	Pump plugging	0.85	0.65	0.80	0.85	
	Perforation plugging	0.50	0.40	0.60	0.60	
	Water-cut rise	0.55	0.40	0.45	0.55	
	Wellhead shut-in	0.35	0.15	0.35	0.35	
	Reservoir pressure increase	0.50	0.35	0.40	0.50	
	Gas influence	0.80	0.75	0.80	0.80	
	Pump wear	0.65	0.55	0.75	0.75	
	Frequency increase	0.15	0.05	0.05	0.15	
	Choke stab	0.10	0.00	0.00	0.10	
	Pump reverse	0.40	0.50	0.80	0.80	
	Tubing plugged	0.50	0.55	0.80	0.80	
well_004	Normal	0.70	0.60	0.10	0.70	Gas influence
	Shaft breakage	0.45	0.55	0.70	0.70	
	Tubing leakage	0.30	0.40	0.75	0.75	
	Pump plugging	0.85	0.70	0.75	0.85	
	Perforation plugging	0.25	0.65	0.55	0.65	
	Water-cut rise	0.30	0.60	0.50	0.60	
	Wellhead shut-in	0.20	0.20	0.20	0.20	
	Reservoir pressure increase	0.55	0.50	0.50	0.55	
	Gas influence	0.70	1.00	1.00	1.00	
	Pump wear	0.35	0.75	0.65	0.75	
	Frequency increase	0.05	0.05	0.05	0.05	
	Choke stab	0.05	0.35	0.05	0.35	
	Pump reverse	0.75	0.25	0.65	0.75	
	Tubing plugged	0.70	0.70	0.70	0.70	
well_005	Normal	0.20	0.30	0.20	0.30	Pump wear
	Shaft breakage	0.55	0.55	0.85	0.85	
	Tubing leakage	0.80	0.45	0.70	0.80	
	Pump plugging	0.75	0.65	0.90	0.90	
	Perforation plugging	0.75	0.75	0.75	0.75	
	Water-cut rise	0.45	0.55	0.55	0.55	
	Wellhead shut-in	0.15	0.25	0.15	0.25	
	Reservoir pressure increase	0.45	0.50	0.45	0.50	
	Gas influence	0.75	0.15	0.85	0.85	
	Pump wear	0.95	0.95	1.00	1.00	
	Frequency increase	0.25	0.25	0.05	0.25	
	Choke stab	0.15	0.05	0.05	0.15	
	Pump reverse	0.55	0.60	0.95	0.95	
	Tubing plugged	0.35	0.65	0.75	0.75	

within 5 minutes, 60 minutes, and 1440 minutes of the time window, see Table 6 for the variation trend of various parameters of different oil wells in the time window.

3.3. Calculation of Fault Probability W_j. The calculation process of fault probability W_j is shown in Figure 11. For data that do not match the multiparameter rule chart, the contribution of fault probability is zero. In the figure, W_1 represents the probability of fault 1.

Based on the calculation steps in Figure 11, calculate the probability of occurrence of different oil wells, different diagnosis time windows, and different working conditions by using formula (6), as shown in Table 7. The greater the fault probability value, the greater the possibility of such a fault.

3.4. Analysis of Fault Diagnosis Results. Under the time window of 5 minutes, 60 minutes, and 1440 minutes, take the maximum value of each fault probability as the final fault probability. In order to illustrate the superiority of the fault diagnosis model in this study, well_002 is selected for example analysis, and the fault diagnosis results based on SPC and the fault diagnosis model in this study are calculated, respectively, as shown in Table 8.

By analyzing Table 8, it can be seen that when the time window is 60 minutes, the fault diagnosis model in this study can correctly diagnose the fault type, while the fault diagnosis model based on SPC cannot correctly diagnose the fault type when the time window is 1440 minutes. By comparing the final diagnosis results of the two methods, there is only one diagnosis result of the fault diagnosis model in this study, which is the same as the label of the fault well, and the diagnosis is correct, while there are two diagnosis results of the fault diagnosis model based on SPC, which cannot correctly diagnose the fault type. Therefore, the fault diagnosis method proposed in this paper needs a smaller time window and higher diagnosis accuracy.

The fault diagnosis results of the other 4 wells are calculated in this study, as shown in Table 9. The diagnosis results are consistent with the fault labels of oil wells. Therefore, setting multiple time windows to maximize the probability is an important guarantee for fault identification.

4. Conclusion

(1) Based on the conventional SPC rules, this study developed 13 kinds of SPC expansion rules suitable for judging the change trend of monitoring parameters of ESP wells, established the SPC expansion rule model, and refined the change trend of multiple monitoring parameters in a specific time window in real time, laying the foundation for fault diagnosis of ESP wells.

(2) The proposed fault probability model and ESP well fault diagnosis method realize the diagnosis of 14 different working conditions, and a priori knowledge, namely multiparameter fault analysis table and weight factor, is introduced into the diagnosis model, which reduces the time window required for fault diagnosis and improves the accuracy of diagnosis results.

(3) By setting multiple time windows of 5 minutes, 60 minutes, and 1440 minutes, the diagnosis of sudden faults and gradual faults has been solved, and the accuracy of fault diagnosis has been improved.

(4) In practical applications, this method can appropriately adjust the multiparameter fault analysis table, SPC expansion rules, weight factors, and time windows according to the fluid properties of ESP wells in different blocks and the type of lifting equipment so that the diagnosis method can be applied to other oil wells with high accuracy.

(5) In the future, with the continuous production of oil wells, the operator can further modify the weight factor table according to the historical data obtained in the actual situation and possible faults to ensure the accuracy of the results.

Data Availability

The data used to support the findings of this study are currently under embargo while the research findings are commercialized. Requests for data, 6/12 months after the publication of this article, will be considered by the corresponding author.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

The authors have read the paper and agree to contribute for publication.

Acknowledgments

This work was supported by the following two fund projects: National Natural Science Foundation of China "Integrated Optimization of Large-scale Nonpipelined Well Production and Tank Truck Scheduling Based on Data Analytics" (No. 51974327); Major special project of CNOOC Energy Development Co., Ltd. "Intelligent Technology Research for Injection and Production well" (No. HFXMLZ-GJ2018-14).

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