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Reliability Analysis of Dragline Subsystem using Bayesian Network Approach

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Abstract

Ensuring high reliability and availability of draglines is imperative for the economic sustainability of a highly productive surface mining project. Draglines are very complex in design and consist of hundreds of components. Reliability modelling of a large complex system is difficult with conventional reliability analysis techniques. The dragging mechanism is a critical subsystem for the smooth operation of the draglines. This study uses the Bayesian Network (BN) model, mapped from the Fault Tree (FT), for the reliability analysis of Dragline. Sensitivity analysis identifies the critical components – helpful information for reliability management. The results demonstrate that three components of the dragging mechanism, namely, the drag motor system, drag brake and drag socket are primarily responsible for the poor reliability of the case study system. This study provides valuable information for maintenance planning of operating draglines and reliability blueprint of future dragline design.

Keywords: *Dragline, Bayesian Network, Fault Tree Analysis, Reliability Analysis*

1. Introduction

Draglines are popular equipment for high productive surface coal mines. The breakdown of draglines has a huge financial impact. Maintaining high reliability and availability is a challenge to mine management. Reliability is the probability that the system performs a specific function under the given conditions for the stated time intervals (Ebeling, 1997). System reliability has played a significant role in many fields to ensure the high quality, better performance of machines and safety assurance. System reliability analysis is critical in surface mines due to the deployment of many highly complex capital-intensive Heavy Earth Moving Machinery (HEMM). Significant research on the reliability analysis of mining equipment is primarily based on the traditional statistical models (Barabady, 2005; Barabady and Kumar, 2008; Rahimdel *et al.*, 2013; Samanta *et al.*, 2004; Kumar *et al.*, 2020). Frequent failures, faults, and various malfunctions are common to mining equipment operations, and these events lead to substantial financial and production loss, sometimes leading to catastrophic failures. Minimizing these problems, maintenance personnel carried out the maintenance plan according to failures of the subsystems or components (Kumar *et al.*, 2020, Gustafson *et al.*, 2015).

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Several conventional methods, primarily based on the statistical inference techniques, are used to determine the system's reliability—for example, Fault Tree Analysis (FTA), Reliability Block Diagram (RBD), Event Tree Analysis (ETA), Markov and semi-Markov Chains, and Petri Nets (PN). Every method has its own advantages and disadvantages as well as applicability. The BN is an alternative technique to evaluate the reliability of complicated systems bedevilled by failure dependencies. The BN models have gained popularity in reliability analysis due to their ability to perform predictive and diagnostic analyses of large complex systems. In predictive analysis, root node probabilities are the prior probability for calculating the occurrence probability of any node. In the diagnostic study, the evidence/observations are used to compute the posterior probability of the given variables (Bobbio *et al.*, 2001).

The bayesian networks have found their applications in reliability and dependability analysis of systems (Weber *et al.*, 2010; Langseth *et al.*, 2007), including uncertainty modelling (Khorshidi *et al.*, 2016; Zhang *et al.*, 2018), risk analysis (Zhang *et al.*, 2018, Liu *et al.*, 2018; Xie *et al.*, 2021), safety analysis(Cai *et al.* 2016), resilience engineering (Cai *et al.*, 2018) and fault diagnosis (Cai *et al.*, 2017; Luo *et al.*, 2018; Wang *et al.*, 2018; Sahu and Palei, 2020; Sahu and Palei, 2022) of complex systems. Weber (Weber *et al.*, 2010) and Cai (Cai *et al.*, 2019) found that BNs are useful in reliability and risk analysis. Langseth and Portinale (Langseth and Portinale, 2005) also studied the BNs in reliability analysis and highlighted the properties of BNs comprehensively. Sigurdsson *et al.* (2001) have thoroughly reviewed the works on reliability analysis using BNs.

Reliability can be evaluated by converting the existing FT into the bayesian or Dynamic Bayesian Network (DBN) using the algorithm presented by Bobbio *et al.* (2006, 2008), Weber and Jouffe (2006) changed the complex dynamic models into equivalent markov chains using a dynamic object-oriented bayesian network. The probability propagation method was used for reliability estimation in which RBD was converted into a BN representation using a general methodology (Torres-Toledano and Sucar, 1998). Further, Kim (2011) presented the method for mapping an RBD to BN without loosing the single matching characteristic for quantitative analysis.

Recently, X. Li *et al.* (2021) estimated the reliability of warm spare gates using the discrete-time bayesian network method. Cal *et al.* (2012, 2013) introduced the BNs models to evaluate the reliability of subsea blowout preventer control systems. The main reason for failure and imperfect coverage of redundant systems were observed in this work. Doguc and Ramirez-Marquez (2009) provide a BN-based methodology to estimate the system's reliability using failure data. A Dynamic Bayesian network has been used to model renewable energy systems' availability using the corrective repair time, logistic delay times, maintenance time and failure time (Neil and Marquez, 2012). Codetta-Raiteri *et al.* (2012) presented the DBNs to study the cascading failure of critical infrastructure systems.

The applications of BNs have faced some challenges in evaluating reliability analysis, fault diagnosis for the integration of different variables like both discrete and continuous variables and the problem of calculation efficiency of BNs for the complex system. Therefore, researchers have developed various methods like the discretisation method (Zwirglmaier and Straub, 2016), the dynamic discretisation method (Marquez *et al.*, 2010), the approximate inference method (Langseth *et al.*, 2009) and the max-flow min-cut theorem-based method (Bensi *et al.*, 2013). In the present research, the BN is used for the reliability analysis of the dragging subsystem and its components of a dragline. For this study, operational data of a dragline and its subsystems were collected from a large surface coal mine situated in the central part of India. The data were analysed using the developed BN model. The structure of this paper is as follows: Section 2 presents the methodology including a brief on the BN and FTA. Section 3 includes the case study. Section 4 shows the result and discussion including sensitivity analysis. Lastly, we conclude the paper in Section 5.

2. Model Development

BN is developed through mapping the systems' FT, as discussed in the following section.

2.1 Fault Tree Analysis

Fault Tree Analysis (FTA) is a reliability analysis technique developed by H. A. Watson at Bell laboratories in 1962 (Vaurio, 2002). FTA is a deductive analytical method that identifies the weak links in the system by progressing from the occurrence of an unwelcome event (top event) to unearth the root causes of that event (basic events) (Gupta and Bhattacharya, 2007). It's a popular technique for both qualitative and quantitative evaluation. In the quantitative phase, all key components are given a probability of occurrence, and the value of the top event is calculated (Ramesh and Saravannan, 2011). The important logic gates used in FT to connect events are: AND gate — where all immediate lower level events must occur for its occurrence and OR gate, where at least one of the immediate lower level events must occur for the top event to occur (Goodman, 1988). Basic FTs with AND gate and OR gate are shown in Figure 1.

During quantification of the FT, AND gates are treated as the intersection of all input event sets, and its probability may be computed using Equation (1).

$$P = \prod_{i=1}^{n} P_i \tag{1}$$

If at least one of the input events occurs, the OR gate's output occurs, and the probability is calculated using Equation (2).

$$P = 1 - \prod_{i=1}^{n} (1 - P_i) \tag{2}$$

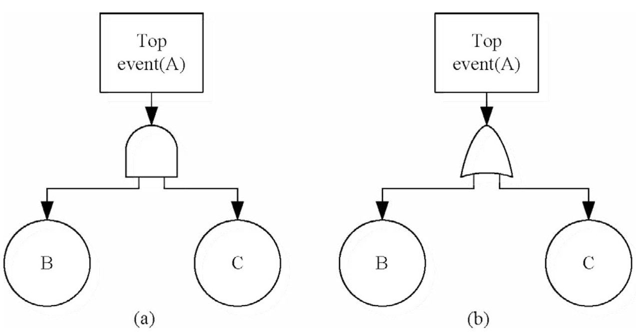

Figure 1. FTs with (a) AND Gate and (b) OR Gate.

2.2 BN Technique

Based on probabilistic and uncertain knowledge, BNs are used to build system reliability models. A Bayesian network is a Directed Acyclic Graph (DAG). BNs can be made up of qualitative or quantitative components or both. A BN comprises nodes and directed edges (edges for short). Edges show causal linkages between linked nodes, while nodes represent random variables. Parent nodes (the ones that an edge starts with) and child nodes (the ones that an edge points to) are the two types of node[8] that develop the BN. An edge extending from A to B denotes that the value of the child node B is dependent on the value of the parent node A, or that A influences B, and that the strength of the impact is protected by the Conditional Probability Table (CPT) of node A (parent node) (Langseth and Portinale, 2005). Borunda *et al.* (2016) assign marginal probability distributions to root nodes that have no parent, whereas CPTs are set to intermediate nodes. Thus CPT can be determined by the relationships between variables and their corresponding states (Torres-Toledano and Sucar, 1998).

The two typical information propagation procedures of BNs are top-down (predictive support reasoning) and bottom-up (diagnostic support reasoning) (Rebello *et al.*, 2018). The joint probability distribution *P(X)* propagates information in the top-down reasoning pattern following equation (3):

$$\begin{aligned} &P(X_1, X_2, X_3, \ldots\ldots\ldots, X_n) = P(X_n \mid X_{n-1}, X_{n-2}, \ldots\ \ldots X_1) \\ &P(Xn-1 \mid Xn-2, Xn-3, \ldots\ldots X1) \ldots\ldots\ldots P(X_2 \mid X_1) P(X_1) \\ &= \prod_{i=1}^{n} P(X_i \mid P_a(X_i)) \end{aligned} \tag{3}$$

However, The joint probability distribution *P(X)* of BN follow the conditional independence and chain rule. Thus, BNs represent *P(X)* of variables $X = \{X_1, X_2, X_3, \ldots \ldots \ldots X_n\}$ included in the network as

$$P(X) = \prod_{i=1}^{n} P(X_i | P_a(X_i)) \tag{4}$$

where, $P_a(X_i)$ are the parents of X_i in the BN, and *P(X)* reflects the properties of the BN (Jensen, 2007).

The probability distribution of a given variable can be derived by marginalising the joint probability distribution about it. This is known as marginalisation and can be used to calculate system reliability (Weber *et al.*, 2010, Langseth and Portinale, 2005). The bottom-up inference algorithm follows a junction tree or variable elimination, help to estimate the posterior probability distribution of a particular variable based on Bayes theorem and given the observation of another set of evidence (set E) (Adnan, 2009).

$$P(X \mid E) = \frac{P(E \mid X) P(X)}{P(E)} = \frac{P(X, E)}{\sum_X P(X, E)} \tag{5}$$

Due to interdependencies between the failure causes and causal complexity of failures of the dragging subsystem, the standard BN approach was chosen over the widely used conventional techniques to estimate the subsystem's reliability. Figure 2 shows the flow chart of the developed methodology for BN-based reliability analysis.

2.3 Mapping of FT into BN

Bobbio *et al.* (2001), stated that any FT has its corresponding BN. The basic events of the FT corresponds to the root nodes, the intermediate events are the intermediate nodes, and the top events are the leaf node or child node in the BN with each node having its CPT. For an example let A, B, and C are the random variables with two states: 0 and 1 where 0 indicates that the event occur, and 1 indicates that event does not occur. The FT representation of A,B,C and its accompanying BN is appeared in Figures 3 and 4 using OR and AND gate respectively. The CPT is shown in Table 1 for OR gate and Table 2 for AND gate.

3. Case Study

The proposed model has been demonestrted through a case study. Reliability of the dragging subsystem of a

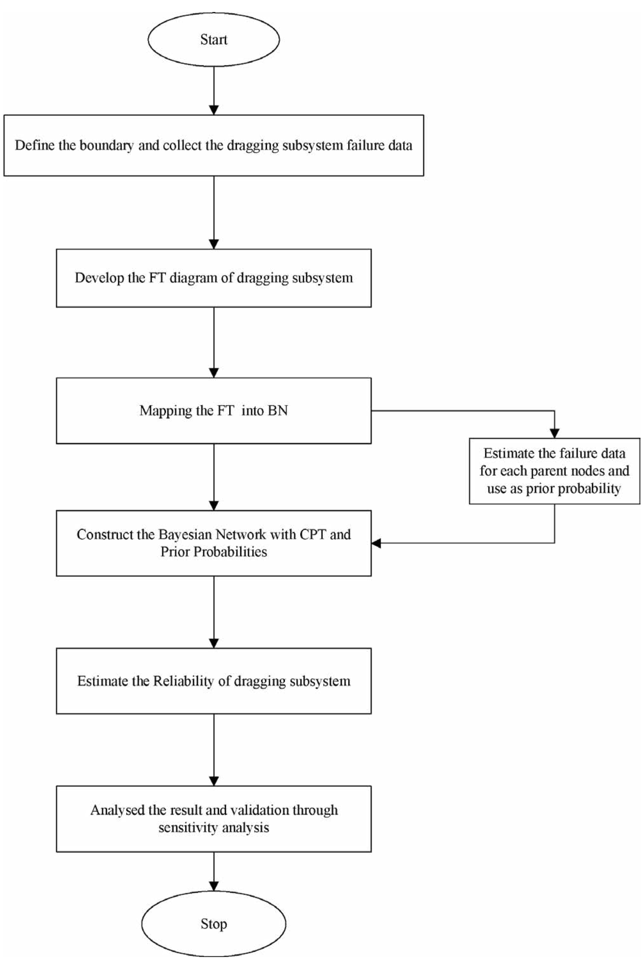

Figure 2. Flow chart of the developed methodology for BN-based reliability analysis.

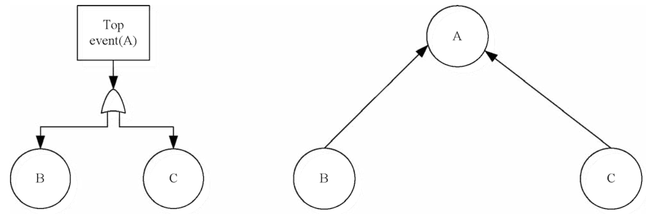

Figure 3. Mapping of OR gate in FT into BN.

Table 1. Conditional probability Table corresponding to OR gate.

Parents		Top event(A) P(A=X,Y)
B	C	
0	0	0
1	0	0
0	1	0
1	1	1

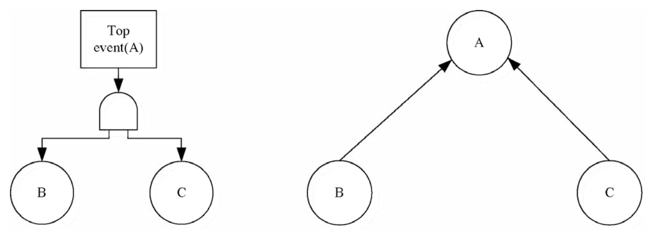

Figure 4. Maping of AND gate in FT into BN.

Table 2. Conditional probability table corresponding to AND gate.

Parents		Top event(A) P(A=B,C)
B	C	
0	0	0
1	0	1
0	1	1
1	1	1

dragline has been analysised with the help of developed BN model.

3.1 Overview of The Case Study System

The data used in this study are operational field data collected from the maintenance log book of a dragline, deployed in a highly productive surface coal mining project in central India. Dragging mechanism is a critical subsystem of a dragline. It helps to operate the dragline efficiently and effectively. This study has used data of a dragline with the following specification:

Bucket capacity: 24m^3,

Boom length: 96m,

Boom angle: 30°,

Operating radius: 88m, and

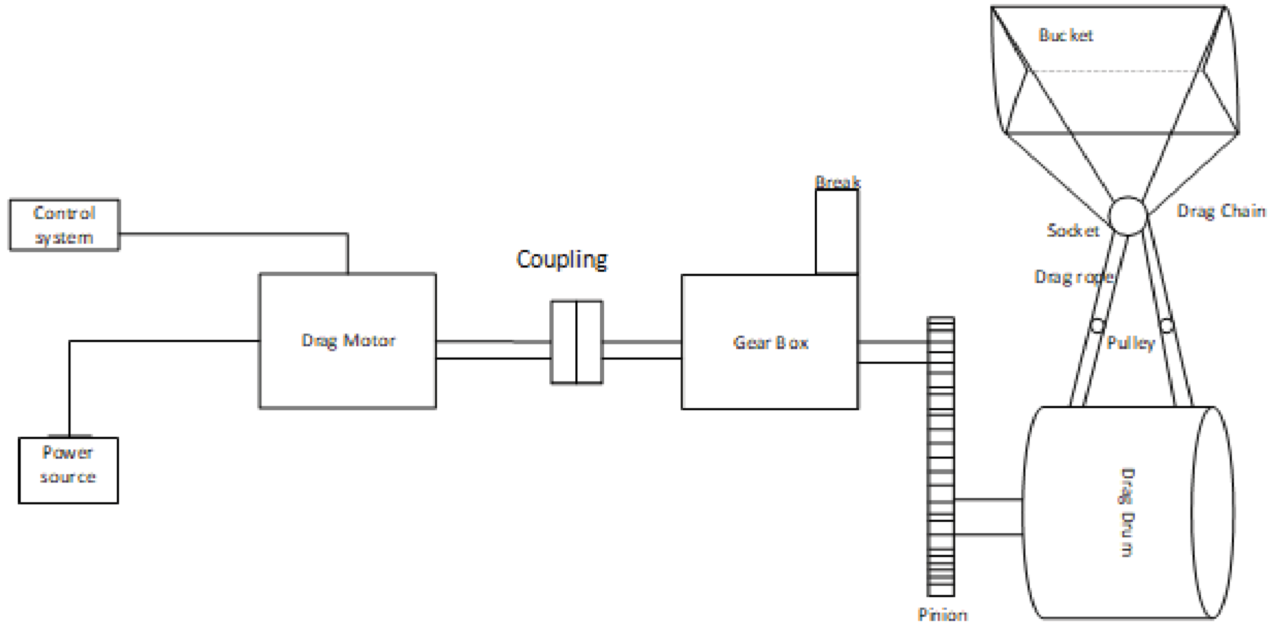

Figure 5. Schematic diagram of the dragging subsystem.

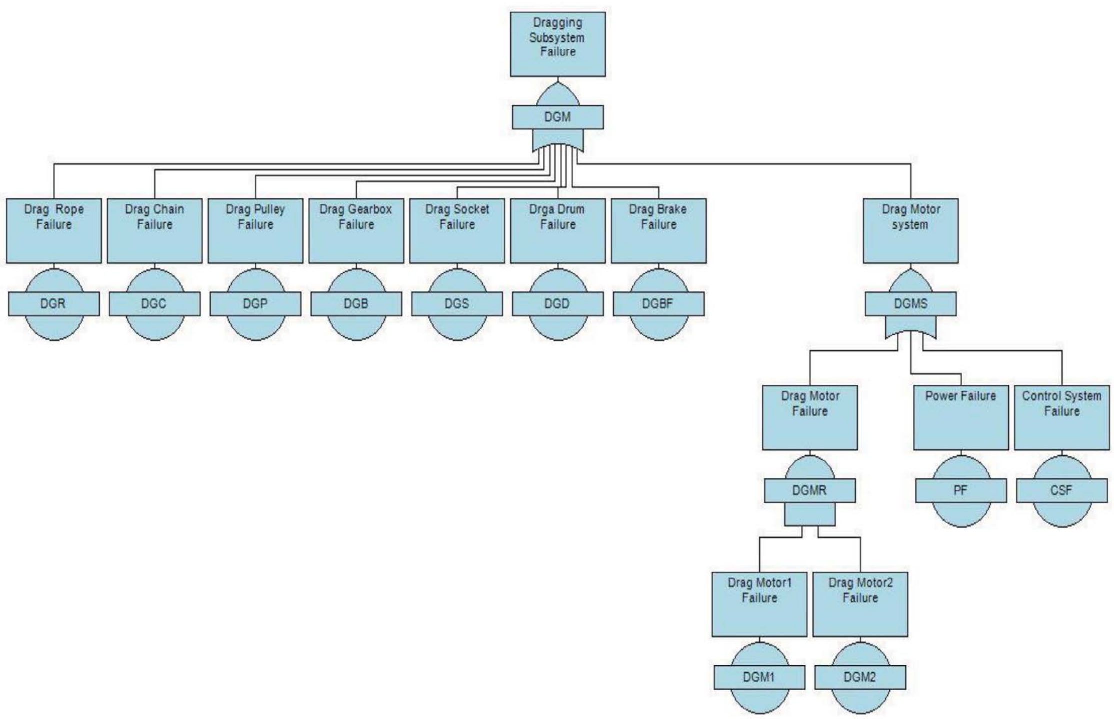

Figure 6. The FT diagram of the dragging subsystem of a dragline.

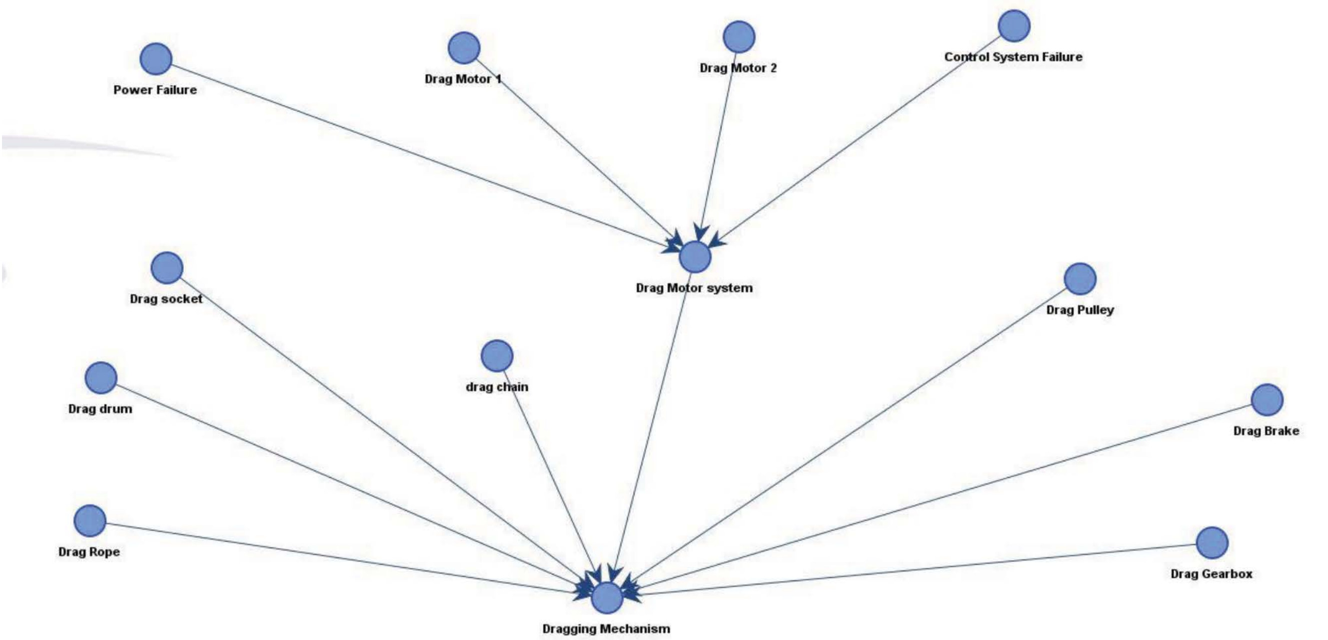

Figure 7. Bayesian Network of the dragging subsystem mapped from fault tree.

Maximum suspended load: 77t.

Drag mechanism mainly consists of a drag rope, motor, gearbox, brake, socket, drum, control system, pulley and chain. It has two motors which help to bind the drag rope on the drag drum with the help of gear box. The control sytem regulates the functions of these drag motors. The drag motors are attached to the gearbox. Drum speed is controlled with the help of a pinion gear arrangement and the brake. Drag rope is used to drag the overburden into the bucket. The socket connects the drag rope and the drag chain. All these components perform their defined function for smooth operation of the drag mechanism. Thus, high reliability of each component is essential for the higher reliability of the drag mechanism. Figure 5 presents a schematic diagram of the dragging subsystem with various interconnection between the components.

3.2 Development of the BN for the Dragging Subsystem

As discussed in section 2.1, the FT of the dragging subsystem of the case study dragline has been developed and presented in Figure 6. Developed FT has been mapped to a BN as described in section 2.3 and presented in Figure 7.

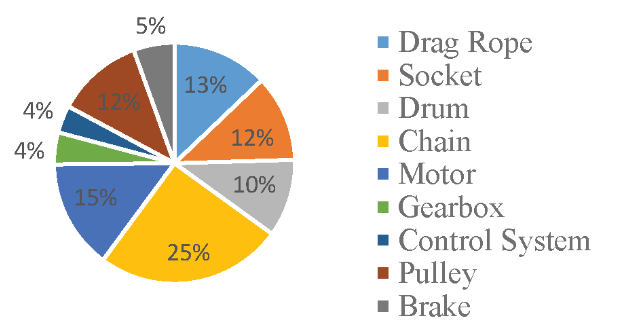

Figure 8. Failure frequency of different components of dragging subsystem.

4. Result and Discussion

4.1 Analysis of the Data

Analysis of the field data shows that the failure frequency of the drag chain is maximum, followed by the motor. Figure 6 presents a pie chart of the failure frequency of all the components of the dragging subsystem.

Table 3. Best fit distribution for components of the dragging subsystem

Components		Exponential	Weibull	Lognormal	Best-fit distribution
Drag Rope	Loglikehood(max)	-448.2771	-436.8179	-442.9095	Weibull distribution
	AIC(min)	898.5542	877.6357	889.8189	
	BIC(min)	900.8446	882.2167	894.3998	
Chain	Loglikehood(max)	-97.12713	-93.83206	-95.66817	Weibull
	AIC(min)	198.2543	191.6641	195.3363	
	BIC(min)	199.2241	192.6339	196.3061	
Pulley	Loglikehood(max)	-40.82124	-40.33906	-40.39448	Weibull
	AIC(min)	85.64249	84.67812	84.78896	
	BIC(min)	84.86137	83.89699	84.00784	
Socket	Loglikehood(max)	-119.8885	-102.2423	-102.2625	Weibull
	AIC(min)	243.7769	208.4845	208.5249	
	BIC(min)	245.055	209.7626	209.803	
Drum	Loglikehood(max)	-58.63928	-55.20817	-55.91413	Weibull
	AIC(min)	121.2786	114.4163	115.8283	
	BIC(min)	121.1704	114.3082	115.7201	
Gearbox	Loglikehood(max)	-73.28532	-69.64592	-71.29547	Weibull
	AIC(min)	150.5706	143.2918	146.5909	
	BIC(min)	150.7295	143.4507	146.7498	
Brake	Loglikehood(max)	-91.6794	-87.44974	-89.01978	Weibull
	AIC(min)	187.3588	178.8995	182.0396	
	BIC(min)	188.1546	179.6953	182.8353	
Motor	Loglikehood(max)	-97.12713	-93.83206	-95.66817	Weibull
	AIC(min)	198.2543	191.6641	195.3363	
	BIC(min)	199.2241	192.6339	196.3061	
Control System	Loglikehood(max)	-55.74668	-54.26466	-54.47788	Weibull
	AIC(min)	115.4934	112.5293	112.9558	
	BIC(min)	115.0769	112.1128	112.5393	
Power Failure	Loglikehood(max)	-180.3845	-158.5522	-159.5287	Weibull
	AIC(min)	364.7689	321.1044	323.0574	
	BIC(min)	366.858	323.1934	325.1465	

The statistical analysis of failure data comprises trend analysis, selecting the best-fit distribution, and calculating distribution parameters. The results of the trend and correlation test shows that the data follows iid and it is observed that the Weibull distribution is the best fit distribution for the components of the dragging subsystem (Table 3). The failure density function of the Weibull distribution is

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-(t/\eta)^{\beta}} \tag{6}$$

where, β is the shape parameter, and η is the scale parameter.

The Weibull distribution parameters (β, η) of different components of the dragging subsystem are tabulated in Table 4.

4.2 Reliability Estimation

The failure probabilities of different components of the dragging subsystem have been evaluated from the distribution parameters given in Table 4 and used as the prior probabilities in BN model. The bayesian network

Table 4. Different components of the dragging mechniasm and their failure parameters

Intermediate node	Root node		Abbreviation	Parameters(β, η)
Dragging Mechanism	Drag ropeFailure		X1	(0.8459544,751.4251942)
	Drag chainFailure		X2	(0.8558992, 433.3874504)
	Drag PulleyFailure		X3	(0.6272825, 574.7544588)
	Drag SocketFailure		X4	(0.5766803, 589.4482878)
	DrumFailure		X5	(0.9205495, 920.5721644)
	Gear BoxFailure		X6	(0.7733964, 2076.3137742)
	Drag BrakeFailure		X7	(0.5239005, 866.9491335)
	Motor system Failure(IE1)	Control System Failure	X8	(1.064601, 3199.956666)
		Drag Motor 1 Failure	X9	(0.5273567, 427.7129938)
		Drag Motor 2 Failure	X10	(0.5273567, 427.7129938)
		Power Failure	X11	(0.4800574, 1212.5756900)

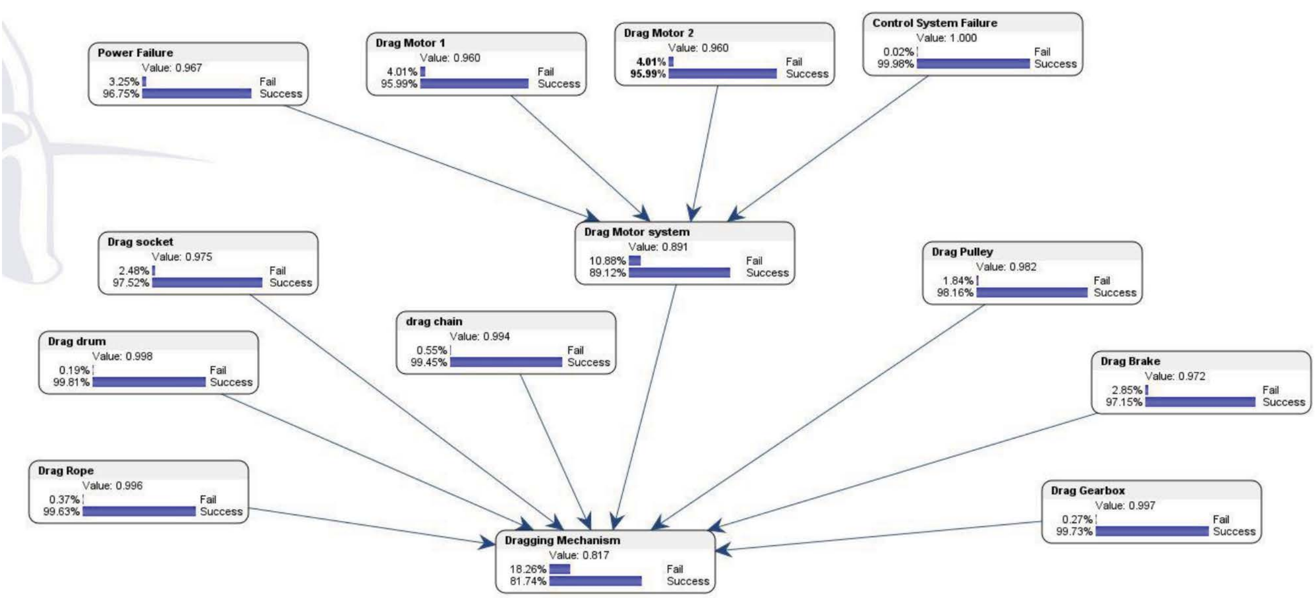

Figure 9. Reliability assessment of the dragline system

diagram of the dragging subsystem is mapped from the FT already shown in the Figure 7 whereas Figure 9 shows the reliability assessment of the subsystem.

It is observed that the reliability is estimated to be 81.75% at 1h, 60.66% at 5h and 47.45% at 10h. Reliability of the dragging subsystem has been estimated at every 5h intervals up to 100h and plotted in Figure 10. The reliability is only 5% at 100h of machine operation.

4.3 Failure Diagnosis

The failure diagnosis of the dragging mechanism using BN has been done by updating the network nodes' failure probabilities, as appears in Figure 11. Here, the failure probability of the child node i.e. the dragging subsystem is set to 100% individually, and the node probabilities of the BN have been updated. Under this condition, it is observed that the drag motor system has the highest

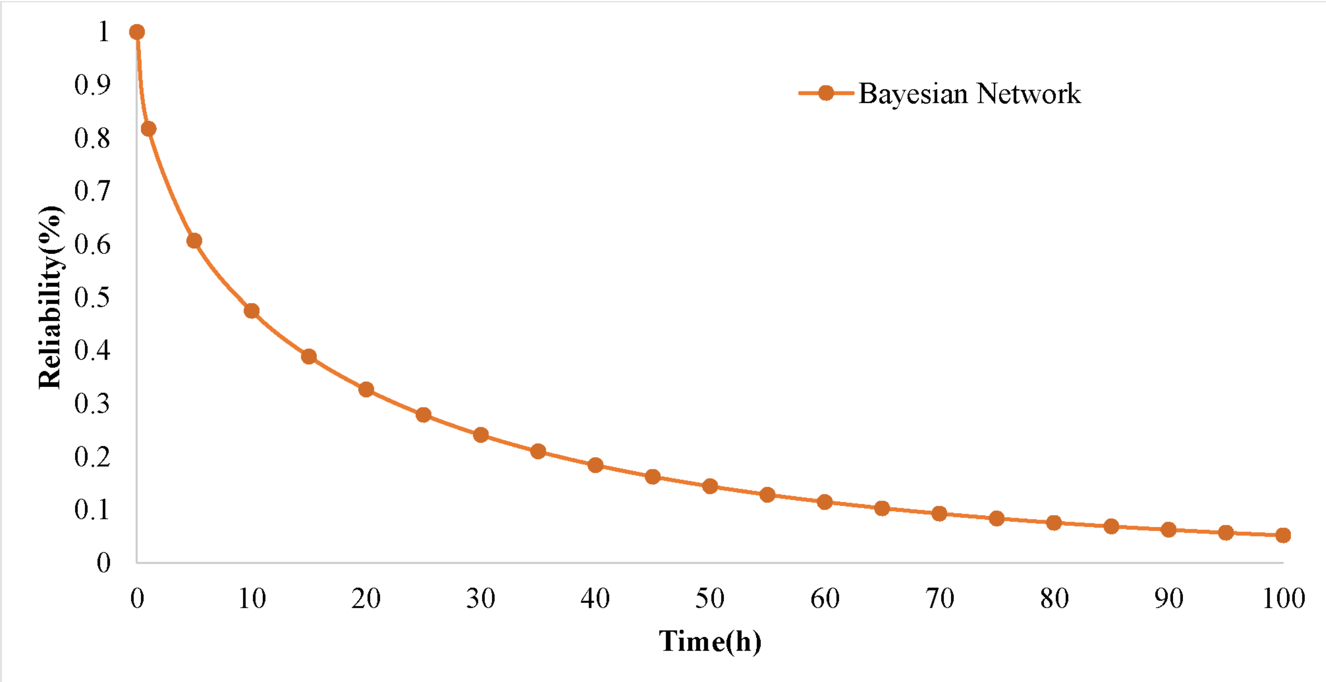

Figure 10. Reliability curve of the dragging mechanism.

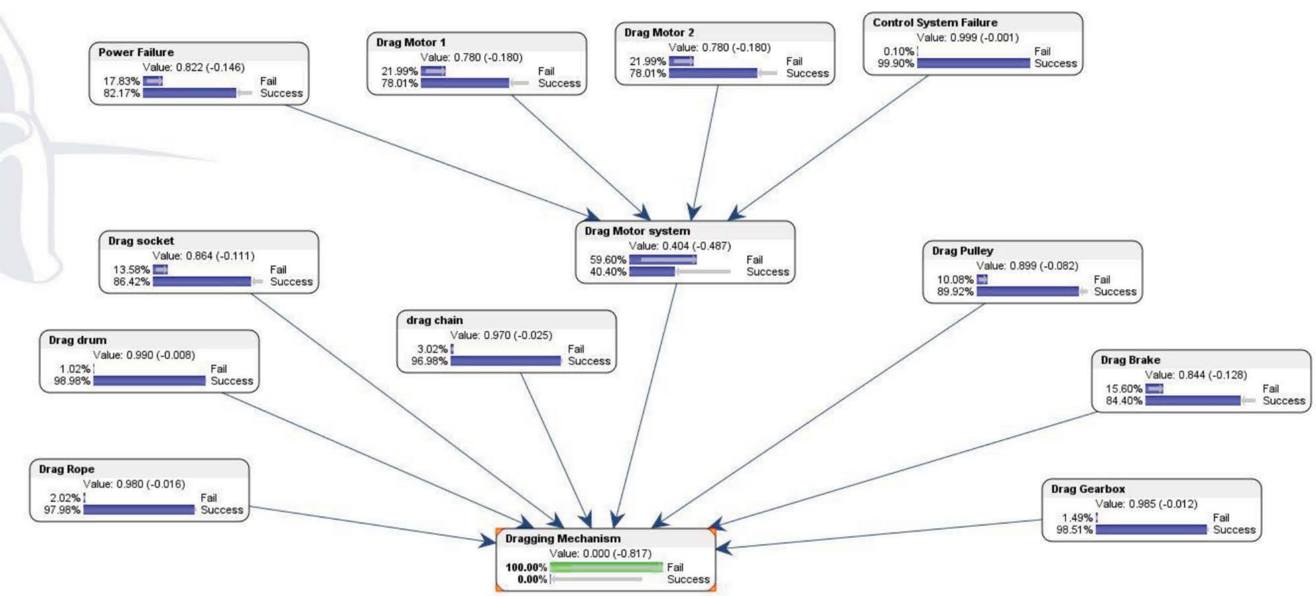

Figure 11. Updated BN of the dragging mechanism with 100% failure.

failure probability of 59.60%. Further, the drag motors of the motor system have the highest failure probability of 21.99%, followed by the power failure with a failure probability of 17.83%, and the drag brake with a failure probability of 15.60%.

The posterior probabilities of all the components of the dragging subsystem under this conditions has been shown in the Table 4. This table also demonstrates the changes in probabilities from prior to posterior during the model update.

4.4 Sensitivity Analysis

Relative importance of the parent nodes is important for reliability improvement and devising countermeasures for failures. Sensitivity analysis, based on information theory, may be performed for the importance ranking of variables in BN. Mutual Information (MI) values between pairs of random variables can reveal the degree of dependency between two random variables. This approach states that the state of one node provides a lot of information about the state of another node if they are connected (Chen *et al.*, 2008).

MI between two random variables X and Y is denoted by $I(X;Y)$, and mathematically defined as (Naidoo and Naidoo, 2021):

$$I(X;Y) = H(X) - H(X \mid Y) \tag{7}$$

where, $H(X)$ and $H(Y)$ represent the entropies of random variables X and Y, respectively, and $H(X|Y)$ represents the conditional entropy of random variable X given Y. The entropy and conditional entropy are mathematically defined as follows:

$$H(X) = -\sum_{i=1}^{n} P(X_i)\log(P(X_i)) \tag{8}$$

$$H(X|Y) = -\sum_{i=1}^{n}\sum_{j=1}^{m} P(X = x_i, Y = y_i) * \log\left(P(X = x_i | Y = y_i)\right) \tag{9}$$

where, n and m represent the number of discrete states represented by the random variables X and Y; and $P(X = x_i, Y = y_i)$ represents the joint probability distribution of the X and Y.

Using these MI approach the sensitivity analysis for the present study has been carried out. The mutual

Table 4. Prior and Posterior probability of the components of the dragging mechanism

Nodes	Prior Probability	Posterior Probability
Drag rope(X1)	0.9963	0.9798
Drag Chain(X2)	0.9945	0.9698
Drag Pulley(X3)	0.9816	0.8992
Drag SocketX(4)	0.9751	0.8642
Drag drum(X5)	0.9981	0.9898
Drag Gearbox(X6)	0.9973	0.9851
Drag Brake(X7)	0.9715	0.8441
Control System Failure(X8)	0.9998	0.999
Drag Motor1(X9)	0.9599	0.7801
Drag Motor2(X10)	0.9599	0.7801
Power Failure(X11)	0.9675	0.8217
Drag motor system(IE1)	0.8912	0.4040

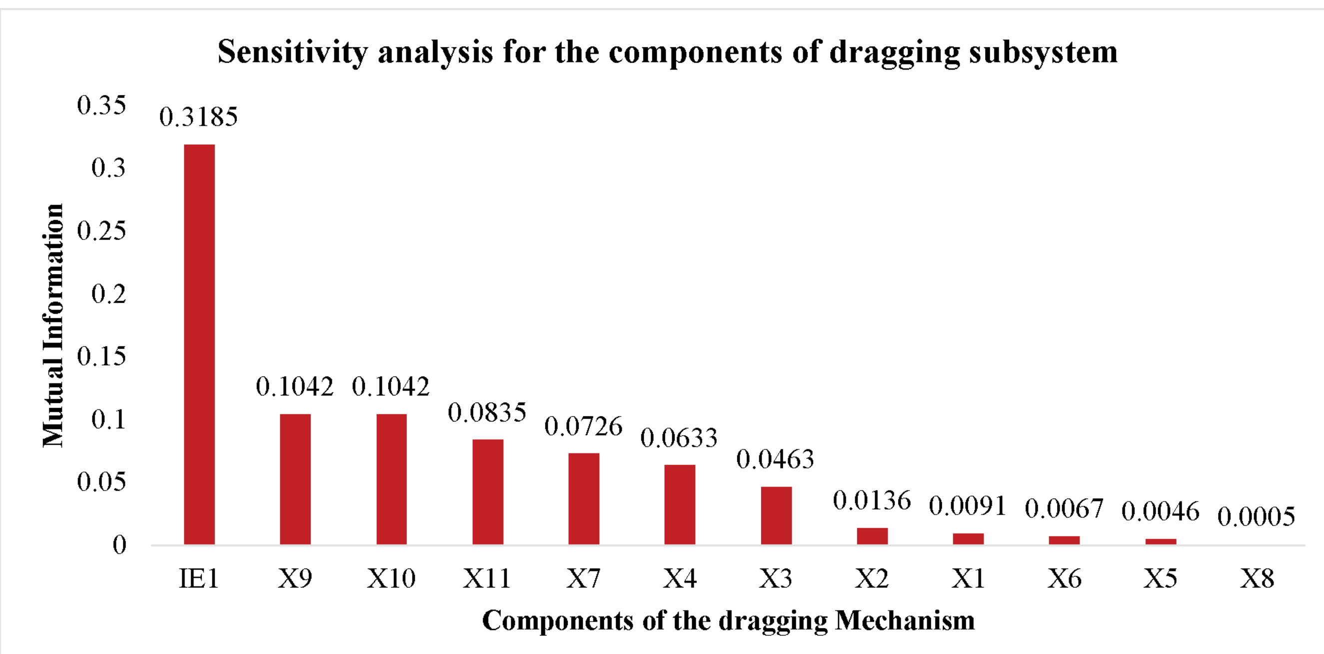

Figure 12. Importance ranking of components of dragging subsystem

information values for different components of dragging subsystems has been plotted in Figure 12.

It is observed that the MI value between the drag motor subsystem and overall dragging subsystem is estimated to be 0.3185. From this information, it can be said that the failure of drag motor subsystem (IE1) is the most critical in the dragging subsystem failure, contributing about 31.85% of the overall failure. Similarly drag motor1 (X9) and drag motor2 (X10), each contributes 10.42% of failure of dragging subsystem. The results of sensitivity analysis reveal that the drag motors are the most important component in the dragging subsystem.

To improve the reliability of the dragline, it is necessary to improve the reliability of the dragging mechanism. Thus, the quality enhancement of dragline depends on the reliability improvement of the components of the dragging subsystem. Therefore, it should be highlighted in the maintenance policy of the dragline.

5. Summary and Conclusion

This study proposed the BN model for the reliability analysis of the dragging subsystem of a dragline. Reliability, failure probability, and failue diagnosis of the subsystems through the BN model have been studied. The drag motors were identified as the most failure-prone component, having a failure probability of 4.01% within an hour of operation, followed by power failure (3.25%), drag brake (2.85%), drag socket (2.48%) and drag pulley (1.84%). The reliability of the dragging subsystem was 81.75% during the 1h and 0.05% during the 100h of the machine operation.

Failure diagnosis of the subsystem revealed that the drag motor, power failure, and drag brake are the three main contributors to overall dragging subsystem failure. For improving the realibility and performance of the overall dragline system, preventive measures should be taken for the identified critical components of the dragging subsystem. Also, different maintenance strategies can be developed for the said subsystem/components according to their failure probability and criticality.

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