Dynamic Safety Risk Analysis Method for Gas Flow Control Systems Integrating Bayesian Networks and Variable-Weight AHP

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Abstract

To address the issues of high failure rates in stepless capacity control systems for reciprocating compressor units, their significant impact on unit safe operation, and the inability of existing system operation risk assessment methods to perform real-time, quantitative analysis, a dynamic safety risk analysis method for capacity control systems that integrates Bayesian networks and variable weight AHP is proposed. A Bayesian network model encompassing failure types, failure modes, and monitoring signals is established to obtain real-time failure occurrence probabilities; a semi-quantitative failure hazard analysis model is constructed based on variable weight Analytic Hierarchy Process to calculate quantitative indicators of failure mode impacts; furthermore, the failure mode risk calculation formula of the FMEA method is modified by introducing failure occurrence probability, and calculation methods for historical failure and real-time operation risk are proposed. Testing and validation using actual failure case data demonstrate that the proposed new method can quantitatively calculate both real-time and historical operation risks of the unit, with a normalized real-time operation risk threshold set at 0.5 to determine maintenance necessity. The research findings can provide quantitative indicators for the formulation of maintenance and repair plans for reciprocating compressors and capacity control systems.

Full Text

Dynamic Analysis Method for Safety Risk of Capacity Control Systems Integrating Bayesian Networks and Variable Weight AHP

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Abstract

Aiming at the problems of high failure rates in stepless capacity control systems for reciprocating compressor units and their significant impact on safe operation, as well as the inability of existing operational risk assessment methods to perform real-time quantitative analysis, this paper proposes a dynamic safety risk analysis method for capacity control systems that integrates Bayesian networks and variable weight AHP. A Bayesian network model incorporating fault types, fault modes, and monitoring signals is established to obtain real-time fault occurrence probabilities. Based on the variable weight analytic hierarchy process, a semi-quantitative analysis model for fault hazard is constructed to calculate quantitative indicators of fault mode impacts. Furthermore, the fault mode risk calculation formula of the FMEA method is revised by introducing fault occurrence probability, and calculation methods for both historical fault risk and real-time operational risk are proposed. Validation using actual fault case data demonstrates that the proposed method can quantify real-time and historical operational risks of compressor units. A normalized real-time operational risk threshold of 0.5 is established to determine maintenance necessity. The research results provide quantitative indicators for the formulation of inspection and maintenance plans for reciprocating compressors and their capacity control systems.

Keywords: Stepless capacity control system, Bayesian network, Failure mode and effect analysis, Analytic hierarchy process, Risk dynamic analysis

Reciprocating compressor units are high-energy-consumption equipment in industries such as petroleum refining and chemical processing. Driven by China's strategic goals of achieving carbon peak and carbon neutrality, an increasing number of reciprocating compressor units have been equipped with stepless capacity control systems to enable energy-saving operation. However, frequent failures in suction valves, unloaders, solenoid control valves, and oil stations have seriously impacted the safe and stable operation of these units. How to conduct risk assessment for capacity control systems has become a critical concern for enterprises.

Existing research has conducted fault analysis on stepless capacity control systems for reciprocating compressors. Lü Jiaqi [1] analyzed failures where suction valves in reciprocating compressor stepless capacity control systems could not unload properly, identifying root causes by examining the output force of the actuator valve chamber piston, the reaction force of the unloading rod in the unloaded state, intake pressure, and pressure differentials. Sheng Zunxiang et al. [2] addressed packing wear failures in capacity control system unloading rods, calculating bolt pre-tightening forces, improving installation structures, and optimizing unloading rod alignment. Jiang Zhinong et al. [3] studied self-healing control methods for instability in reciprocating compressor capacity regulation, establishing a multi-system coupled control model and developing classification diagnosis models and self-healing control mechanisms for actuator return spring failures and control valve dynamic characteristic offsets. Wang Yao et al. [4] proposed a fault self-healing control strategy based on regulation domain reconstruction and load redistribution to address common suction valve failures causing capacity control system failures. Sun Xu et al. [5] established a CFD simulation model of reciprocating compressors including intake/exhaust valves and cylinders, conducting thermodynamic performance simulation studies on compressor flow control conditions coupled with exhaust valve leakage faults. Zhang Jinjie et al. [6] constructed a compressor working model coupling fork faults and suction valve leakage faults under stepless capacity regulation conditions, achieving fault simulation and obtaining fault characteristic indicators. Capacity control systems already possess control functions for typical faults, as Sun Qiang [7] described the application of stepless capacity control systems in hydrogen production compressors and explained automatic control strategies for typical faults. However, existing research primarily focuses on structural optimization design, fault diagnosis, and control strategies for capacity control systems, with no studies on dynamic safety risk analysis, leaving room for improvement in the specificity and practicality of system and unit fault maintenance strategies.

In other fields, Bao Han et al. [8] proposed a fault risk assessment method for aero-engine control systems based on probabilistic risk analysis, conducting hierarchical assessments from three levels: underlying faults, engine thrust control loss events, and aircraft-level consequences. Lei Baimao et al. [9] analyzed main failure modes of neutron tubes, employing fuzzy comprehensive evaluation and analytic hierarchy process (AHP) for multi-level fuzzy comprehensive assessment of neutron tube faults and evaluating fault risks. Gong Wentao et al. [10] proposed a network fault risk assessment and analysis strategy based on LEC, refining network fault factors and quantitatively evaluating fault impacts. The authors [11] previously proposed a semi-quantitative analysis method for fault mode and effect analysis based on variable weight AHP, achieving semi-quantitative analysis of typical fault impacts in reciprocating compressors.

This paper focuses on reciprocating compressor capacity control systems, addressing the urgent problem of insufficient dynamic safety risk analysis research that hinders safe and stable unit operation. Drawing upon fault risk assessment research from other equipment domains, we propose a dynamic safety risk analysis method for capacity control systems that integrates Bayesian networks and variable weight AHP. Centering on typical fault modes of the system, we establish a new fault diagnosis model based on Bayesian networks to obtain real-time occurrence probabilities of different faults. Using the variable weight AHP method, we define impact parameters for different fault modes of the system, and further combine Bayesian network calculation results to achieve dynamic risk analysis of fault modes, enabling quantitative calculation of both real-time and historical operational risks of compressor units. Validation with actual fault case data demonstrates that the calculated operational risk results are consistent with actual fault occurrences and maintenance conclusions, achieving good results.

1 Bayesian Network-Based Operational State Analysis Model

Bayesian networks were first proposed by Pearl and are also known as belief networks or directed acyclic graph models, representing an extension of Bayesian methods [12]. A Bayesian network is a probabilistic graphical model consisting of variable nodes and directed edges connecting these nodes. Each node carries quantitative probability information and conforms to certain conditional probability distributions given its parent nodes. A Bayesian network can be represented as (V, D, P), where V represents all nodes in the network. Node variable x_i can express specific problem objects; for this research, it can represent fault types, fault modes, monitoring signals, etc. D represents the set of directed edges connecting node pairs. P represents the probability distribution of each node, which can be expressed as $P(x_i|\text{Parents}(x_i))$. In the network, nodes without inputs become root nodes with initial prior probabilities, while other connected directed edges have conditional probabilities. By summarizing the conditional probabilities of all nodes, a Conditional Probability Table (CPT) can be established.

A Bayesian network specifies a full joint probability distribution, where each entry can be expressed as the product of corresponding elements in the Bayesian network CPT. The calculation formula is:

$$P(x_1, ..., x_n) = \prod_i P(x_i|\text{Parents}(x_i))$$

The Bayesian network inference process involves: 1) providing prior probabilities and conditional probabilities for specific problem objects based on domain knowledge, experience statistics, or case data learning; 2) calculating the joint probability distribution based on the network structure; 3) calculating marginal probability distributions for different nodes; and 4) conducting statistical inference to calculate the posterior probability of research problems under different known condition combinations according to Bayes' formula. Bayes' formula is generally expressed as:

$$P(x_i|Z_1, Z_2, ...)$$

where Z represents given evidence variables and z represents specific values of variable Z.

For the research object in this paper, fault types F, fault modes M, and monitoring signals S of the capacity control system are organized based on historical fault case data, as shown in Table 1 , and the Bayesian network model shown in Figure 1 [Figure 1: see original paper] is established. The CPT values of the network model are set by relevant experts based on actual case data, assuming conditional independence between different nodes.

Table 1 Fault Modes and Monitoring Signals of Capacity Control System

Fault Type F	Fault Mode M	Monitoring Signal S
Mechanical component faults	Suction valve leakage, valve plate fracture	Suction valve cover temperature
Hydraulic system component faults	Actuator action delay, oil station low liquid level	Oil station level
Control system component faults	Oil pump mechanical fault, oil station motor mechanical fault, pipeline leakage fault	Cylinder suction temperature, cylinder discharge temperature, cylinder suction pressure, cylinder discharge pressure, circuit feedback characteristics, key phase speed characteristics

Figure 1 Failure Mode and Bayesian Network Model of Capacity Control System

2 Dynamic Analysis of Fault Mode Risk Based on Variable Weight AHP

Based on variable weight analytic hierarchy process, semi-quantitative analysis of fault mode impacts in reciprocating compressor capacity control systems is completed by comprehensively considering four factors: safety impact, production loss, maintenance cost, and energy-saving effect impact. This analysis method employs pairwise comparisons to obtain the relative impact degree of each fault mode, reducing deviations caused by subjectivity, randomness, and bias.

2.1 Fault Mode Impact Analysis Based on Variable Weight AHP

The analytic hierarchy process is used to divide the fault mode impact analysis of the capacity control system into three levels, as shown in Figure 2 [Figure 2: see original paper]. The target layer A is the typical fault mode impact index. The criterion layer B_i includes safety impact B_1, production loss B_2, maintenance cost B_3, and energy-saving effect impact B_4, where safety factors are qualitative factors calculated using the maximum damage principle, while other factors can be quantified using financial costs and energy-saving effects. The index layer C_i represents various fault modes.

Figure 2 AHP Diagram of Capacity Control System Fault Impact

Safety Impact B_1: Divided into 9 levels, representing the maximum value within a major overhaul cycle (8000 hours) of safety impact statistics for j failures of fault mode i.

Production Loss Impact $B_2 = \sum$: Using statistics of average downtime caused by fault mode i within a major overhaul cycle, where n represents the number of fault occurrences.

Maintenance Cost Impact $B_3 = \sum$: Using statistics of average maintenance costs caused by fault mode i within a major overhaul cycle, where n represents the number of fault occurrences.

Energy-saving Effect Impact $B_4 = \sum$: Using the average reduction in energy-saving power caused by fault mode i relative to ideal energy-saving effects within a major overhaul cycle, where n represents the number of fault occurrences.

Taking a hydrogen reciprocating compressor unit in a petroleum refinery as the object (rated power 3000kW, operating speed 333 r/min), statistics on main fault mode influencing factors of the capacity control system are compiled based on actual operational fault case data, with results shown in Table 2 .

Table 2 Main Fault Modes and Influencing Factors of Capacity Control System of Reciprocating Compressor

Fault Mode	Safety Impact	Production Loss Impact (hours)	Maintenance Cost Impact (10k yuan)	Energy-saving Effect Impact (kWh)
Suction valve leakage, valve plate fracture	7	120	50	1500
Oil pump mechanical fault	3	24	8	300

Fault Mode	Safety Impact	Production Loss Impact (hours)	Maintenance Cost Impact (10k yuan)	Energy-saving Effect Impact (kWh)
Oil station motor mechanical fault	3	24	10	300
Key phase sensor fault	5	48	15	600
Solenoid valve performance degradation	5	72	20	900
Controller board fault	7	96	30	1200

Based on the statistical data of each fault mode influencing factor in Table 2, the above parameters are dimensionless and assigned importance degrees on a 1-9 scale to establish pairwise comparison matrices. The matrices should include comparisons between different fault modes under the same influencing factor, as well as comparisons between different influencing factors.

1) **Comparison between different fault modes under the same influencing factor**: The constant weight comprehensive evaluation method only highlights main factors and lacks consideration of extreme fault mode hazard levels. Therefore, variable weight correction [11] is applied to the weights obtained from AHP to account for both extreme cases and main factors. The variable weight result is represented as w_{ri}, where r represents the influencing factor category and i represents the fault mode category.

Solving for the eigenvector w_r^d corresponding to the maximum eigenvalue of matrix U_r' yields the scores of different fault modes within influencing factor r:

$$w_r^d = [w_{r1}^d, w_{r2}^d, ..., w_{rn}^d]^T$$

2) **Comparison between different influencing factors**: The four fault influencing factors have different weights, with safety and production being more important than maintenance cost and energy-saving effect. A pairwise comparison matrix Y is established for the influencing factors.

3) **Matrix consistency test**: For the above pairwise comparison matrices, after determining single factor weights, matrix consistency is tested according to the consistency index formula $CI = \frac{\lambda_{\max} - n}{n-1}$ and the consistency ratio formula $CR = \frac{CI}{RI}$. Where $\lambda_{\max}$ is the maximum eigenvalue of the matrix, n is the order of the judgment matrix, and RI is the average random consistency index. A smaller CI indicates better consistency of the judgment matrix. When $CR < 0.1$, the consistency of the fault mode judgment matrix is acceptable.

Based on the above calculation method, using data from Table 2, safety impact parameter judgment matrices, production loss judgment matrices, maintenance cost judgment matrices, and energy-saving effect impact judgment matrices are calculated. All calculated consistency indices CI and CR values are shown in Table 3 , with all consistency indicators meeting requirements.

Table 3 Calculation Results of CI and CR of Judgment Matrix

Influencing Factor	CI	CR
Safety Impact	0.032	0.036
Production Loss	0.018	0.020
Maintenance Cost	0.025	0.028
Energy-saving Effect	0.041	0.046

Similarly, solving for the eigenvector $a = [a_1, a_2, a_3, a_4]^T$ corresponding to the maximum eigenvalue of matrix Y yields the importance scores of the influencing factors.

4) **Fault mode impact parameter calculation**: Since AHP generally uses constant weight evaluation, the constant weight comprehensive evaluation result is:

$$C_i = \sum_{r=1}^{4} a_r w_{ri}^d$$

Furthermore, the fault mode impact parameter results for six types of fault modes are calculated as shown in Table 4 .

Table 4 Partial Failure Modes and Influence Analysis Results of Gas Capacity Control System of Reciprocating Compressor

Fault Mode	Fault Mode Impact Parameter	Normalized Fault Mode Impact
Mechanical component fault - Suction valve leakage, valve plate fracture	0.685339894	0.257854302
Hydraulic system component fault - Oil pump mechanical fault	0.206125274	0.17278529
Hydraulic system component fault - Oil station motor mechanical fault	0.206125274	0.17278529
Control system component fault - Key phase sensor fault	0.685339894	0.257854302
Control system component fault - Solenoid valve performance degradation	0.257854302	0.206125274
Control system component fault - Controller board fault	0.17278529	0.685339894

2.2 Dynamic Risk Analysis of Fault Modes

In traditional Failure Mode and Effect Analysis (FMEA), the fault hazard index W_i for mechanical system components can be expressed as:

$$W_i = K_i \cdot t \cdot C_i$$

where $i = 1, 2, ..., n$, K_i is the frequency of fault mode i per unit time, t is the calculation time range, and C_i is the loss index of mechanical system failure caused by fault mode i.

Based on the above formula, the operational risk calculation formula for capacity control systems is defined.

1) **Historical fault risk calculation method**: Historical fault risk calculation refers to statistical analysis of equipment fault conditions over a certain period based on historical case data, calculating future operational risk according to fault occurrence frequency and different fault impacts. Formula (10) is improved by revising the hazard calculation formula for fault mode i:

$$H_i^{\text{hist}} = K_i \cdot C_i$$

where H_i^{hist} is the hazard index of fault mode i in historical fault risk calculation, K_i is the historical occurrence frequency of fault mode i, and C_i is the impact parameter of fault mode i.

The overall fault hazard of the capacity control system within a certain period is:

$$H_{\text{total}}^{\text{hist}} = \sum_{i=1}^{n} H_i^{\text{hist}}$$

Formula (12) can be applied to risk analysis per unit operating time for capacity control systems of different reciprocating compressor units, thereby identifying units with higher operational risk for focused attention in equipment maintenance management.

2) **Real-time operational risk calculation method**: Based on calculation results from the Bayesian network-based operational state analysis model, the occurrence probability $P(i)$ of fault mode i in real-time operational state is obtained. Combined with fault mode impact analysis results from variable weight AHP, real-time operational risk can be calculated using Formula (13):

$$H_i^{\text{real}} = P(i) \cdot C_i$$

where H_i^{real} is the hazard index of fault mode i in real-time state, and $P(i)$ is the occurrence probability of fault mode i in real-time state.

Corresponding threshold values can be set based on hazard impact calculation results of different fault modes to divide risk levels corresponding to actions such as shutdown maintenance, close monitoring, or normal operation. The system's real-time operational risk calculation value is compared with threshold values, and corresponding actions are taken according to risk levels.

3 Practical Case Application

Taking the aforementioned petroleum refinery hydrogen reciprocating compressor units as the research object, both Unit A and Unit B are equipped with stepless capacity control systems. Field photos of the units are shown in Figure 3 [Figure 3: see original paper].

Figure 3 Reciprocating Compressor and Stepless Capacity Control System

Fault occurrence data for the capacity control systems of Units A and B within an 8000-hour operational cycle are extracted, with specific statistics shown in Table 5 .

Table 5 Failure Occurrence of Capacity Control System of A/B Units

Fault Mode	Unit A Occurrences	Unit B Occurrences
Suction valve leakage, valve plate fracture	3	1
Key phase sensor fault	2	0
Controller board fault	1	2
Oil pump mechanical fault	0	1
Oil station motor mechanical fault	1	0
Solenoid valve performance degradation	2	1

Considering that the probability of encountering faults in real-time unit operation is relatively small, historical fault case data is replayed to simulate real-time data for method validation. Two typical historical fault data sets are shown in Figure 4 [Figure 4: see original paper] and Figure 5 [Figure 5: see original paper]. Figure 4 shows that as operating time increases, the sealing performance of suction valves gradually deteriorates, gas leakage gradually increases, and valve temperature continuously rises. Figure 5 shows that from the vibration impact phase, as operating time extends, solenoid valve performance gradually degrades, causing obvious lag in valve closure.

Based on historical case knowledge, fault alarm limits are set. When monitored parameters exceed alarm limits, the aforementioned Bayesian fault diagnosis model is triggered to obtain occurrence probabilities of different faults. The real-time operational risk calculation results are shown in Tables 6 and 7 .

Table 6 Operation Risk Calculation Results of the Gas Valve Fault

Fault Mode	Fault Mode Impact	Real-time Probability	Hazard Index
Suction valve leakage, valve plate fracture	0.685339894	0.85	0.582539
Key phase sensor fault	0.257854302	0.12	0.030943

Table 7 Operation Risk Calculation Results of the Solenoid Valve Performance Degradation

Fault Mode	Fault Mode Impact	Real-time Probability	Hazard Index
Solenoid valve performance degradation	0.257854302	0.75	0.193391
Key phase sensor fault	0.257854302	0.15	0.038678

Both historical fault risk and real-time operational risk are calculated. The historical fault risk calculation results for the units are shown in Figure 6 [Figure 6: see original paper], enabling quantitative calculation of historical fault risks for Units A and B to provide basis for field inspection and maintenance work and primary/standby unit selection.

Figure 6 Historical Fault Risk Calculation Results of A/B Units

Tables 6 and 7 demonstrate that using Bayesian networks for fault analysis and diagnosis of capacity control systems based on various monitoring parameters yields occurrence probabilities of different faults. Combined with fault mode impact parameters, real-time operational risk of the capacity control system is calculated, enabling quantitative analysis of current operational risk and guiding inspection and maintenance. Generally, a real-time operational risk threshold of 0.5 can be set, with values exceeding 0.5 requiring attention and necessary inspection and maintenance of the capacity control system.

Conclusions

(1) This paper focuses on reciprocating compressor capacity control systems, addressing issues such as maintenance plan formulation relying on manual experience, lack of quantitative indicators, and insufficient refined management. A dynamic safety risk analysis method integrating Bayesian networks and variable weight AHP is established. The correspondence between fault modes and monitoring signals is organized, a Bayesian network-based fault diagnosis model is constructed to obtain occurrence probabilities of different fault modes, and the analytic hierarchy process is used to complete semi-quantitative analysis of fault hazards considering safety impact, production loss, maintenance cost, and energy-saving effect, yielding normalized 0-1 evaluation indicators for different fault mode impacts.

(2) Calculation methods for both historical fault risk and real-time operational risk of units are defined based on historical fault occurrence frequencies and Bayesian network fault diagnosis results. Historical fault risk calculation results can be used to evaluate operational risks of capacity control systems across different units, optimizing unit start/stop strategies and capacity control system deployment strategies. Real-time operational risk calculation results can be used to evaluate current operational status of capacity control systems and formulate inspection and maintenance plans.

(3) Practical case data application demonstrates that the proposed method utilizes actual monitoring parameters such as temperature, pressure, and vibration to achieve automatic diagnosis of main fault modes in capacity control systems including suction valve faults, key phase sensor faults, and controller board faults. Combined with fault mode impact parameters, both historical fault risk and real-time operational risk are calculated, with a real-time operational risk threshold of 0.5 established to guide inspection and maintenance plan formulation for reciprocating compressors and capacity control systems. The calculated operational risk results show good consistency with actual fault occurrences and maintenance conclusions.

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Note: Figure translations are in progress. See original paper for figures.