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Joint Optimization of Preventive Maintenance and Spare Parts Inventory for Gas Compressor in Pipeline System

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ABSTRACT

Efficient maintenance management of devices is fundamental to ensuring supply reliability of natural gas pipeline system. A joint optimization model of preventive maintenance and spare parts ordering for the gas compressor in pipeline system based on supply reliability is developed aiming to maximize system gas supply reliability and minimize maintenance costs. The model consists of three parts: calculation of the maximum gas supply capacity, modeling of the joint optimization problem and using a genetic algorithm to find the optimal solution. The effectiveness of the proposed method is validated on a European gas pipeline network. The results show that the proposed joint optimization strategy outperforms others in identifying optimal maintenance strategies.

Keywords: natural gas pipeline system, supply reliability, preventive maintenance, spare part inventory.

NONMENCLATURE

Abbreviations	
CBM	condition-based maintenance
RCM	reliability-centered maintenance
CU	customer
p_{ij}	transition probability
V	the set of edges in the capacity network
E	the set of nodes in the network
X	pipeline failure event
Y	gas shortage event
P	state of the pipe segment
C	state of the compressor station
$p(y_i)$	the marginal probability of event occurrence
$p(x_i\|y_i)$	conditional probability
$p(y_i\|x_i)$	posterior probability
x_j	failure event of the *j*th pipeline
y_i	gas shortage event of customer *i*
$C_{cu,j}$	cost of gas shortage of CU *i*
$C_{sys,t}$	cost of gas shortage at the system level at discrete time *t*
$Q^{d}_{i,t}$	the planned amount of natural gas supplied to CU *i* at discrete time *t*
$Q^{ac}_{i,t}$	the actual amount of natural gas supplied to CU *i* at discrete time *t*
C_r	replacement cost rate
c_p	preventive maintenance cost
c_f	cost of corrective maintenance
t_o	ordering time
t_r	replacement time
T_w	waiting time of spare part
$\overline{F}(t)$	component reliability

1. INTRODUCTION

As a clean, low-carbon fossil energy source, natural gas plays a key role in achieving the goal of peak carbon and carbon neutrality. The operation risk is often induced by the inadequate monitoring and maintenance of key equipment and facilities at stations, and the lack of risk management capabilities resulting in the unexpected economic costs [1]. How to develop an efficient and comprehensive approach to guaranteeing the reliable and safe supply of natural gas is an important issue that needs to be addressed.

Efficient and reliable management of natural gas transmission is becoming even more important than before with its potential to improve operation efficiency and guarantee supply reliability. The current maintenance strategy for units in long-distance pipelines relies on the scheduled maintenance [2], which involves the same maintenance interval for the same type of unit. However, differences in the working environment and operation conditions lead to different degradation rates

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of units. The scheduled maintenance strategy is always accompanied by under-maintained or some other over-maintained units, which increases the management investment and reduces operation efficiency. A common method is to establish an optimization model [3–5] to maximize system reliability and minimize the expected cost within the preventive maintenance framework.

To solve this problem, the worldwide pipeline industry has developed some advanced maintenance strategies, condition-based maintenance (CBM) and reliability-centered maintenance (RCM) [6,7], drawing on the experience of the power, aerospace and mechanical sectors. For example, Shi [8] developed a CBM optimization for multi-component systems and introduce Bayesian updating to improve the prediction accuracy. In [9], a CBM optimization with an imperfect inspection scheme and a two-stage inspection scheme is proposed. A numerical experiment and a real case study prove its effectiveness. However, for the complex and expensive gas compressor system, the number of spare parts is often limited and the delivery time for spare parts is not negligible.

CBM and RCM mainly focus on ensuring reliable operation and functional integrity of individual units[10]. However, a reliable unit does not necessarily mean a reliable system. Equipment maintenance should not only focus on its performance but also system performance. Among the classical reliability methods, reliability allocation [11] is an important technique for improving system reliability. At present, reliability allocation methods for natural gas pipeline systems focus on individual components or simple structured industrial systems. Methods such as fault trees [12], fuzzy sets [13] and hierarchical analysis methods [14] have been introduced into reliability allocation in the literature to improve the applicability of allocation algorithms to complex systems. However, the above methods are mainly applicable to the system planning and design stages, with insufficient consideration for reliability assurance in the system operation stage, and they cannot consider the impact of dynamic gas pipeline transmission capacity on system reliability. Therefore, the above methods cannot directly guide the optimization of maintenance strategies for gas pipeline systems. In this paper, we propose a joint optimization of preventive maintenance and spare part inventory of gas compressor in pipeline system considering the deliver time of spare part. The proposed method can reduce the maintenance cost (includes shortage cost, storage cost, repair cost, etc.) and improve the supply reliability of the pipeline system.

The main contribution of our work can be summarized as follows:

1. A joint optimization of preventive maintenance and spare part inventory is proposed to give better performance than the sequential optimization model.

2. A novel method based on Bayesian network for evaluating the supply reliability of pipeline system is proposed, which allows for identifying the risk nodes and improving operation efficiency.

3. A maintenance optimization is proposed for gas compressors by referring to the supply reliability of pipeline system rather than the working condition of devices.

The rest of the paper is organized as follows. In Section 2, we briefly describe the methodology of our work. Section 3 mainly describes the demonstration scenario. The final section summarizes the work in this paper and indicates future research directions.

2. GENERAL DESCRIPTION OF THE METHODOLOGY

2.1 Calculation of the lifetime distribution

There are various operation states for units in pipeline system, which derives from the complex operation condition and external environmental disturbs. These operating states can convert to each other with a certain probability. A discrete Markov process is introduced here to describe the stochastic process of the unit state transition. The probability of the unit state transition from s_i to s_j at time t_n can be represented by:

$$\begin{aligned} &P\{X(s+t)=j \mid X(s)=i, X(u)=x(u), 0<u<s\} \\ &=P\{X(s+t)=j \mid X(s)=i\} \end{aligned} \tag{1}$$

p_{ij} represents the one-step transition probability of Markov processes. Considering all possible states N of the system, the state transition probabilities in a time step can be written into a (N × N) matrix A. Two properties of the transition matrix can be found in follows:

$$\begin{array}{c} i/j \\ 1 \\ A=2 \\ \vdots \\ N \end{array} \begin{pmatrix} 1 & 2 & \cdots & N \\ p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{pmatrix} \tag{2}$$

$$0 \le p_{ij} \le 1 \quad i, j \in \{1, 2, \cdots, N\} \tag{3}$$

$$\sum_{N}^{j=1} p_{ij} = 1 \quad i \in \{1, 2, \cdots, N\} \tag{4}$$

For the compressor station, the working and degeneration are two typical operation states in Fig. 1. When the degeneration occurs, the compressor station will maintain the gas transportation ability, but, the capacity of the surrounding pipelines reduces to a certain level. In the paper, we assume that a compressor station failure reduces the surrounding pipeline capacity by 20% [15].

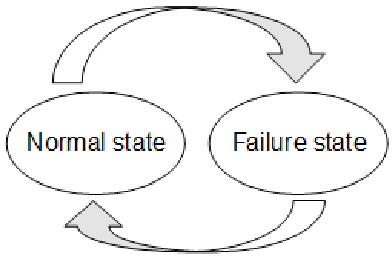

Fig.1 Description of the state transition process for the pipeline and compressor units

2.2 Gas supply capacity model

A model for calculating the gas transmission capacity of a pipeline can determine the maximum amount of gas that can be allocated to each user under different scenarios. Natural gas pipeline systems consist of of pipe segments and compressors.Here introduce the graph theory to characterize the system topology and logical relationships is an effective way to analyze the system's gas supply capacity. The capacity network in G(V, E), where V denotes the set of edges in the capacity network, corresponds to the pipeline segments in the natural gas system. In the capacity network, the value of each edge represents the maximum gas delivery capacity of the pipeline segment, which varies with the pipeline state; E denotes the set of nodes in the network, where gas sources, users, compressor stations and connections of pipeline segments are represented as nodes in the network.

When the state of natural gas pipeline equipment changes, the distribution of flow in the pipeline needs to be readjusted to meet the gas demand of downstream users to the maximum extent. Therefore, the maximum flow algorithm is introduced to calculate the maximum gas supply of the natural gas pipeline system under different operating conditions [16].

2.3 Supply reliability calculation

Random failures of key units in compressors and pipe sections within a natural gas pipeline system can lead to gas shortages for downstream users, and the causal relationships between variables can be described using Bayesian networks[17]. Bayesian networks are typical directed non-loop graphs, which mainly consist of nodes and directed edges. Nodes represent random variables, directed edges represent interrelationships between nodes, and the strength of interactions between two variables is expressed as conditional probabilities. The structure of Bayesian networks intuitively reflects the causal logic among variables and can clearly describe the propagation process of unit uncertainty in pipeline systems.

$$P(Y \mid X) = \frac{P(X \mid Y) \cdot P(Y)}{P(X)} \tag{5}$$

where X represents a pipeline failure event and Y represents a gas shortage event for the downstream users of the pipeline. The analysis of gas supply reliability of pipeline system using Bayesian network includes four key steps:

(1) Intergrate the expert experience and pipeline operation data, determine Bayesian network variable nodes as well as a network structure.

(2) Consider the unit life distribution and calculate the unit transient failure probability as the input of Bayesian network node edge distribution.

(3) Combine the maximum flow algorithm with Monte Carlo to simulate the gas shortage state under different unit failures, and conduct parameter learning to determine the Bayesian network node conditional distribution.

(4) Perform Bayesian inference to calculate the probability distribution of user nodes and establish the system gas supply reliability evaluation index.

2.3.1 marginal probability distribution

A simplified natural gas pipeline system consists of four key elements: the gas source, the gas station, the pipeline and the customer(CU). In a natural gas pipeline system, failure of pipe segment or an adjacent compressor station in an abnormal state will lead to a decrease in the supply capacity of the pipeline segment, as well as a decrease in gas supply to downstream users and a gas shortage. As shown in Fig. 2, a Bayesian network is used to describe the event relationships. The root nodes P and C denote the state of the pipe segment and the compressor station, and the leaf node CU (no sub-node) denotes the state of gas for users. Fig. 2(a) indicates that the state of pipe segment 1 - 4 directly affects the probability of CU1 is in different states; Fig. 2(b) indicates that when the state of compressor station C changes, the gas supply capacity of its surrounding pipe segments P_1 and P_2 is affected. The marginal probability distribution of the units within the pipeline system, which describes the probability of the units being in normal and abnormal states, can be obtained by solving Eqs. (1) - (4).

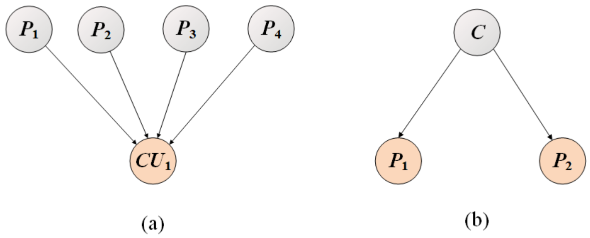

Fig. 2 Two typical relationships of variables in the Bayesian network

2.3.2 Conditional probability distribution

The basis for querying the distribution of variables using Bayesian networks is to obtain the conditional probability distribution of the nodes and to calculate the model parameters using Bayesian estimation [18].

$$p\left(y_i \mid x_j\right)=\frac{p\left(y_i\right) p\left(x_j \mid y_i\right)}{\sum_{n}^{i=1} p\left(y_i\right) p\left(x_j \mid y_i\right)} \tag{6}$$

where $p\left(y_i\right)$ denotes the marginal probability of event occurrence, $p\left(x_j \mid y_i\right)$ is the conditional probability distribution obtained from historical data, and $p\left(y_i \mid x_j\right)$ denotes the posterior probability. x_j denotes the failure event of the jth pipeline, and y_i denotes the gas shortage event of customer i. Eq. (6) indicates that the probability of gas shortage in CU i caused by pipeline j can be obtained by Bayesian estimation.

For pipeline systems, the conditional probability distribution reflects the intrinsic relationship between the pipeline or compressor station being in an abnormal operating condition and a downstream customer gas shortage event. Obtaining the conditional probability distribution based on the data is the key to constructing a Bayesian network. For this purpose, the maximum flow algorithm combined with Monte Carlo simulation is used to generate the operational data of the pipeline system, which describes the gas supply state of the CUs at each node when different units fail. Based on this data, maximum likelihood estimation is used for Bayesian network parameter learning to calculate the conditional probability distribution between unit nodes and CU nodes.

2.3.3 System supply reliability.

Indexes of gas shortage cost are given as:

$$C_{cu,i}=\frac{\sum_{t=1}^{T} P_{i,t}\cdot\left|Q_{i,t}^{d}-Q_{i,t}^{ac}\right|}{T} \tag{7}$$

$$C_{sys,t}=\frac{\sum_{n=1}^{N} P_{i,t}\cdot\left|Q_{i,t}^{d}-Q_{i,t}^{ac}\right|}{N} \tag{8}$$

where $C_{cu,i}$ represents the cost of gas shortage of CU i for the T period and $C_{sys,t}$ represents the cost of gas shortage at the system level. $Q_{i,t}^{d}$ represents the planned amount of natural gas supplied to CU i at discrete time t and $Q_{i,t}^{ac}$ indicates the actual amount of natural gas supplied to CU i. Note that, the cost of gas shortage can describe the potential system costs due to the absence of spare parts.

2.4 Maintenance optimization model

2.4.1 maintenance optimization

The lifetime distribution of the component is $F(t)$. The maintenance optimization problem aims to identify the optimal inspection interval to minimize the expected cost of the system.

$$C_0=c_p\overline{F}\left(t_r\right)+c_f F\left(t_r\right) \tag{9}$$

Let the time interval between two successive replacements be defined as a cycle, it is known that the cycle lengths are independently and identically distributed. Correspondingly, the replacement cost rate C_r can be expressed by:

$$C_r=\frac{c_p\overline{F}\left(t_r\right)+c_f F\left(t_r\right)}{\int_0^{t_r}\overline{F}(t)dt} \tag{10}$$

where c_p is the preventive maintenance cost; c_f is the cost of corrective maintenance; t_r is the replacement time; the cumulative distribution function of component failure denotes as $F(t)$; $\overline{F}(t)$ represents the component reliability, and we get $\overline{F}(t)=1-F(t)$. In particular, the above replacement costs include material buying costs, labor costs, economic costs caused by downtime and other costs.

2.4.2 Spare parts inventory optimization

When compressor failure occurs, a spare part is used to replace the failure component to restore the compressor to its normal state. Assume the compressor in a normal state at time t=0. Order a spare part at time t=t_0. After time T_w, the repairer will receive the spare part and perform maintenance activities. Let the moment at which each spare part returns to normal be the regeneration time.
The excepted downtime cost C_1 within a cycle is:

$$C_1 = k_f \int_{t_o}^{t_o+T_w} F(t)dt \tag{11}$$

The excepted storage cost within a cycle is:

$$C_2 = k_h \int_{t_o+T_w}^{\infty} \overline{F}(t)dt \tag{12}$$

The excepted ordering cost within a cycle is:

$$C(t_r) = \frac{C_1 + C_2}{E(CC)} = \frac{k_f \int_{t_o}^{t_o+T_w} F(t)dt + k_h \int_{t_o+T_w}^{t_r} \overline{F}(t)dt}{\int_0^{t_r} \overline{F}(t)dt + \int_{t_o}^{t_o+T_w} F(t)dt} \tag{13}$$

2.4.3 Joint maintenance optimization

The sequential optimization strategy based on the time to failure distribution does not take into account the interaction between maintenance and inventory. This optimization model yields a partially optimal solution. The joint optimization strategy takes replacement time and ordering time as decision variables to minimize the average cost.

If the spare part fails before time t_r, it is immediately replaced if spare parts are available, or if they are not available, they have to wait for them to arrive; if the failure does not occur before t_r, then preventive replacement is carried out at the moment of t_r. If the part fails before t_o, then order the spare part and replace it when the spare part arrives; otherwise, order the spare part at the time t_o. Combining the cost rate functions in Eq. (13) and expected cycle lengths in Eq. (10), a joint cost function for t_r and *to* can be derived as follows.

$$JCF(t_o, t_r) = \frac{C_0 + C_1 + C_2}{E(CC)} \tag{14}$$

3. CASE STUDY

3.1 Description of the Pipeline System

To evaluate the performance of the proposed method, we conducted experiments on a European pipeline system derived from [15]. The topology of the tested gas pipeline system is presented in Fig. 3. The pipeline system contains 2 gas sources, 2 compressor stations and 8 CUs. The length of the pipeline is 692.8 km. The outside diameter of gas pipeline segments is 1067 mm, the pipe thickness is 12.5 mm, and the designed pressure is 10 MPa. The supply temperature is 293 K. All end-customers are in a pressure-controlled model, the minimum pressure for customers is between 4 - 7 MPa. The contract pressure at the end node is 6 MPa. The parameters of the pipeline segment are described in Table 1. The information regarding the demand nodes and supply nodes are presented in Table 2.

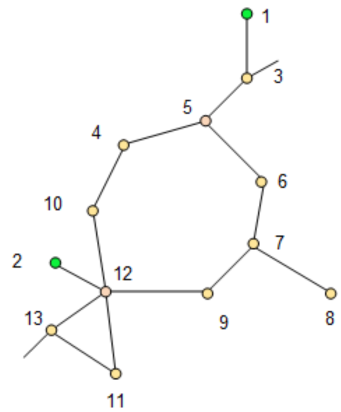

Fig. 3 The topology structure of the tested NGPN

Table 1 Parameters of the pipeline segment

Start	End	Capacity (mcm/d)	Length (km)	Start	End	Capacity (mcm/d)	Length (km)
1	3	12.11	60	7	8	12.11	46
2	12	10.45	1.8	9	7	1.2	60
3	5	12.11	0.01	10	12	3	50
4	10	6.2	60	12	9	2	70
5	6	6.6	86	12	11	2.5	12
5	4	1.4	86	12	13	4	60
6	7	0.83	86	13	11	4.2	15

Table 2 Properties of demand nodes and supply nodes

Start	End	Demand(mcm/d)
4	14	0.54
7	14	0.6
8	14	0.8
9	14	1.2
10	14	6
11	14	1.4
13	14	1.8
0	1	8
0	2	4.34

3.2 Supply reliability of pipeline system

This section focuses on the calculation of the supply reliability of the pipeline system. The results regarding the gas supply reliability for CUs are presented in Fig. 4. The orange lines show the cumulative distribution functions, while the bar histograms depict the empirical probability distribution functions of CUs' gas supply reliability. The statistical results for the distribution are given in Table 3. Under the proposed maintenance strategy, the value of the gas supply reliability of CUs has a probability of 0.889 to fall within the interval [0.9, 1]. The comparison findings show that preventative maintenance is efficient in ensuring operation safety and supply reliability.

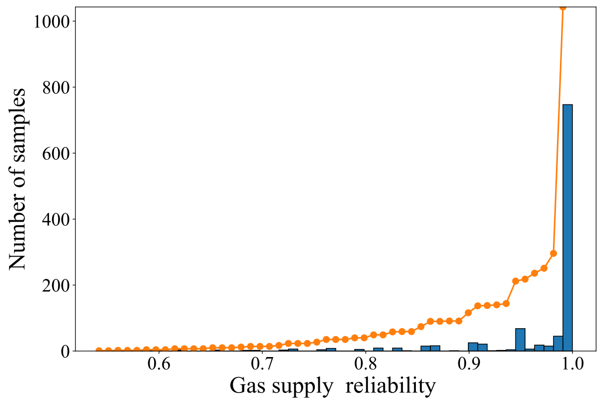

Fig. 4 Distribution of gas supply reliability samples

Table 3 Distribution of gas supply reliability for CUs

Reliability interval	Counts	Cumulative percentage
(0.95, 1.0]	863	0.8274
(0.9, 0.95]	65	0.8897
(0.85, 0.9]	56	0.9434
(0.8, 0.85]	19	0.9616
(0.75, 0.8]	17	0.9779
(0.7, 0.75]	9	0.9865
(0.65, 0.7]	7	0.9932
(0.6, 0.65]	3	0.9961
(0.55, 0.6]	3	0.9990
(0.5, 0.55]	1	1

A comparison of the average supply reliability of all CUs over the evaluation period is shown in Fig. 5. By observing the Figure, CU10 has the highest reliability among all users with a reliability of 0.9984; CU4 has the lowest reliability with a reliability of 0.9898. This is due to the fact that the allocation of the gas supply is prioritized to the lower-cost CUs, and after the high-priority CUs are satisfied, the remaining capacity is allocated downwards. The delivery cost of a pipeline segment depends on the length of the segment and the design capacity of the pipeline. Here, CU10 gets a higher priority in the allocation of gas deliveries and has higher reliability of supply.

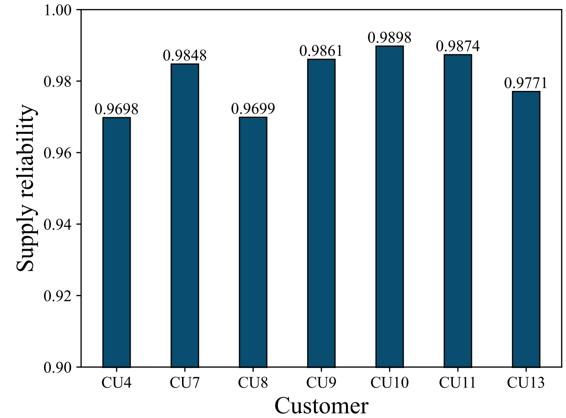

Fig. 5 Average gas supply reliability for CUs

3.3 Comparison of maintenance strategy

In this subsection, a numerical experiment is conducted to show how to determine the optimal maintenance interval and ordering time of spare parts. To evaluate the performance of the proposed maintenance strategy, we use sequential optimization strategies as a benchmark. The details of the proposed maintenance strategy are summarized below.

Joint optimization strategy: Considering the relationship between the inspection time and the ordering time of spare parts, the inspection time and the ordering time of spare parts are used as variables. with the lowest expected cost of the pipeline system as the optimization objective.

Sequential optimization strategy: Firstly, the optimal inspection time of components is obtained with the lowest maintenance cost of the system without considering the spare parts; further, based on the calculated inspection time, the spare parts ordering time is optimized and solved by employing an optimization model for the spare parts ordering cycle.

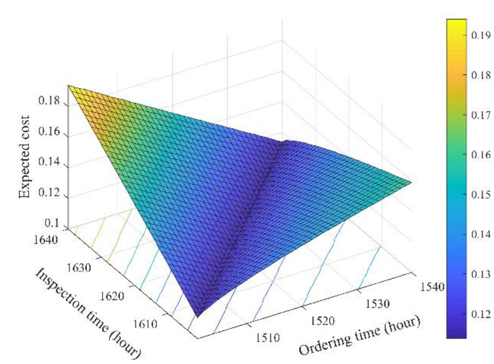

Fig.6. Expected cost with different inspection time and ordering time of spare parts

The three-dimensional and contour map of expected cost for various inspection time and ordering time is depicted in Fig. 6. The high expected cost is represented by the yellow points, the low expected cost is presented by the blue points. Obviously, just increasing the time it takes to order spare parts will not always lower the estimated cost per unit of time, and hence is not always an appropriate maintenance program. The contour plot shows that the projection of the contour on the x-axis is a linear function. This means that while the difference between inspection and ordering time is constant, the average costs for the two cases are comparable but not precisely equal.

Table 4 Comparison of different maintenance strategies

	Optimal ordering time	Optimal replacement time	Average cost
Proposed optimization strategy	1521.1	1621.2	0.1226
Sequence optimization strategy	1532.4	1665.8	0.1422

Table 4 summarizes the optimal inspection time and optimal ordering time for the three maintenance strategies. The results show that the optimal detection time under the joint optimization model is 1521.1 hours and the optimal ordering time of spare parts is 1621.2 hours, with an average cost of 0.1226. The average losses for the sequential optimization model and the sequential maintenance strategy are presented respectively. The joint optimization strategy achieves a smaller cost. Furthermore, the optimum spare parts ordering time is approximately 100 hours earlier than the optimal spare parts replacement time. The stochastic nature of spare part delivery times, the possibility of the early arrival of spare parts incurring additional storage costs, and the delayed arrival of replacement components causing unexpected downtime and increasing the risk of downstream gas shortages all contribute to this. Therefore, the spare parts ordering time is approximately 100 hours longer than the equipment inspection time, proving that managers prefer to reduce the risk of delays.

Table 5 Supply reliability of CUs under different maintenance strategies

	CU4	CU7	CU8	CU9	CU10	CU11	CU13
Proposed strategy	0.9698	0.9848	0.9699	0.9861	0.9898	0.9874	0.9771
Sequence optimization strategy	0.9673	0.9763	0.9606	0.9836	0.989	0.9803	0.9676

Table 5 shows the reliability of gas supply for users with different strategies. It can be found that CU10 has the highest gas supply reliability. The CUs that closer to the gas source have a higher gas supply reliability. The average value of gas supply reliability for users with the joint maintenance strategy is 0.9807 and the average value of system reliability for users with the sequential maintenance strategy is 0.975. The lowest supply reliability for the sequential maintenance strategy is 0.9606.

4. CONCLUSION

In this paper, we propose a joint optimization of preventive maintenance and spare parts ordering for the gas compressor in the pipeline system. The approach can minimize the maintenance cost and maximize supply reliability. To overcome the high computational cost of Monte Carlo, Bayesian network is used to describe the mapping relationship between compressor failure in the pipeline system and gas shortage of downstream users, and to quickly calculate the reliability of gas supply in the pipeline system. A genetic algorithm is used to find the optimal solution. The proposed method is applied to solve the problem of optimization of the maintenance management of pipeline systems. We have measured that the results obtained by the joint optimization strategy are more efficient than the traditional sequential strategy. In the future, the present model will be further analyzed by exploring system management strategies under demand variations and considering the randomness of the delivery time of spare parts.

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REFERENCE

[1] Company PP. Optimization and application of maintenance strategies for mechanical equipment at the stations of long-distance pipelines 2018:475–80.

[2] Fan L, Su H, Wang W, Zio E, Zhang L, Yang Z, et al. A systematic method for the optimization of gas supply reliability in natural gas pipeline network based on Bayesian networks and deep reinforcement learning. Reliab Eng Syst Saf 2022;225:108613.

[3] Zhang N, Si W. Deep reinforcement learning for condition-based maintenance planning of multi-component systems under dependent competing risks. Reliab Eng Syst Saf 2020;203:107094.
[4] Erguido A, Márquez AC, Castellano E, Flores JL, Fernández JFG. Reliability-based advanced maintenance modelling to enhance rolling stock manufacturers' objectives. Comput Ind Eng 2020;144:106436.
[5] Mohamadi M, Karbasian M. Developing an economical model for reliability allocation of an electro-optical system by considering reliability improvement difficulty, criticality, and subsystems dependency. J Ind Eng Int 2019;15:379–93.
[6] Dong W, Liu S, Joo S, Cao Y. Reliability modelling for multi-component systems subject to stochastic deterioration and generalized cumulative shock damages. Reliab Eng Syst Saf 2021;205:107260.
[7] Ye Y, Grossmann IE, Pinto JM, Ramaswamy S. Modeling for reliability optimization of system design and maintenance based on Markov chain theory. Comput Chem Eng 2019;124:381–404.
[8] Shi Y, Zhu W, Xiang Y, Feng Q. Condition-based maintenance optimization for multi-component systems subject to a system reliability requirement. Reliab Eng Syst Saf 2020;202:107042.
[9] Hao S, Yang J, Berenguer C. Condition-based maintenance with imperfect inspections for continuous degradation processes. Appl Math Model 2020;86:1–24.
[10] Alaswad S, Xiang Y. A review on condition-based maintenance optimization models for stochastically deteriorating system. Reliab Eng Syst Saf 2017;157.
[11] Su H, Zio E, Zhang J, Li Z, Wang H, Zhang F, et al. A systematic method for the analysis of energy supply reliability in complex Integrated Energy Systems considering uncertainties of renewable energies, demands and operations. J Clean Prod 2020.
[12] Kabir S, Papadopoulos Y. Applications of Bayesian networks and Petri nets in safety, reliability, and risk assessments: A review. Saf Sci 2019;115:154–75.
[13] Garg H, Sharma SP. Multi-objective reliability-redundancy allocation problem using particle swarm optimization. Comput Ind Eng 2013;64:247–55.
[14] Prakash G. A Bayesian approach to degradation modeling and reliability assessment of rolling element bearing. Commun Stat - Theory Methods 2020;0:1–22.
[15] Praks P, Kopustinskas V, Masera M. Probabilistic modelling of security of supply in gas networks and evaluation of new infrastructure. Reliab Eng Syst Saf 2015;144:254–64.
[16] Praks P, Kopustinskas V. Monte-Carlo based reliability modelling of a gas network using graph theory approach. Proc - 9th Int Conf Availability, Reliab Secur ARES 2014 2014:380–6.
[17] Dindar S, Kaewunruen S, An M. Bayesian network-based human error reliability assessment of derailments. Reliab Eng Syst Saf 2020;197:106825.