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Original Paper

Risk analysis and maintenance decision making of natural gas pipelines with external corrosion based on Bayesian network

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ABSTRACT

Buried natural gas pipelines are vulnerable to external corrosion because they are encased in a soil environment for a long time. Identifying the causes of external corrosion and taking specific maintenance measures is essential. In this work, a risk analysis and maintenance decision-making model for natural gas pipelines with external corrosion is proposed based on a Bayesian network. A fault tree model is first employed to identify the causes of external corrosion. The Bayesian network for risk analysis is determined accordingly. The maintenance strategies are then inserted into the Bayesian network to show a reduction of the risk. The costs of maintenance strategies and the reduced risk after maintenance are combined in an optimization function to build a decision-making model. Because of the limitations of historical data, some of the parameters in the Bayesian network are obtained from a probabilistic estimation model, which combines expert experience and fuzzy set theory. Finally, a case study is carried out to verify the feasibility of the maintenance decision model. This indicates that the method proposed in this work can be used to provide effective maintenance schemes for different pipeline external corrosion scenarios and to reduce the possible losses caused by external corrosion.

1. Introduction

Most natural gas transportation occurs through pipelines due to their high efficiency, low cost, and inability to be easily affected by the transportation environment (Cui et al., 2020; Wang et al., 2020; Turkowski and Szudarek, 2019; Hao et al., 2019). The extension of pipeline service life leads to a greatly increased probability of pipeline accidents (Xing et al., 2020; Wang et al. 2017, 2020; Liu et al., 2018; Lu et al., 2015; Badida et al., 2019; Guo et al., 2016). Some characteristics of the soil, such as salinity, may have a negative effect on pipelines due to long-term contact. (Li et al., 2018; Wang et al., 2015a). External corrosion has been determined to be one of the main reasons for the failure of buried pipelines (Liu et al., 2018; Li et al., 2018; Gadala et al., 2016). Once a pipeline fails, disastrous consequences such as fires, explosions, and environmental pollution can result (Cui et al., 2020; Zhou et al., 2020; Liu et al., 2018). The timely maintenance of corroded pipelines is important for preventing unnecessary losses (Bastian et al., 2019; Liu et al., 2018). However, excessive maintenance may reduce the efficiency of pipeline transportation. For this reason, risk-based maintenance has been applied to provide a balance between safety and efficiency (Li et al., 2017). In other words, maintenance plans need to be optimized with a consideration of both the costs and the failure risks of pipelines.

It is necessary to analyse the causes of buried pipeline external corrosion and consider how to take targeted maintenance measures. Several studies have been conducted in the fields of pipeline risk analysis in both qualitative and quantitative ways, especially for the assessment of failure probability and the prediction of corrosion rate (Wang et al., 2015b; Caleyo et al., 2015; Badida et al., 2019; Lecchi, 2011; Guo et al., 2016; Vanaei et al., 2017; Valor et al., 2013; Wang and Duan, 2019; Chen et al., 2020). For example, Allahkaram et al. (2015) estimated the corrosion rate of pipelines under the influence of stray currents. Shan et al. (2018) established an assessment model of gas transmission pipeline failure probability based on historical failure-related data and modification factors. The establishment of maintenance strategies can reduce the probability of failure to some extent. Zakikhani et al. (2020) proposed a maintenance planning framework for the external corrosion of gas transmission pipelines through an availability-centred reliability-based maintenance planning procedure. A multilevel strategy was proposed for the maintenance optimization

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of pipeline systems subjected to external corrosion by XQ Liu et al. (2018). At present, many studies have been conducted on pipeline risk assessment and maintenance (Kimiya et al., 2020). How to combine maintenance decisions and risk assessments to effectively improve the safety of pipeline operation is necessary.

Pipeline risks change when different maintenance decisions are made. This dynamic feature places a high demand on the risk analysis method (Wu et al., 2017; Kabir et al., 2015). However, conventional risk analysis methods like fault tree analysis and event tree analysis (Wu et al., 2017; Naghavi-Konjin et al., 2020) have limitations, such as the inability to analyse the relationship between variables and the absence of specific probability expressions of the events (Guo et al., 2020). Therefore, a risk analysis method that can describe the relationship among variables with uncertainty and multi-state issues is needed (Zhang et al., 2018; Wang et al., 2017). Bayesian network (BN) are one of the most effective theoretical models in the field of uncertain knowledge expression and inference (Zhou et al., 2020). The main advantage of a Bayesian network is that it can update the probability and act as a special dynamic manifestation according to the different settings of the evidence nodes (Li et al., 2020; Dahire et al., 2018; Wang et al., 2017). This advantage can be applied in the external corrosion risk assessment of pipelines with a consideration of pipeline maintenance. During pipeline operation, specific parameters can be obtained through detection or pipeline properties. Those parameters, as well as the assumed maintenance decisions, can appear as evidence nodes in a Bayesian network to update the predicted failure probability.

To reduce the pipeline failure probability caused by external corrosion with reasonable maintenance methods, a maintenance decision model based on a Bayesian network is proposed in this paper. Section 2 describes the framework and the methods employed in this work. Section 3 and Section 4 introduce the risk assessment model and maintenance decision model, respectively. Section 5 illustrates the application of the model through a case study. Section 6 offers conclusions.

Table 1
Linguistic terms and their corresponding fuzzy numbers used to describe the likelihood of an event (Chen and Hwang, 1992).

Linguistic terms	Probability description	Trapezoidal fuzzy numbers
Very low	<1%	(0, 0, 0,0.2)
Low-Very low	1%–5%	(0,0,0.1,0.3)
Low	5%–10%	(0, 0.2, 0.2,0.4)
Fairy low	10%–33%	(0.2, 0.35, 0.35,0.5)
Medium	33%–66%	(0.3, 0.5, 0.5,0.7)
Fairy high	66%–90%	(0.5, 0.65, 0.65,0.8)
High	90%–95%	(0.6, 0.8, 0.8,1)
High-Very high	95%–99%	(0.7,0.9,1,1)
Very high	>99%	(0.75,1, 1, 1)

2. Methodology

This section provides an overview of the proposed methodology. The framework is shown in Fig. 1. First, a fault tree model is established to analyse the risk factors for buried natural gas pipelines. Then, the Bayesian network is determined accordingly. Second, a probability estimation model that combines expert experience and fuzzy set theory is established to determine the conditional probability tables (CPTs) and some parts of the prior probability in the BN. Finally, the maintenance decision model based on the BN is proposed.

2.1. Fault tree analysis

Fault tree (FT) is a deductive failure analysis method used to analyse the unwanted state of a system from the result to the causes (Gachlou et al., 2019; Badida et al., 2019; Yin et al., 2020). It is mainly used in the fields of reliability engineering and safety engineering to find the causes of accidents. In practical applications, fault tree analysis is good at finding the weak part of a system. However, a FT cannot express the uncertainty of an event accurately. The probability of the events in a FT is expressed in Boolean algebra with “AND” and “OR” gates. Its conditional probability has only two values, 0 or 1. This is much different from a real situation. For example, the occurrence of a stray current could enhance the possibility of external corrosion but not definitely lead to the failure

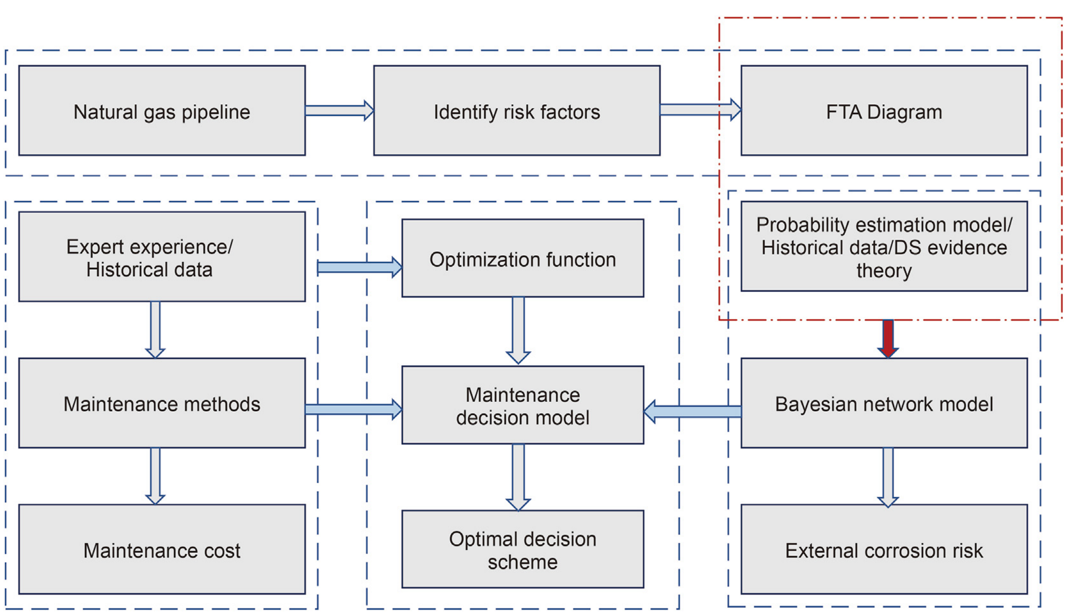

Fig. 1. The framework of the proposed methodology.

of a pipeline. In contrast, a Bayesian network has a flexible structure and a better representation of the probability of events (Badida et al., 2019; Villa et al., 2016).

2.2. Bayesian network

A Bayesian network, also known as a belief network, is a directed acyclic graph model. It is comprised of nodes representing stochastic variables and directed arcs symbolizing probabilistic conditional dependencies among the variables (Khakzad et al., 2011; Tien and Kiureghian, 2016). A Bayesian network is a causal association model that has a strong ability to deal with uncertainties. This was first proposed by Judea Pearl in 1985 and has since become one of the main techniques for dealing with uncertain information (Pearl, 1985). Usually, a BN consists of nodes, directed edges and conditional probabilistic tables (CPTs) (Li et al., 2020). The nodes, including parent nodes and child nodes, represent random variables. The directed edges show the dependencies among the variables. The CPTs show the conditional probabilities between the dependent variables and the parent nodes. (Khakzad et al., 2013).

A joint probability distribution over a set of variables $X = \{X_1, X_2, \dots, X_n\}$ is shown as follows:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i | Pa(X_i)) \tag{1}$$

where $X_i \in X$. $Pa(X_i)$ is the parent set of the variable X_i (Li et al., 2020).

Given new observations or evidence, the prior probability of the variable can be updated. Then, the posterior probability of the variable can be obtained as (Caleyo et al., 2015):

$$P(X_j|X_i) = \frac{P(X_i, X_j)}{P(X_i)} = \frac{P(X_i|X_j) \cdot P(X_j)}{\sum\limits_j P(X_i|X_j)P(X_j)} \tag{2}$$

2.3. Probabilistic estimation model

For accurate failure probabilities that are difficult to obtain through inadequate historical data, a probabilistic estimation model combining experts' judgement and fuzzy set theory can be used as an alternative. There are many applications of fuzzy set theory that deal with uncertainty and inaccuracy in expert judgements in linguistic terms (Yazdi and Kabir, 2017). Trapezoidal fuzzy numbers are adopted in this study to express the probability of occurrence of an event (Li et al., 2019).

The membership function of a trapezoidal fuzzy number has the following form:

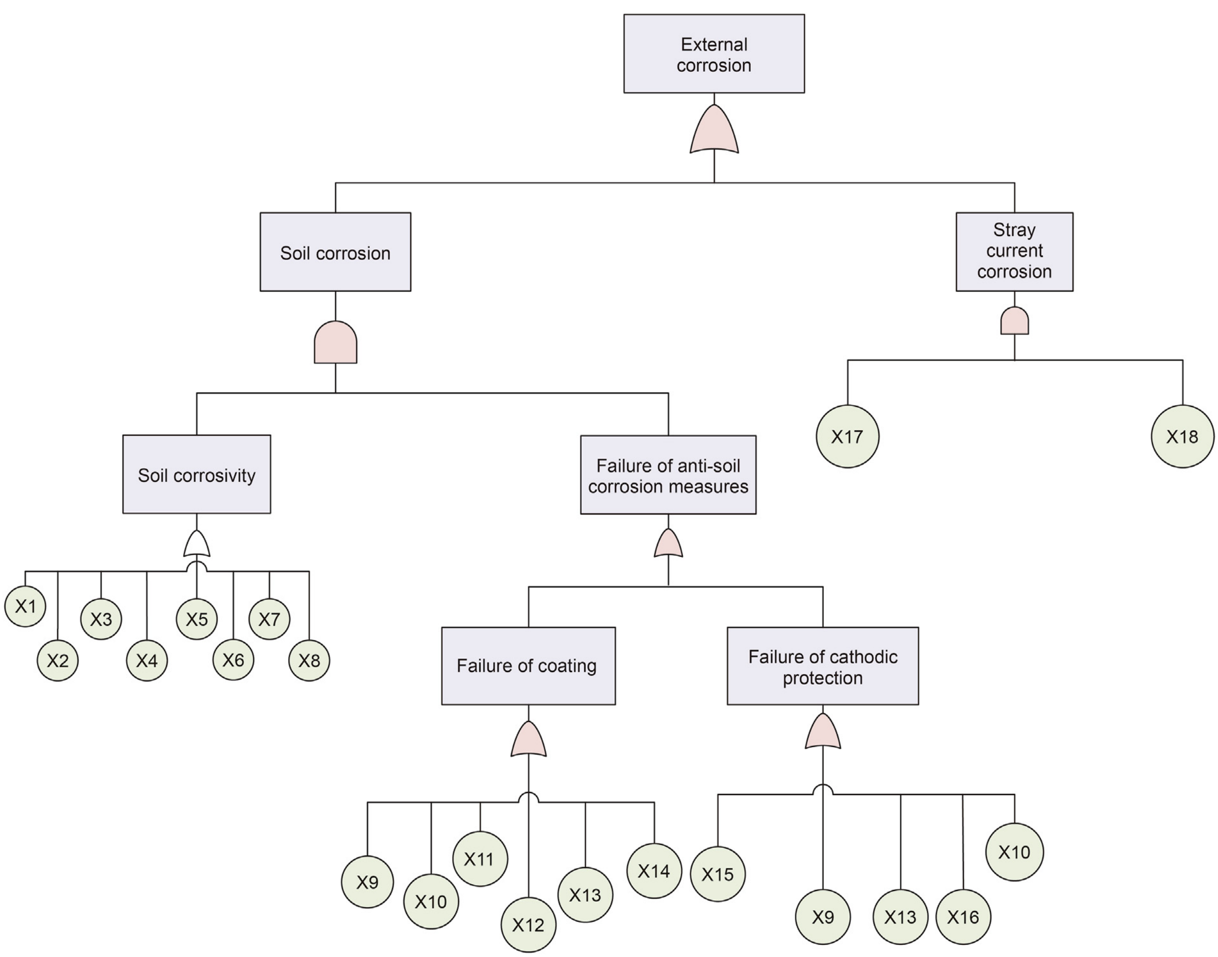

Fig. 2. Fault tree diagram.

Table 2
Basic events of FT.

Symbol	Description	Symbol	Description
X_1	pH value	X_{10}	Construction quality issues
X_2	Resistivity	X_{11}	Service time of the pipe
X_3	Soil moisture	X_{12}	Coating quality issues
X_4	Redox potential	X_{13}	Insufficient inspection frequency
X_5	Soil salinity	X_{14}	Improper selection of coating
X_6	Soil texture	X_{15}	Line failure
X_7	Free corrosion potential	X_{16}	Part failure
X_8	Chloride content	X_{17}	Stray current
X_9	Third party activities	X_{18}	Failure of stray current protective measures

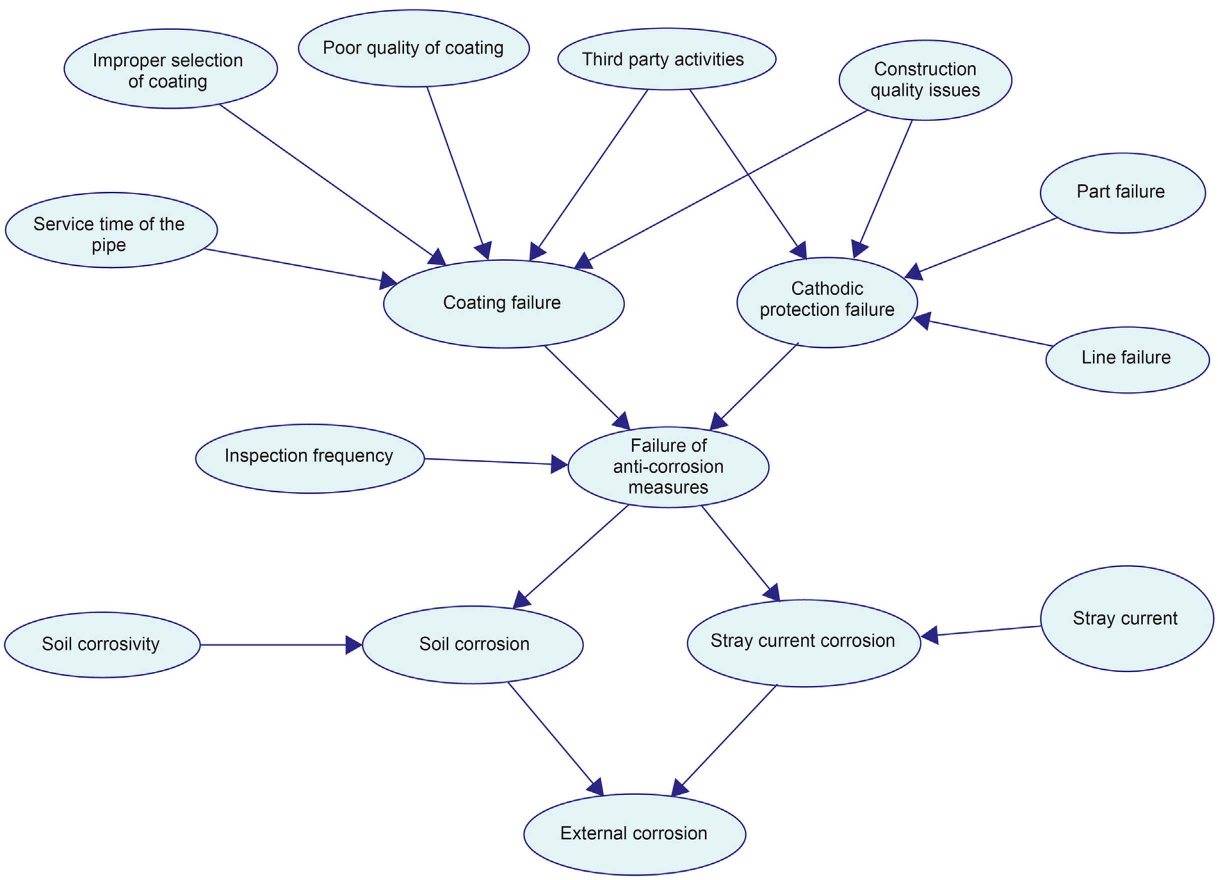

Fig. 3. Bayesian network for buried pipeline external corrosion.

$$\mu(x) = \begin{cases} 0, x < a \\ \dfrac{x-a}{b-a}, a \le x \le b \\ 1, b \le x \le c \\ \dfrac{d-x}{d-c}, c \le x \le d \\ 0, x > d \end{cases} \tag{3}$$

Where $A = (a, b, c, d)$ is a group of trapezoidal fuzzy numbers.

In this paper, 9 linguistic terms are used to estimate the occurrence probability of events. Three experts are asked to describe the probability of the basic events with “Very low, Low-Very Low, Low, Fairy low, Medium, Fairy high, High, High-Very High, and Very high”. Fuzzy set theory is applied to transform the description of linguistic terms into fuzzy numbers, as shown in Table 1. Because the professional and education levels of experts are not exactly the same, different experts are assigned weights expressed by $\omega = (\omega_1, \omega_2, \omega_3)$. The influencing factors of the weights are professional position, education level, experience and age (Ramzali et al., 2015). The fuzzy failure possibility of event i in state j can be calculated with Eq. (4)

$$\tilde{P_{ij}} = \sum_{l=1}^{3} \omega_l \otimes A_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij}) \tag{4}$$

where $P(\sim)_{ij}$ is the trapezoidal fuzzy probability of event i, A_{ij} is the expert's description of event i corresponding to a fuzzy array, and ω_l is the weight of expert l, $l = 1,2,3$. In general, the number of experts should be at least 3 to reduce the subjectivity of judgment.

To obtain a representative probability value of the basic events, the fuzzy numbers must be defuzzified. Based on obtaining the

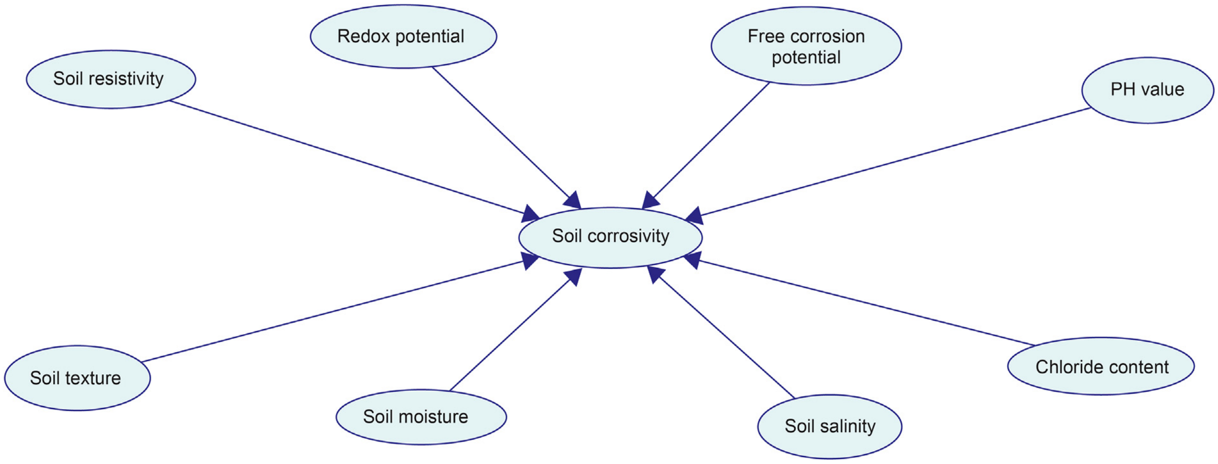

Fig. 4. Bayesian network of soil corrosivity.

Table 3
Nodes illustration in the Bayesian network of soil corrosivity.

Node classification	Bayesian nodes	States of nodes
Leaf nodes	Soil corrosivity	strong/medium/weaker/weak
Root nodes	Soil resistivity	<20//20–50/>50, Ω· m
	Redox potential	<100/100–200/200–400/>400, mV
	Free corrosion potential	<-550/-550∼-450/-450∼-300/>-300, mV
	pH value	<4.5/4.5–5.5/5.5–7.0/7.0–8.5/>8.5
	Soil texture	Sandy soil/loam/clay
	Soil moisture	≤7/7–10/10–12/12–25/25–30/30–40/>40,%
	Soil salinity	≤0.05/0.05–0.15/0.15–0.75/>0.75, %
	Chloride content	≤0.005/0.005–0.01/0.01–0.05/>0.05, %

Table 4
Description of means of maintenance.

Repair parts	Maintenance means
Coating	Repair/Replace
Cathodic protection system	Parts maintenance/Line maintenance
Stray current	Direct drainage/Ground drainage
Severe external corrosion	Replace the pipe

trapezoidal fuzzy probability, the fuzzy possibility scores P^* of the node are calculated with the centre area method, as shown in Eq. (5)

$$P^* = \frac{\int \mu(x)xdx}{\int \mu(x)dx} = \frac{\int_a^b \frac{x-a}{b-a}xdx + \int_b^c xdx + \int_c^d \frac{d-x}{d-c}xdx}{\int_a^b \frac{x-a}{b-a}dx + \int_b^c dx + \int_c^d \frac{d-x}{d-c}dx} = \frac{1}{3}\frac{(d+c)^2 - dc - (a+b)^2 + ab}{d+c-a-b} \tag{5}$$

Finally, the fuzzy probability scores are converted to the fuzzy probability based on a function developed by Onisawa (1988), as shown in Eq (6).

$$FP = \begin{cases} \frac{1}{10^k}, P^* \neq 0 \\ 0, P^* = 0 \end{cases}, K = \left[\left(\frac{1-P^*}{P^*}\right)\right]^{\frac{1}{3}} \times 2.301 \tag{6}$$

where K is a constant and FP is the fuzzy probability of the event.

Table 1 shows the probability ranges and fuzzy numbers corresponding to different fuzzy terms for event likelihood. For the prior probability that cannot be obtained according to the historical data, as well as the CPTs that are not simply converted from the logic gates, the probabilistic estimation model is an alternative.

2.4. Optimization function

Maintenance plays an important role in reducing the risk. The main concept of the maintenance decision model is to analyse the effect of maintenance strategies on reducing the failure probability. At the same time, the cost of the maintenance method should also be reasonable.

For pipeline external corrosion, the maintenance cost, inspection cost and expected failure loss are considered. The maintenance decision is made based on the optimization of the total cost, which can be calculated as:

$$R = \sum_{i=1}^{n} C_{Ri} + \sum_{j=1}^{m} C_{Fj}P_{Fj} + \sum_{k=1}^{s} C_{Dk}P_{Dk} \tag{7}$$

where R is the total cost. C_{Ri} is the cost when choosing maintenance method i. C_{Fj} is the loss of failure mode j, and P_{Fj} is the probability of failure mode j after maintenance implementation. C_{Dk} is the cost of the routing inspection, and P_{Dk} is the certain inspection frequency, which is determined by DS evidence theory. m is the total number of failure modes, while s is the total number of inspection frequency classifications.

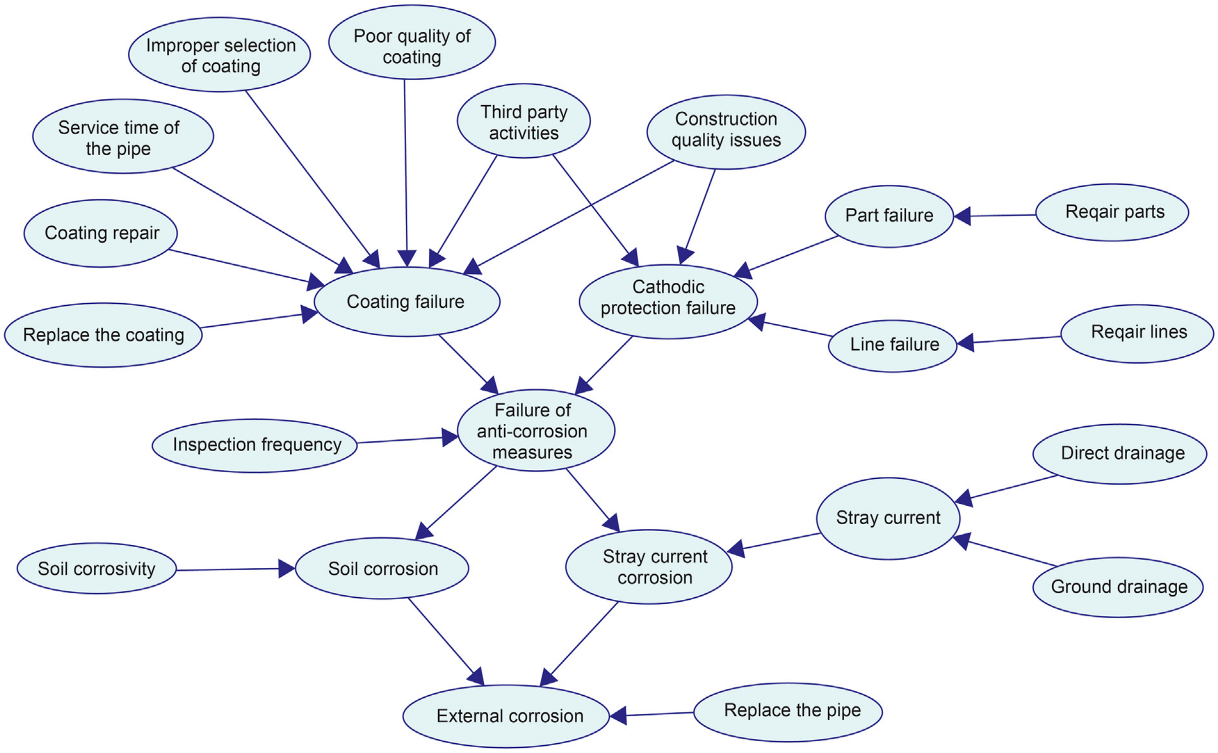

Fig. 5. Maintenance decision model.

Table 5
Node illustration in the maintenance decision model.

Node classification	Bayesian nodes	States of nodes
Leaf nodes	External corrosion	Yes/no
Intermediate nodes	Soil corrosion	Yes/no
	Failure of anti-corrosion measures	Yes/no
	Stray current	Weak/medium/strong/no
	Cathodic protection failure	Yes/no
	Coating failure	Yes/no
	Stray current corrosion	Yes/no
	Cathodic protection parts failure	Yes/no
	Cathodic protection lines failure	Yes/no
Root nodes	Third party activities	Yes/no
	Service time of the pipe	<20/20–30/>30 (year)
	Poor quality of coating	Yes/no
	Construction quality issues	Yes/no
	Improper selection of coating	Yes/no
	Inspection frequency	no/once a day/once a week/once a month
	Soil corrosivity	Strong/medium/weaker/weak
Root nodes (maintenance nodes)	Repair the coating	Yes/no
	Replace the coating	Yes/no
	Cathodic protection parts maintenance	Yes/no
	Cathodic protection lines maintenance	Yes/no
	Ground drainage	Yes/no
	Direct drainage	Yes/no
	Replace the pipe	Yes/no

3. Hazard identification and risk assessment model

3.1. Fault tree diagram

In this part, a fault tree that takes external corrosion as the target event is built to analyse the possible reasons for the external corrosion. External corrosion can be categorized into two types: 1) soil corrosion and 2) stray current corrosion (Cui et al., 2016). Either of them will lead to external corrosion of the pipeline. Direct causes are further discussed for these two forms of corrosion, and 18 basic events leading to pipeline external corrosion are obtained. Fig. 2 shows the analysis process of hazard identification, and the basic events are listed in Table 2.

Fig. 2 analyses the possible causes of external corrosion for buried pipelines. However, “Yes” or “No” cannot represent the actual states of some basic events of the fault tree. For example, the nodes “inspection frequency” and “service time of the pipe” have 3–4 states. For this reason, the FT needs to be transferred into a BN to solve those problems, especially for events with multiple states.

Table 6
Prior probability of root nodes.

Root nodes		Prior probability
Poor quality of coating		2.2E-03
Construction quality issues		2.2E-03
Improper selection of coating		1.5E-05
Third party activities		0.009
Cathodic protection part failure		1E-04
Cathodic protection line failure		3E-03
Service time of the pipe, years	<20	0.61
	20–30	0.26
	>30	0.13
Inspection frequency	no	0.01
	Once a day	0.9
	Once a week	0.078
	Once a month	0.012

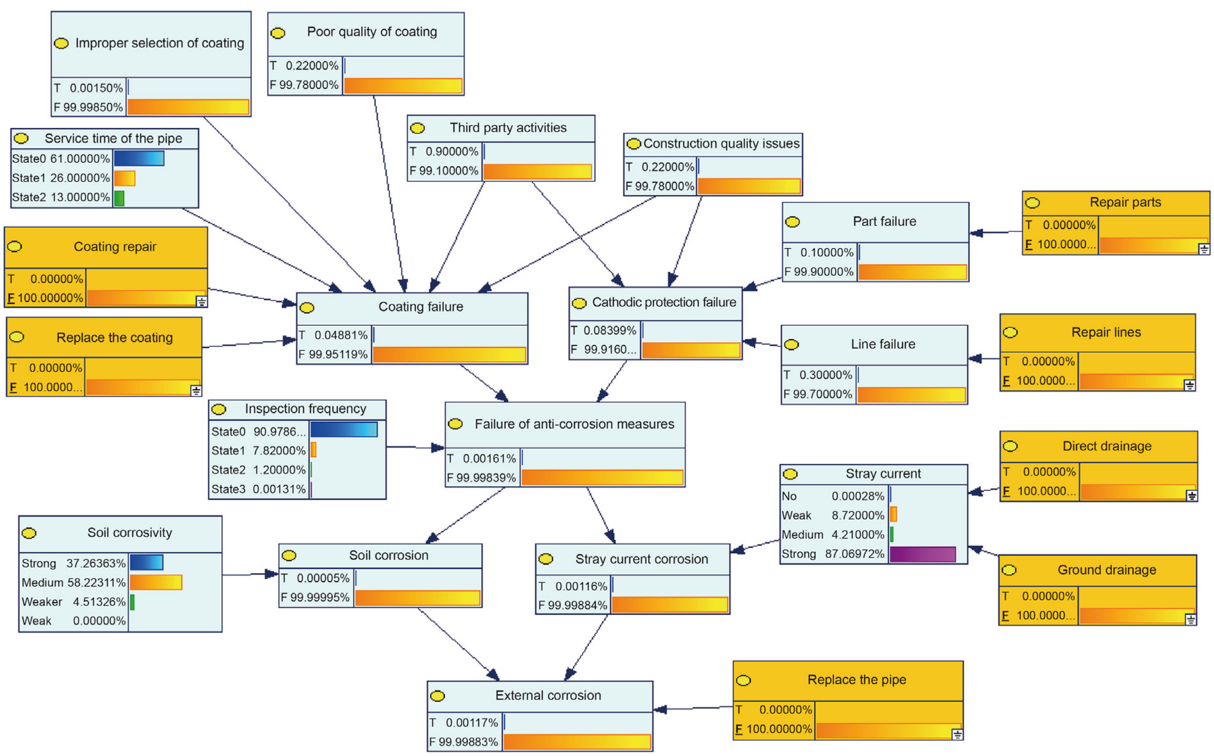

Fig. 6. Marked observable nodes in the Bayesian network.

Table 7
The CPT of the node “External corrosion”.

Replace the pipe		Yes				No			
Soil corrosion		Yes		No		Yes		No	
Stray-current corrosion		Yes	No	Yes	No	Yes	No	Yes	No
External corrosion	Yes	0	0	0	0	1	1	1	0
	No	1	1	1	1	0	0	0	1

3.2. External corrosion analysis with BN

All the basic events in the FT correspond to the root nodes in the Bayesian network. According to the relationship of the events in the FT, the nodes are connected in a Bayesian network with directional edges. It should be noted that the directional direction of the edges is consistent with the output direction of the logic gates in the FT. The established FT in Fig. 2 is transformed into a Bayesian network, and the corresponding revisions are made. The revised structure of the Bayesian network is shown in Fig. 3.

The nodes in this Bayesian network and their corresponding states are described in detail in Section 4.2.

Soil corrosivity plays an important role in influencing factors of the external corrosion of buried pipelines. Many factors influence soil corrosivity, and the classification is complex. Therefore, soil corrosivity was modelled separately in this study. According to GB/

Table 8
Part of CPT for "coating failure" node.

Precondition	Parent nodes					Expert judgement			FP
	C	T	P	I	S	1	2	3	
Take the maintenance method of coating repair	No	Yes	No	No	>30	FL	M	L-VL	9.27E-02
	No	Yes	No	No	20–30	V-VL	M	FL	8.15E-02
	No	Yes	No	No	<20	FL	L	L	6.08E-03
	No	No	No	Yes	>30	FL	M	L-VL	8.52E-02
	No	No	No	Yes	20–30	V-VL	FL	L	2.91E-02
	No	No	No	Yes	<20	L	FL	V-VL	2.73E-03

Table 9
Soil parameter hypothesis.

Parameters	Value	Parameters	Value
Soil resistivity, Ω· m	32.6	Soil water content, %	26.2
Redox potential, mV	101	Soil salt content, %	0.06
Free corrosion potential, mV	−323	Soil cl^- content, %	0.007
Soil PH	9.2	Soil texture	Sandy

T 19,285–2014, there are 8 main factors affecting soil corrosivity. Fig. 4 shows the Bayesian network of the soil corrosivity, which includes the soil resistivity, redox potential, free corrosion potential, pH value, chloride content, soil salinity, soil moisture, and soil texture. Table 3 exhibits the nodes and the states variables.

According to GB/T 19,285–2014, each grade of the above parameters was assigned a score. The sum of the scores of the 8 parameters can be divided into 4 grades presenting the soil corrosivity. The CPT of soil corrosivity is determined by the sum of the evaluation scores. The probability of soil corrosivity at different levels can then be obtained from the BN mentioned in Fig. 4 accordingly.

4. Maintenance decision model

4.1. Determination of maintenance measures

To address the external corrosion of natural gas pipelines, maintenance measures are divided into four parts: 1) maintenance of coating; 2) maintenance of cathodic protection system; 3) stray current; and 4) pipeline replacement. The corresponding maintenance means for each part are shown in Table 4.

In the engineering practice, "direct drainage" and "ground drainage" are more convenient and economical. Therefore, other drainage modes were not considered in this study. All the repair parts of the pipe are listed in Table 4. The external corrosion caused by the different parts of the pipeline refers to different failure scenarios. In the face of various maintenance methods, choosing appropriate maintenance means in the face of different failure scenarios is a problem that needs to be solved.

4.2. Establishment of maintenance decision model

A Bayesian network can flexibly delete and add nodes. Taking advantage of this feature, maintenance strategies are considered the parent nodes of pipeline failure causes and are inserted into the BN in Fig. 3. The risk, or the pipeline failure probability, can then be reassessed under the assumption that maintenance measures have been conducted. A decision can be made according to the optimization function combining the reassessed risk and the costs, as mentioned above in Eq. (7). For a given pipeline, the costs of specific maintenance measures, failure loss and inspection frequency can be obtained from historical experience and expert estimation.

Fig. 5 shows the maintenance decision model, which is based on the BN in Fig. 3, with the maintenance nodes added. The illustrations of the nodes are listed in Table 5.

4.3. Model parameters

The prior probabilities and the CPTs are pre-set parameters in the BN. In this work, the prior probabilities and the CPTs are obtained by combining historical statistical data and expert estimations.

The prior probability of some nodes can be obtained from statistics. For example, according to statistics, the probability of a pipe being less than 20 years old is 0.61, and the probability that it is between 20 and 30 years old is 0.26. The specific statistical results are taken as the prior probabilities of the "service time of the pipe" node. However, it is not practical to obtain all prior probability from historical statistics because of the limitation of data access. The probabilistic estimation model based on expert experience can be an alternative.

Experts are asked to describe the probability of BN nodes using linguistic terms. Based on the methods proposed in Section 2.3, the fuzzy probability (*FP*) can be calculated as the prior probability of root nodes. Table 6 lists the prior probability of each basic event.

It is particularly noted that maintenance strategies are observable nodes in the BN. The states of the maintenance nodes can be directly determined through observation. Therefore, no prior probability is assigned to such nodes. Regarding another observable node "inspection frequency", the experts' judgement may differ due to different statistical cycles and methods. DS evidence theory is applied here to calculate the posterior probability distribution, considering all expert judgements. The use of DS evidence theory in Bayesian networks can be found in Ref (Hui et al., 2017). The observable nodes are marked in a deeper colour in the Bayesian network, as shown in Fig. 6.

The BN is mapped from the FT, but the logic gates in the FT cannot be converted to the CPTs in the BN directly. In this paper, the CPTs are determined with both logic gates and the probability estimation model mentioned in Section 2.3. Logic gates represent deterministic relationships among variables (Gachlou et al., 2019; Badida et al., 2019; Yin et al., 2020; Yu et al., 2019). The external corrosion node reflects the OR gate relationship. It's assumed that when "replace the pipe" is "Yes", external corrosion is eliminated. If no maintenance measures are taken, either soil corrosion or stray current corrosion occurs, the state of external corrosion is "Yes". Table 7 shows this relationship.

For the BN in Fig. 6, the CPTs of some nodes are complex. For example, "coating failure" has 7 parent nodes, leading to the CPT of 192 combinations. It is difficult to ask experts to put such numerous cases into linguistic terms. For the sake of simplification, some assumptions are employed. It is assumed that replacement of the coating leads to a coating failure probability of zero. When the coating is not replaced, the coating failure risk is the sum of the failure probabilities of each risk factor separately.

The part of the fuzzy probability of the "coating failure" node

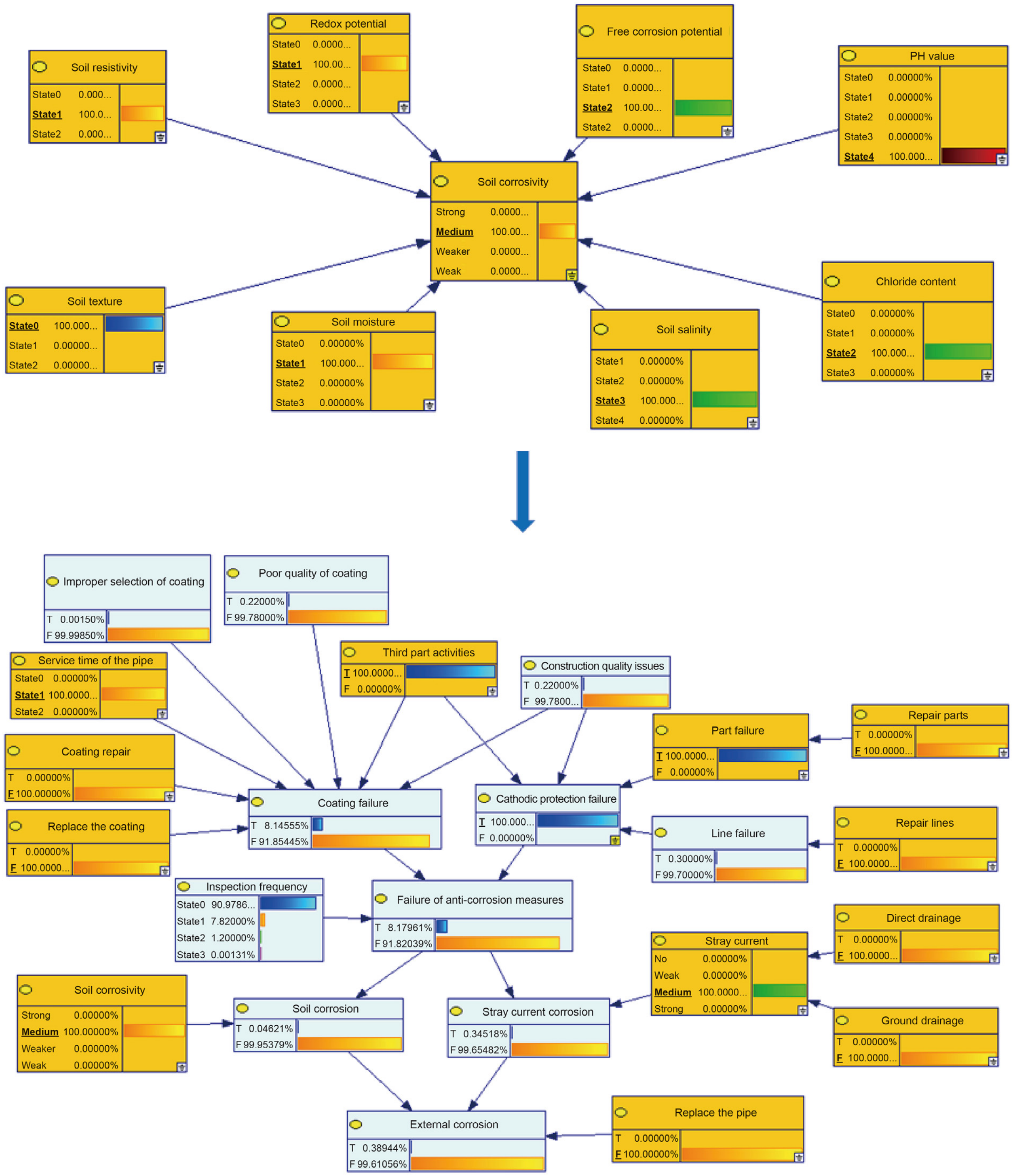

Fig. 7. Initial condition of Bayesian network.

after simplification is shown in Table 8, where “C” “T” “P” “I” and “S” represent “construction quality issues”, “third party activities”, “poor quality of coating”, “improper selection of coating”, and “service time of the pipe”, respectively.

5. Case study

5.1. Scene description

For a 23-year-old buried natural gas pipeline, Table 9 shows the parameters of the soil to which the pipe is exposed. It was found that the pipeline faces a medium strength stray current, and part of the cathodic protection system fails to work. Third-party activity was observed along the pipeline. Before the decision making, none of the maintenance methods are taken. The corresponding conditions are set as evidence nodes in the maintenance decision model and are shown in deeper colour in Fig. 7. The inference of the BN indicates that the pipeline has a 0.389% chance of external corrosion.

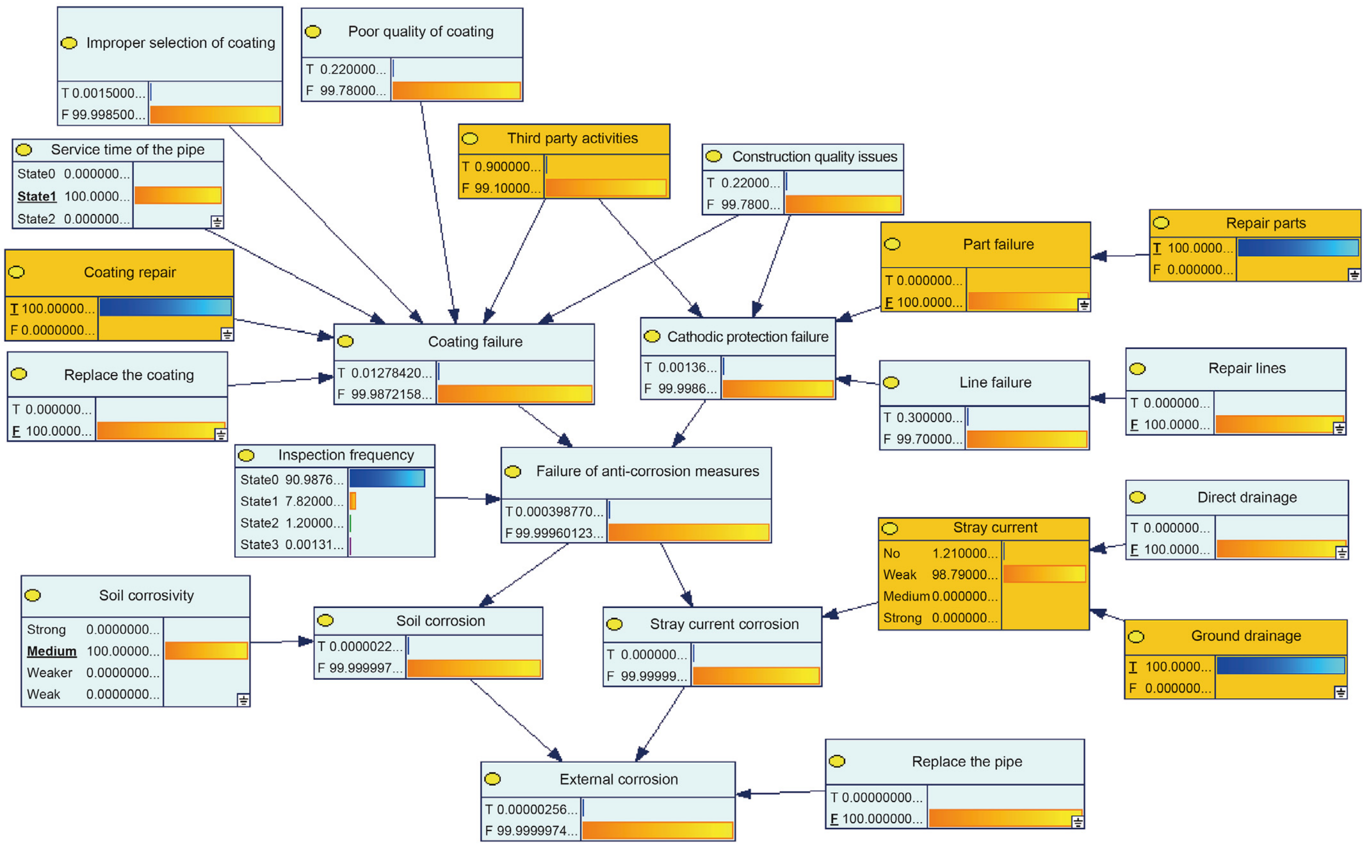

Fig. 8. Bayesian network after taking maintenance measures.

Table 10
The cost setting.

Nodes	States	Failure probability	Cost, million
Coating	Repair	0–50%	0.01
		>50%	0.03
	Replace	–	0.30
Cathodic protection part	Repair parts	0–50%	0.02
		>50%	0.03
Cathodic protection line	Repair lines	0–50%	0.005
		>50%	0.01
Stray current	Direct drainage	–	0.02
	Ground drainage	–	0.03
Pipe system	Replace the pipe	–	2.0
Inspection frequency	Once a day	–	0.02
	Once a week	–	0.003
	Once a month	–	7E-04
	no	–	0

5.2. Maintenance decision

Under the above conditions, a decision should be made on how to maintain the pipeline. It is assumed that coating repair and grounding drains are adopted, and parts of cathodic protection are determined to be repaired. At this point, it can be observed that the probability of external corrosion is reduced to 2.56E-08, as shown in Fig. 8. According to the historical data and expert judgements, the cost values of different repair parts and methods are determined in Table 10. The inspection costs and the failure losses are also obtained in the same way. To simplify the calculation, all descriptions are specific to a pipe segment.

Different combinations of maintenance means correspond to different cost values. The loss amount of external corrosion is considered to be 80 million. If the pipe is replaced, the external corrosion probability is reduced to zero, but the total cost is 2.018 million. In addition, a summary of all available means of maintenance and the corresponding cost values are given in Table 11.

The variation in the risk of external corrosion and the costs under the above four maintenance conditions are shown in Fig. 9. The numbers 1–17 correspond to the 17 maintenance plans in Table 11. According to the optimization function proposed in Section 2.4, the maintenance methods of coating repair will optimize the situation.

6. Conclusions

In this paper, a fault tree model is first used to analyse the causes of external corrosion in buried pipelines, including corrosion factors and anti-corrosion measures. A novel maintenance decision model based on a Bayesian network is proposed accordingly to analyse the maintenance cost and the effect of external corrosion maintenance strategies on failure probability. Fuzzy set theory was employed with domain expert knowledge to estimate the occurrence probabilities of the root events and the CPTs. Events with observable or measurable states are set as evidence nodes to represent the pipeline conditions and the implemented maintenance measures. The effect of maintenance on failure reduction is illustrated through a case study. It shows that the maintenance decision model is practicable for selecting the optimal maintenance plan, as well as realizing the risk reassessment after the implementation of maintenance measures. It is verified that the method proposed in this paper is feasible for decision making regarding the maintenance of pipeline external corrosion, as well as other failure scenarios, which will be studied in the future work.

Table 11
Maintenance means summary.

No	For coating	For cathodic protection	For stray current	External corrosion probability	Failure Loss, Million	Optimization result, Million
1	Repaired	No	Direct drainage	2.44E-06	0.0002	0.0482
2	Repaired	No	Ground drainage	2.78E-06	0.0002	0.0582
3	Repaired	No	No	2.05E-05	0.0016	0.0296
4	Repaired	Repair parts	Direct drainage	2.25E-08	1.80E-06	0.0680
5	Repaired	Repair parts	Ground drainage	2.56E-08	2.05E-06	0.0780
6	Repaired	Repair parts	No	1.90E-07	1.52E-05	0.0480
7	Replace	No	Direct drainage	1.73E-06	0.0001	0.3380
8	Replace	No	Ground drainage	1.97E-06	0.0002	0.3480
9	Replace	No	No	1.46E-05	0.0012	0.3190
10	Replace	Repair parts	Direct drainage	2.86E-11	2.29E-09	0.3580
11	Replace	Repair parts	Ground drainage	3.25E-11	2.60E-09	0.3680
12	Replace	Repair parts	No	1.69E-10	1.35E-08	0.3380
13	No	No	Direct drainage	4.63E-04	0.0370	0.0750
14	No	No	Ground drainage	5.26E-04	0.0420	0.0901
15	No	Repair parts	Direct drainage	1.43E-05	0.0011	0.0591
16	No	Repair parts	Ground drainage	1.63E-05	0.0013	0.0693
17	No	Repair parts	No	1.20E-04	0.0096	0.0476

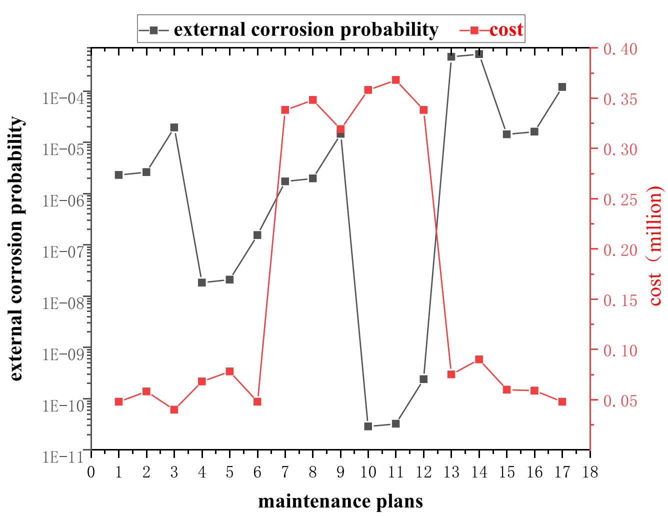

Fig. 9. External corrosion risk and cost variation.

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