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Dynamic risk assessment of train brake system failures considering the component degradation

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Train brake system plays a vital role in train safety. In this paper, a hybrid model is proposed to evaluate the train brake system failure risk. The hybrid model, which combines fault trees with Bayesian networks, has a good logical structure and probabilistic reasoning ability. The fault tree model is used to identify the risk influencing factors in the brake system, while the failure dynamic nature is captured by the Dynamic Bayesian network. In particular, we evaluate the degradation of four common failures, insufficient braking, brake test failure, braking relieve failure and wheel lock. The risk influencing factors of the brake system and their relevance are also identified. A model based on fault tree and Dynamic Bayesian network for the train brake system is developed. The model can capture the spatial variability of parameters and simulates the evolution of brake faults in time and space. The information is used to perform sensitivity analysis and diagnostic inference on the model.

Keywords: Dynamic risk assessment (DRA), Train brake system, Bayesian network (BN), Probabilistic Risk Assessment (PRA), Fault Tree (FT).

1. Introduction

As an important train operation safety barrier, train brake systems (TBS) are exposed to risks from the system inside. The risks will lead to TBS failure, and even cause serious accidents. For instance, on July 23, 2011, the train D3115 from Hangzhou to Fuzhou South Station, had an electrical problem occurred causing the brake to fail to relieve. It was hit by another car, which cause huge injuries and enormous economic loss. Thus, it is warranted to assess brake system risks to identify the risk sequences and facilitate the risk management work. The risk assessment will help us to identify the vulnerable parts of the system timely and implement protection proactively.

The research on TBS failure based on the simulation model is concerned about components' failure diagnosis. Sang et al. proposed a data-based detection strategy for train air braking systems, which was shown to enhance the detection robustness of a brake test platform. The brake disc simulation model showed the thermal fatigue crack expansion of brake discs in order to obtain the brake discs' thermal fatigue life. Machine learning algorithms were used in the study of TBS to predict brake disc temperatures. These studies are useful for determining the component degradation state.

whereas they are unable to explain the relationship between component failures at the system level. Therefore, we need to conduct a TBS risk assessment to understand the relationship between the failure causes and provide knowledge for train maintenance.

There are several commonly used risk assessment methods among which Bayesian Networks (BNs) are mostly used for failure maintenance. BNs have the advantage of rigorous probabilistic inference and have been used in train risk assessment, such as high-speed train wheel polygon risk assessment and onboard high-speed train control systems. However, it is difficult to achieve the research objectives with a single method. To obtain a clear structure and rigorous inference, Meng et al. developed an emergency operation failure FT-DBN model in the study of deep water blowout accidents. A hybrid model was developed by Jafari et al. to improve the reliability of the fire alarm system. The above mentioned references illustrate that the hybrid model can perform effective probabilistic risk assessment work and provide guidance for the system overhaul. Using FT analysis, we can get the logical relationship from TBS failure performance to reason. While DBN can be applied to capture the component degradation process.

A key issue in this thematic field is to express the repair strategy using DBN. Components such as pipes and brake discs suffer from the degradation process, which can affect the whole system performance. Therefore, a variety of maintenance strategies, including repairing maintenance and preventive maintenance, to ensure train operational safety is urgent to carry out. Cai et al. evaluated subsea blowout preventer control systems through DBN and presented the effects of perfect and imperfect repair on multi-state nodes, and the study of preventive maintenance was made by changing the node state transition relationship. Therefore, we can resort to the state transfer relationship to develop different maintenance strategies.

In this paper, we develop a FT-DBN hybrid model to conduct the dynamic risk assessment of the TBS. Compared to the existing studies, the original contributions lie in:

a FT-DBN hybrid model for TBS is developed;

classification of multi-state components into repairable or unrepairable components according to the repair strategy.

The rest of paper is organized as follows. Section 2 mainly introduces the modeling process and node state transfer rules. In Section 3, a case of TBS failure is analysed and a FT-DBN model is built accordingly. After that, a model studied for different repair conditions is conducted. Finally, work is concluded in Section 5.

2. Methodology

2.1.*Scenario definition*

The braking system is designed to slow down or stop the train to ensure the safety. However, the failure of components or human error may cause the brake system to fail and lead to serious accidents. Therefore, it is necessary to perform a risk analysis of TBS.

The train braking force is provided by air brake system and electric brake system. Train parking brakes and emergency braking and other actions rely on the air brake. Thus this paper mainly analyses the air brake system. Insufficient brake, brake test failed, brake relieve failure, and wheel locking are common failures, which will cause a long braking distance or the train cannot start normally. Based on the common brake failures, we use FT-DBN for risk assessment.

2.2.*Fault tree*

For any upper-level fault event, there may be two or more lower-level events that are the cause of its occurrence, i.e., there are multiple input events corresponding to each output event. The logical relationships between output events and input events are logical with, logical or and logical not. Building a brake system FT model can help us understand the causes of system failure and the logical relationship between events. Moreover, the structure of the DBN modeling built according to the FT will be logical.

2.3. *Dynamic Bayesian network*

2.3.1. *Basic Definition*

BNs calculate posterior probabilities based on evidence as well as prior probabilities, the updating equation can be written as:

$$P(a/X)=\frac{P(X/a)\times P(a)}{P(X)} \tag{1}$$

where $P(a)$ is the prior probabilities, and $P(X/a)$ is the conditional probability of X given a. $P(a)$ is the probability of observation or evidence, and $P(a/X)$ is the conditional probability of a given X.

According to the chain rule, the joint probability distribution (JPD) of the network can be obtained by:

$$P(X_1,X_2,...,X_n)=\prod_{i=1}^{n}P(X_i/Pa(X_i)) \tag{2}$$

where $Pa(X_i)$ is the parent set of any node X_i, and n is the number of nodes in the network.

Based on BN, DBN adds the concept of the time slice, which gives BN dynamic characteristics. The transition relationship between time slices can be expressed as:

$$P(Z_t/Z_{t-1})=\prod_{i=1}^{n}P(Z_{i,t}/Pa(Z_{i,t})) \tag{3}$$

where $Z_{i,t}$ is i th node at time t, and $Pa(Z_{i,t})$ is the parent nodes of $Z_{i,t}$ from the same nodes in the time $t-1$.

2.3.2. *Determination of Transition Probability Table*

In the real world, the time-dependent components degrade during its lifetime and the degradation process follows a discrete state discrete time Markov model with a finite state space. The key step to studying multi-state components reliability is to determine their degradation and repair relationships. In this paper, repairing maintenance imperfections will be considered. Imperfect repairs can return components to a normal or degraded state, while perfect repairs return parts to a normal state. The difference between a perfect repair and an imperfect repair can be considered in the modelling.

According to the characteristics, the components in the system can be classified as common component and multi-state component. Common component does not have a degraded state and usually have a constant probability of failure, so they are replaced after failure.

For multi-state component that follows a Markov model with a finite state space, as shown in Fig. 1. Here, we assume that the component is usually in a normal state after first replacement. And the component state transition rate in the study is constant. After working for some time, the components will transfer to a degraded state 1. In this case, the components can still work normally, but their failure probability will change. However, when components are in a degraded state 2, it will affect the system's normal operation. Therefore, we can improve the condition of the components through maintenance. Some multi-state components that called repairable components, such as brake pipe systems whose degraded state can be repaired. However, for repair work on some consumable components, such as brake discs, the replacement strategy is usually adopted. It is also assumed that the failure occurs randomly and the overhaul does not take time.

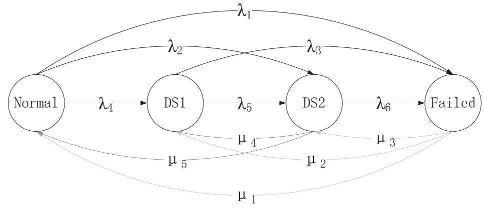

Fig. 1. Multi-state component status conversion.

$$\lambda_2=\lambda_3 \tag{4}$$

$$\lambda_4 = \lambda_5 = \lambda_6 \tag{5}$$

$$\lambda_1 + \lambda_2 + \lambda_4 = \lambda \tag{6}$$

$$\lambda_1 : \lambda_2 : \lambda_4 = 1:3:6 \tag{7}$$

$$\mu_3 = \mu_4 \tag{8}$$

$$\mu_2 = \mu_5 \tag{9}$$

$$\mu_1 + \mu_2 + \mu_3 = \mu \tag{10}$$

$$\mu_1 : \mu_2 : \mu_4 = 1:2:7 \tag{11}$$

We can obtain the repairable components' relations from moment t to $t+\Delta t$. To study the performances of different repair actions, we enumerate the state transition probability table (TPT) for various repair conditions as follows.

Table 1. Multi-state components without repair.

Node state at time t	**Node state at time $t+\Delta t$**	
	Normal	**DS1**
Normal	$e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t}$	$\frac{\lambda_4(1-e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t})}{(\lambda_1+\lambda_2+\lambda_4)}$
DS1	0	$e^{-(\lambda_3+\lambda_5)\Delta t}$
DS2	0	0
Failed	0	0
Node state at time t	**Node state at time $t+\Delta t$**	
	DS2	**Failed**
Normal	$\frac{\lambda_2(1-e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t})}{(\lambda_1+\lambda_2+\lambda_4)}$	$\frac{\lambda_1(1-e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t})}{(\lambda_1+\lambda_2+\lambda_4)}$
DS1	$\frac{\lambda_5\left(1-e^{-(\lambda_3+\lambda_5)\Delta t}\right)}{(\lambda_3+\lambda_5)}$	$\frac{\lambda_3\left(1-e^{-(\lambda_3+\lambda_5)\Delta t}\right)}{(\lambda_3+\lambda_5)}$
DS2	$e^{-\lambda_6\Delta t}$	$1-e^{-\lambda_6\Delta t}$
Failed	0	1

Table 2. Multi-state components with perfect repair.

Node state at time t	**Node state at time $t+\Delta t$**	
	Normal	**DS1**
Normal	$e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t}$	$\frac{\lambda_4(1-e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t})}{(\lambda_1+\lambda_2+\lambda_4)}$
DS1	0	$e^{-(\lambda_3+\lambda_5)\Delta t}$
DS2	0	0
Failed	$1-e^{-(\mu_1+\mu_2+\mu_3)\Delta t}$	0
Node state at time t	**Node state at time $t+\Delta t$**	
	DS2	**Failed**
Normal	$\frac{\lambda_2(1-e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t})}{(\lambda_1+\lambda_2+\lambda_4)}$	$\frac{\lambda_1(1-e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t})}{(\lambda_1+\lambda_2+\lambda_4)}$
DS1	$\frac{\lambda_5(1-e^{-(\lambda_3+\lambda_5)\Delta t})}{(\lambda_3+\lambda_5)}$	$\frac{\lambda_3(1-e^{-(\lambda_3+\lambda_5)\Delta t})}{(\lambda_3+\lambda_5)}$
DS2	$e^{-\lambda_6\Delta t}$	$1-e^{-\lambda_6\Delta t}$
Failed	0	$e^{-(\mu_1+\mu_2+\mu_3)\Delta t}$

Table 3. Multi-state components with imperfect repair.

Node state at time t	**Node state at time $t+\Delta t$**	
	Normal	**DS1**
Normal	$e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t}$	$\frac{\lambda_4(1-e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t})}{(\lambda_1+\lambda_2+\lambda_4)}$
DS1	0	$e^{-(\lambda_3+\lambda_5)\Delta t}$
DS2	0	0
Failed	$\frac{\mu_1(1-e^{-(\mu_1+\mu_2+\mu_3)\Delta t})}{(\mu_1+\mu_2+\mu_3)}$	$\frac{\mu_2(1-e^{-(\mu_1+\mu_2+\mu_3)\Delta t})}{(\mu_1+\mu_2+\mu_3)}$
Node state at time t	**Node state at time $t+\Delta t$**	
	DS2	**Failed**
Normal	$\frac{\lambda_2(1-e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t})}{(\lambda_1+\lambda_2+\lambda_4)}$	$\frac{\lambda_1(1-e^{-(\lambda_1+\lambda_2+\lambda_4)\Delta t})}{(\lambda_1+\lambda_2+\lambda_4)}$
DS1	$\frac{\lambda_5(1-e^{-(\lambda_3+\lambda_5)\Delta t})}{(\lambda_3+\lambda_5)}$	$\frac{\lambda_3(1-e^{-(\lambda_3+\lambda_5)\Delta t})}{(\lambda_3+\lambda_5)}$
DS2	$e^{-\lambda_6\Delta t}$	$1-e^{-\lambda_6\Delta t}$
Failed	$\frac{\mu_3(1-e^{-(\mu_1+\mu_2+\mu_3)\Delta t})}{(\mu_1+\mu_2+\mu_3)}$	$e^{-(\mu_1+\mu_2+\mu_3)\Delta t}$

2.3.3.*Mapping Algorithm*

In this paper, a hybrid model for TBS risk assessment is developed, in which DBN can handle uncertainty information using probabilistic data. FT is applied to optimize the logical structure between nodes. To build a hybrid model, we map the brake system FT model into a DBN, as shown in Fig 2. Each event in the FT is transformed into a node in a DBN. In FT model, the upper-level fault event is the result of the lower-level fault event, and the lower-level event is the cause of the upper-level fault event. While in DBN, the parent node represents the cause and the children represent the result, which is usually represented by a directed arc. However, the logical relationships between events are represented by logic gates, which are usually represented by conditional probability tables in DBN. The conditional probability table is information that represents the values of the parent node probability domain associated with the child node. In a FT model, logic gates link events and represent the logical cause-and-effect relationships between events. So when mapping, the logical gates in the FT will be transformed into a conditional probability table in a DBN. The values in the conditional probability table are determined by the logic gates in the FT.

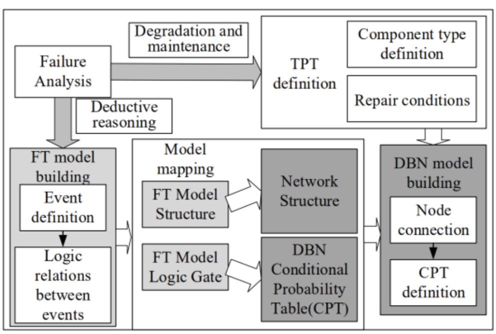

Fig. 2. FT-DBN mapping algorithm.

3. Application

In this section, we develop a FT-DBN model with a real date to evaluate brake system failure risk. In section 3.1, we analyze the brake system failure. Then, in Sect 3.2, a FT model is built and mapped to a DBN mode. At last, the conditional probability table (CPT) and node state TPT are calculated separately.

3.1.*Case Study*

Before building the FT model, we need to analyse the research scope and basic triggering factors of train brake failure. For assessing the brake failure risk, we select four common failures of TBS: insufficient brake, brake test failed, brake relieve failure, and wheel locking as the failure causes. Insufficient brake can seriously affect braking system function, which can lower the system control capability. The brake control unit is a general term for a brake computer and different types of air control valves integrate together. The failure of the components that make up the brake control unit will result in the brake command not being properly transmitted to the base brake unit. Insufficient braking may also be caused by the inability to obtain sufficient force, which is usually the result of a malfunctioning cylinder, brake transmission, brake disc, etc.

According to the regulations, before the train departs or during the maintenance process, the TBS needs to be tested and this test will determine whether the train departs. The braking command cannot be transmitted properly resulting in the loss of braking efficiency, which is one of the reasons for the brake test failed. The tests usually require complex operations by workers, so human factors are also a cause of this failure.

3.2.*Prior probability*

In this paper, the node prior probability is calculated from the failure rate of the basic event of the node found in the literature. And the repair rate is used as the inverse of the mean time to repair (MTTR). The failure rate of some electronic components is calculated according to the relevant standards. The failure distribution is exponential and the cumulative failure probability function as:

$$F(t) = 1 - e^{-\lambda t} \quad (12)$$

where the λ is the failure rate of a basic event.

Brake relieve failure and wheel locking are failures that occur during train braking, usually due to the failure of control components. After analysis, it is possible to obtain 24 basic events that lead to train brake failure. The basic event symbols and data obtained by reviewing information and industry standards are shown in Table 4.

Table 4. Basic event symbols.

Symbol	Basic event data			Symbol	Basic event data		
	Risk factors	Failure rate	Repair rate		Risk factors	Failure rate	Repair rate
X1	Loose optical fiber connector	3.98E-08	-	X13	Brake disc failure	1.53E-04	3
X2	Modules of Terminal device failure	1.49E-08	-	X14	MVB communication interruption	3.98E-08	-
X3	Brake cylinder failure	6.39E-06	0.833333	X15	BCU Failure 2	4.04E-05	1.960784
X4	Main duct leakage	5.07E-07	0.19685	X16	Man-made causes	-	-
X5	Solenoid valve failure	6.39E-06	0.833333	X17	Brake cylinder failure2	6.39E-06	0.833333
X6	Generator signal feeder disconnection	3.98E-08	-	X18	BCU Failure 3	4.04E-05	1.960784
X7	Generator failure	5.20E-06	0.444444	X19	Relay valve failure	8.56E-05	0.641026
X8	UBTRTD relay failure	1.49E-06	-	X20	EP valve failure2	2.60E-06	0.408163
X9	Brake pipe leakage	3.99E-06	2.380952	X21	Pressure sensor failure	1.71E-04	0.826446
X10	EP valve failure 1	2.60E-06	0.408163	X22	Speed sensor disconnection	1.07E-04	0.398406
X11	Detecting sensor failure	1.07E-04	0.398406	X23	PCIS anti-slip valve failure	4.28E-05	0.819672
X12	BCU Failure 1	4.04E-05	1.960784	X24	BCU internal glide	4.04E-05	1.960784

3.3. *Model Formulations*

Based on the brake system failure causes, a FT model is obtained, as shown in Fig. 3. The FT model contains 24 basic events, 11 intermediate events, 12 OR gates, and an AND gate. Then, we map the node structure of the FT model to the DBN. The mapped BN can perform probabilistic inference and has a logical structure. Firstly, we transform the basic event in the FT model into the node in the DBN. And there are 37 nodes in the TBS-DBN. Then some directed arcs are used to connect the nodes. For nodes with temporal characteristics, we need to add time arcs to them, which can be used to build a transfer relationship between different time slices of this node, as shown in Fig. 4.

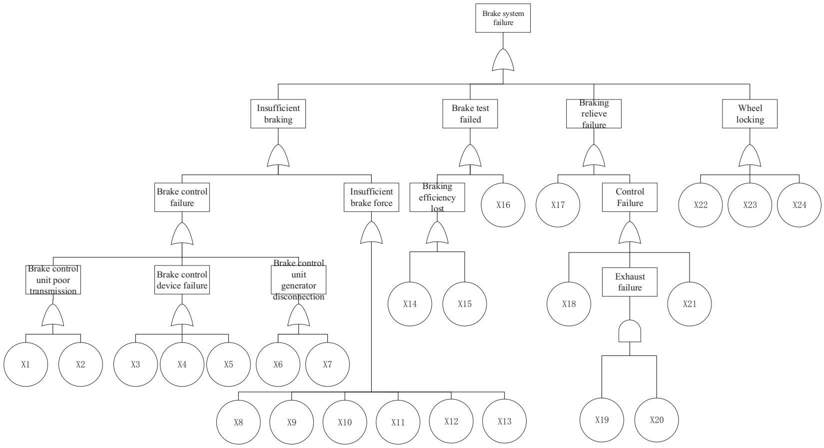

Fig. 3. TBS failure FT model.

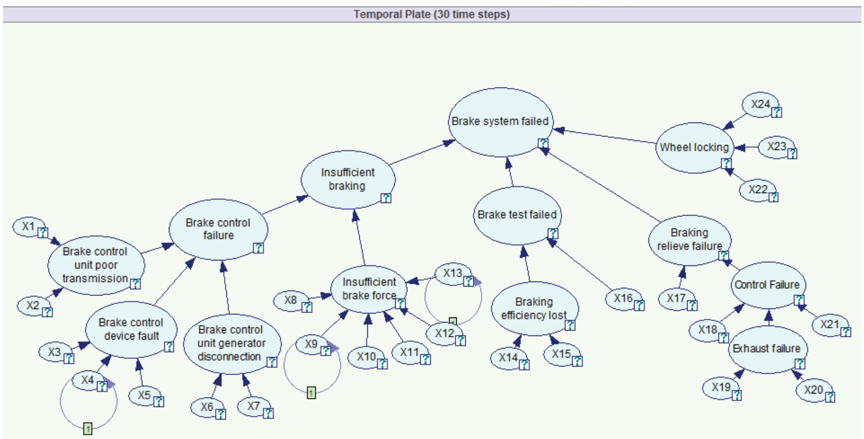

Fig. 4. TBS failure DBN model.

3.4.*Bayesian Network CPT*

In the DBN, CPTs are used to replace logic gates in FT model. For example, brake control unit poor transmission is usually caused by X1 (loose optical fiber connector) or X2 (Modules of Terminal device failure). Thus, the logical relationship between X1 and X2 is an OR gate. Only when X1 and X2 nodes (parent node) are normal, the 'Brake control unit poor transmission' node (child node) is normal. According to logical relationships between events, we obtain 'Brake control unit poor transmission' node CPT as shown in Table 5.

Table 5. Brake control unit poor transmission CPT.

Parent	X1	Normal	Failure

node	X2	Normal	Failure	Normal	Failure
Child node	Normal	1	0	0	0
	Failure	0	1	1	1

3.5. *Node State TPT*

By studying the components' maintenance strategies, we can get three multi-state nodes: X4, X9, and X13. And the node state TPT distinguishes their different repair conditions. Nodes X4 and X9 are repairable parts, which state transition relationships for no repair, perfect repair, and imperfect repair can be determined in Table 1, Table 2 and Table 3.

4. Results and Discussion

The state transfer tables of different nodes with different repair conditions are fed into the DBN model to obtain the results for different repair conditions. In this section, we present the results of the repair effectiveness study and the sensitivity of the key node study.

We assume that the failure occurs at the 30th time step and compare the poste probabilities for the three repair conditions as shown in Fig. 5. The results illustrate the key nodes under different repair conditions. X11 (Detecting sensor failure), X13 (Brake disc failure), X16 (Man-made causes), X21 (Pressure sensor failure), and X22 (Speed sensor disconnection) can be regarded as the key factors affecting the failure of the TBS. Whichever repair condition, X13 (Brake disc failure) has the greatest impact on brake system failure rate among these nodes and therefore has the highest association with brake system failure.

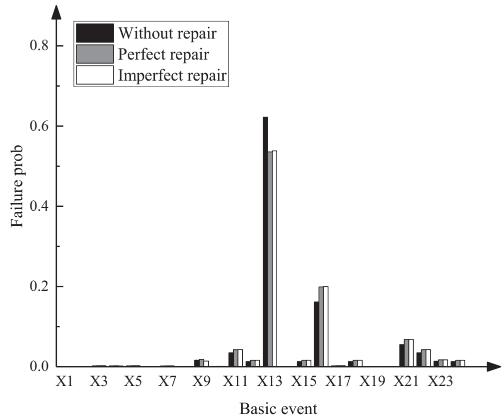

Fig. 5. Multi-state component status conversion.

5. Conclusions

In this paper, a hybrid model has been proposed to evaluate the brake system failure risk. a FT-DBN model is established from the failure symptoms and the causes. The multi-state components is considered in the proposed DBN model according to the component repair strategy, and initially considers the risk of human factors. In addition, a case of a TBS is used to demonstrate the proposed method. The results show that:

- X11, X13, X16, X21, and X22 are the key nodes of the system.
- Node X13 associated with multi-state components has the greatest impact on brake system failures.

References

Amin, M.T., F. Khan, and S. Imtiaz, "Dynamic availability assessment of safety critical systems using a dynamic Bayesian network," in Reliability Engineering & System Safety (2018).

Ammineni, S.P., C. Nagaraju, and D. Lingaraju, "Thermal degradation of naturally aged NBR with time and temperature," in Materials Research Express (2022).

Cai, B., Y. Liu, Q. Fan, Y. Zhang, S. Yu, Z. Liu, and X. Dong, "Performance evaluation of subsea BOP control systems using dynamic Bayesian networks with imperfect repair and preventive maintenance," in Engineering Applications of Artificial Intelligence (2013).

Chemweno, P., I. Morag, M. Sheikhalishahi, L. Pintelon, P. Muchiri, and J. Wakiru, "Development of a novel methodology for root cause analysis and selection of maintenance strategy for a thermal power plant: A data exploration approach," in Engineering Failure Analysis (2016).

Chemweno, P., L. Pintelon, P.N. Muchiri, and A. Van Horenbeek, "Risk assessment methodologies in maintenance decision making: A review of dependability modelling approaches," in Reliability Engineering & System Safety (2018).

Chen, C.-L., "Reshaping Chinese space-economy through high-speed trains: opportunities and challenges," in Journal of Transport Geography (2012).

Chen, J.F., C. Liu, Y.Y. Meng, and M.H. Zhong, "Multi-Dimensional evacuation risk evaluation in standard subway station," in Safety Science (2021).

Ghadimi, B., F. Kowsary, and M. Khorami, "Heat flux on-line estimation in a locomotive brake disc using artificial neural networks," in International Journal of Thermal Sciences (2015).

Institute, C.E.P.R.a.E.T.R., "Handbook of reliability prediction model and data for electronic equipment," (National Government Offices Administration;Standardization Administration of the People's Republic of China, 2019).

Jafari, M.J., M. Pouyakian, A. Khanteymoori, and S.M. Hanifi, "Reliability evaluation of fire alarm systems using dynamic Bayesian networks and fuzzy fault tree analysis," in Journal of Loss Prevention in the Process Industries (2020).

Jiang, L., Y.L. Liu, X.M. Wang, and M.A. Lundteigen, "Operation-oriented reliability and availability evaluation for onboard high-speed train control system with dynamic Bayesian network," in Proceedings of the Institution of Mechanical Engineers Part O-Journal of Risk and Reliability (2019).

Kammouh, O., P. Gardoni, and G.P. Cimellaro, "Probabilistic framework to evaluate the resilience of engineering systems using Bayesian and dynamic Bayesian networks," in Reliability Engineering & System Safety (2020).

Khakzad, N., F. Khan, and P. Amyotte, "Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches," in Reliability Engineering & System Safety (2011).

Liu, H., M. Su, H. Peng, Z. Zhang, and H. Xing, "Braking Performances of Urban Rail Trains," in Journal of Transportation Systems Engineering and Information Technology (2011).

Liu, P., L. Yang, Z. Gao, S. Li, and Y. Gao, "Fault tree analysis combined with quantitative analysis for high-speed railway accidents," in Safety Science (2015).

Meng, H. and X. An, "Dynamic risk analysis of emergency operations in deepwater blowout accidents," in Ocean Engineering (2021).

Montani, S., L. Portinale, A. Bobbio, and D. Codetta-Raiteri, "Radyban: A tool for reliability analysis of dynamic fault trees through conversion into dynamic Bayesian networks," in Reliability Engineering & System Safety (2008).

Pavelčík, V. and E. Kuba, "Application of basic machine learning algorithms in railway brake disc temperature prediction," in Transportation Research Procedia (2021).

Sang, J.X., T.X. Guo, J.F. Zhang, D.H. Zhou, M.Y. Chen, and X.H. Tai, "Incipient Fault Detection for Air Brake System of High-Speed Trains," in Ieee Transactions on Control Systems Technology (2021).

Wu, S.C., S.Q. Zhang, and Z.W. Xu, "Thermal crack growth-based fatigue life prediction due to braking for a high-speed railway brake disc," in International Journal of Fatigue (2016).

Zeng, Y.C., D.L. Song, W.H. Zhang, B. Zhou, M.Y. Xie, and X.Y. Qi, "Risk assessment of wheel polygonization on high-speed trains based on Bayesian networks," in Proceedings of the Institution of Mechanical Engineers Part O-Journal of Risk and Reliability (2021).

Zuo, J.Y., X.P. Wang, S.F. Zhou, and F. Yang, "Simulation and Experimental Study on Abrasive Wear of Brake Discs," in Tribology Transactions.