Chapter – 5
Reliability study of Dragline

5.1 Introduction

The reliability analysis of dragline system using FTA method and BN model has been presented in this chapter. Initially, the basic topology of BN model is discussed. After that the methodology used in reliability analysis of the dragline system is also explained that consists of failure inference, critical subsystem identification and sensitivity analysis. The construction of BN model, mapping the FT into BN model, estimation of CPT, and reliability assessment of dragline are presented here. Sensitivity analysis is done to identifying the critical subsystem of the dragline system. Developed BN model is validated and the results of the analysis have been discussed.

5.2 Fault tree analysis

Fault tree analysis (FTA) is a reliability analysis tool, developed by H. A. Watson at Bell laboratories in 1962[147]. It is a deductive analytical method that discovers the weak links in the system by going from the occurrence of an unwelcome event (top event) to the discovery of the root causes of that event (basic events) [56], [148]. It's a popular technique for both qualitative and quantitative evaluation. A fault tree helps to determine various fundamental events that could lead to the top event. This is known as a cut set, which is defined as a set of basic events that lead to the occurrence of the top event. The chopped groups with the smallest number of items are the most fascinating. A minimum cut set (MCS) is a combination of basic events that generate the unwanted occurrence. A minimum cut set can't be decreased further without losing its cut set status [149]. The minimal cut sets describe the system logic function as Boolean algebra to identify the combination of basic events in component failure modes. In the quantitative phase, all of the key components are given a probability of occurrence, and the value of the top event is calculated [150]. The logic gates in FT connect all of the events, which are essentially: AND gate, where both of the basic events must occur for the top event to occur, and OR gate, where only one of the basic events must occur for the top event to occur [52]. The AND gate is the intersection of all input event sets, and its probability may be computed using equation (1).

$$P = \prod_{i=1}^{n} P_i \quad (5.1)$$

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

$$P = 1 - \prod_{i=1}^{n} (1 - P_i) \quad (5.2)$$

Figure 5.1 presents the FT of a dragline system when the failure of the dragline is the top event.

FTA consists of the following steps as described by Ericson[151]

Step-1 Identify the undesirable event.

Step-2 Identify the basic events of an undesirable event.

Step-3 Provide the probability of basic events.

Step-4 Establish the failure path and their structures.

Step-5 Probabilistic analysis of the system

Failure Probability of the components (basic events) of the dragline has been calculated using the parameters of the best fit distribution (Table 4.2). Table 5.1 is shown the failure probabilities of the components of the dragline, at operating time $t = 1hr$.

Table 5. 1 Failure probabilities of the components of the dragline at $t = 1hr$.

Components	Failure Probability $P(X_i)$	Components	Failure Probability $P(X_i)$	Components	Failure Probability $P(X_i)$
Bucket Teeth(X1)	0.0072	Drag socket(X15)	0.024938	Swing motor(X29)	0.00536
Adapter Pins(X2)	0.019938	Dump rope(X16)	0.00149	Swing motor(X30)	0.003536
Equilisier Pins(X3)	0.002245	Dump pulley(X17)	0.000003	Exciter failure(X31)	0.002201
Anchor Pins(X4)	0.003144	Dump socket(X18)	0.001617	M.G. set failure(X32)	0.022629
Hitch shackle(X5)	0.009226	Hoist motor(X19)	0.018961	Synchronous motor failure(X33)	0.045642
Drag Motor(X6)	0.04014	Hoist motor(X20)	0.018961	DC failure(X34)	0.013421
Drag Motor(X7)	0.04014	Hoist control system(X21)	0.001792	Power failure(X35)	0.032545
Drag Control system(X8)	0.000186	Hoist chain(X22)	0.006965	Trailing cable failure(X36)	0.009588
Drag rope(X9)	0.003684	Hoist brake(X23)	0.000476	Compressor(X37)	0.000004
Drag Gearbox(X10)	0.002715	Hoist rope(X24)	0.00478	Lubrication system(X38)	0.00898
Drag drum(X11)	0.001867	Rotate frame failure(X25)	0.023569	Guide pulley failure(X39)	0.022438
Drag chain(X12)	0.005519	Roller failure(X26)	0.007815	Boom Light failure(X40)	0.009226
Drag Brake(X13)	0.028479	Gearbox failure(X27)	0.018032		
Drag Pulley(X14)	0.018408	Control system(X28)	0.000988		

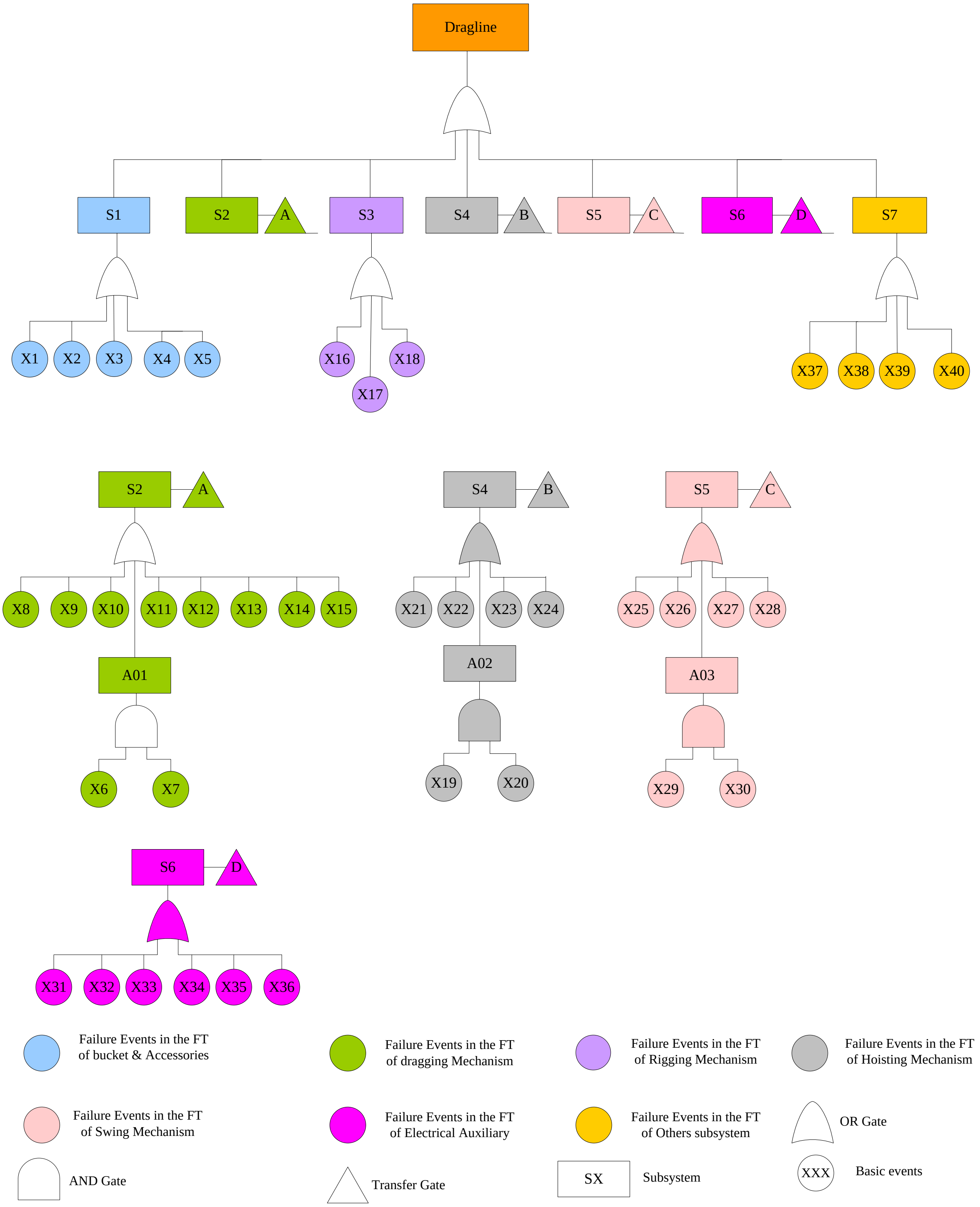

Figure 5. 1 The FT of the dragline failure

5.3 Methodology of BN

The proposed methodology for reliability analysis of a dragline system is outlined in figure 5.2. The developed BN model works on the basic mathematical principle of FTA and BN, as discussed below.

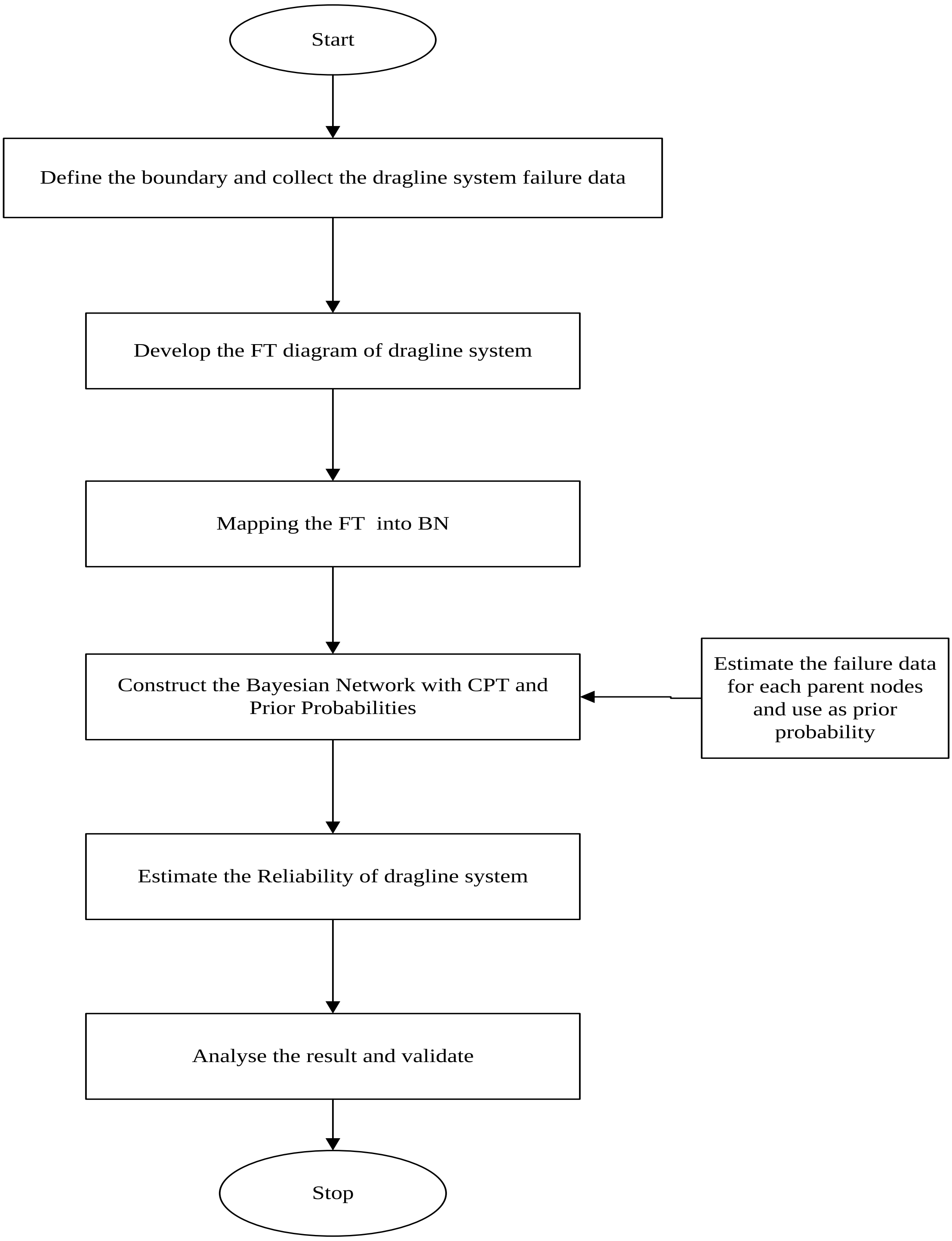

Figure 5. 2 Methodology for estimating the reliability of the dragline

5.4 Mapping of FT into BN

Based on the study of Bobbio et al.(2001)[152], any FT has a corresponding BN. The root nodes in the BN are the events in the FT, the intermediate events are the intermediate nodes, and the top event is the leaf node (child) in the BN, with each node having its CPT. For a more detailed explanation, let X, Y, and Z be random variables with two states: 1 indicates that the events happen, and 0 indicates that they don't. Figure 5.3 illustrates the fault tree for OR-gate and the accompanying BN using the conditional probability table (Table 5.2). In contrast, Figure 5.4 uses the conditional probability table (Table 5.3) to display the fault tree for AND-gate and the corresponding BN.

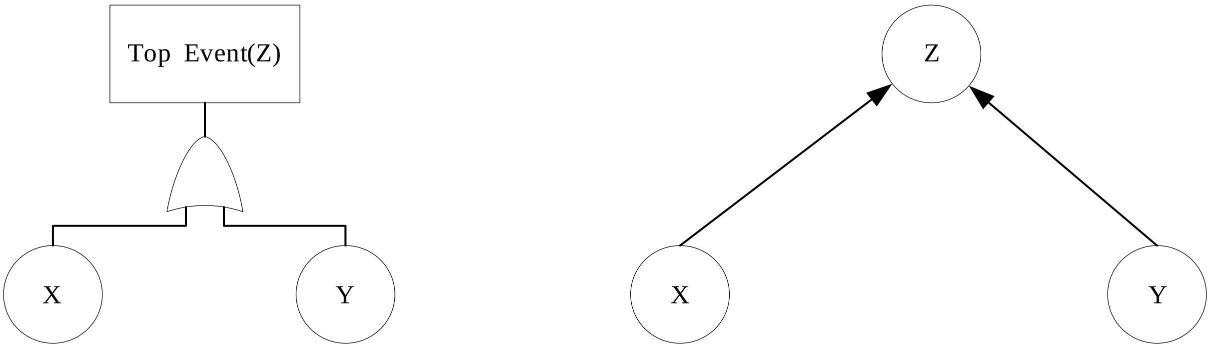

Figure 5. 3 Representation of OR gate in FT and BN

Table 5. 2 Conditional probability table corresponding to OR gate

Parents		Top event(X)
X	Y	P(Z=X,Y)
0	0	0
1	0	1
0	1	1
1	1	1

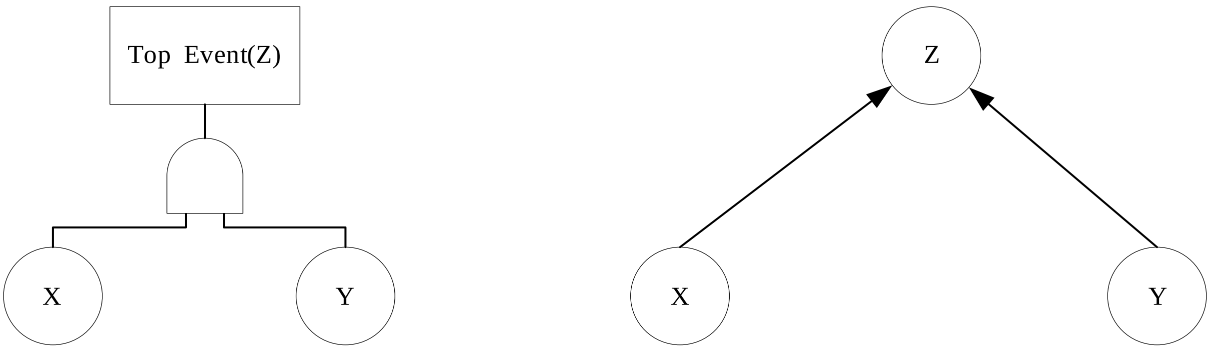

Figure 5. 4 Representation of AND gate in FT and BN

Table 5. 3 Conditional probability table corresponding to AND gate

Parents		Top event(X) P(Z=X,Y)
X	Y	
0	0	0
1	0	0
0	1	0
1	1	1

5.5 Bayesian Network Model for reliability study

Based on probabilistic and uncertain knowledge, BNs are used to build system reliability models, risk management, and safety assessments. A Bayesian network is a directed acyclic graph (DAG), also known as belief networks. BNs can be made up of qualitative or quantitative components or both. It is made of the two components: structure and parameter. A BN is made out of nodes and directed edges (edges for short) [153]. Edges show causal linkages between linked nodes, while nodes represent random variables. Each variable has several possible states (e.g., Yes or No; Low, Medium or High; 0 or 1). Parent nodes (the ones that an edge starts with) and child nodes (the ones that an edge points to) are the two types of nodes[152]. 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 CPT of node A (parent node) [74]. The arc is a connecting link between the variables and direction of arc presents the probabilistic dependences between the variables. The parameter of the BN model presents the prior probability of each root node for each state and the CPT of each child node given parental states. For the construction of BN, first generate the influence diagram to describe the system structure and parameters from the collected historical data. The relationship between system-subsystem-components can be constructed using the CPT of BN, which can be used to estimate the reliability. The CPT can be developed through the relationaship in between the nodes and also used to estimate the probability from the collected data and the causal relationships between parent node and child node [154],

[155], and it has an advantage that it can be regularly updated to generate sufficient information about the health/condition of the system when the new evidence is observed. For reliability analysis of dragline system, structure of BN is expressed: the root node, intermediate node and the leaf node. Root node indicates dragline failure, the intermediate nodes are formed by subsystem failure and leaf nodes are components failure.

When building the BN model, the Bayesian reasoning process grows exponentially as the number of variables rises. There are three independence assumptions that help to alleviate the joint probability distribution calculation's complexity [13]. The initial presumption is that every root node in the BN is distinct from every other node. In this study, such as $X = \left(R_1, R_2, \ldots, R_q; I_1, I_2, \ldots, I_m; L_1, L_2, \ldots L_p\right)$ three sets of variables—denoted system, subsystems, and components, respectively—are taken into consideration. Here q is the number of system nodes denoted as $R_1, R_2, \ldots, R_q$; m is a number of subsystem nodes denoted as $I_1, I_2, \ldots, I_m$; and p is the number of components nodes denoted as $L_1, L_2, \ldots L_p$ and the total number of nodes is n when $(n = q + m + p)$ in the BN model. The general equation for the calculation joint probability distribution can be given as a product of the specified conditional probability as presented in Eq. (5.3) [156], [157]:

$$P(X) = P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \mid Parents\ (\mathrm{X}_i)) \tag{5.3}$$

where $X = X_1, X_2 \ldots, X_n$ is a set of variables in the BN model and n is the number of variables.

The joint probability distribution for a given BN model can be calculated using Eq. (5.4) (ref. Figure 5.5).

$$P(R_1, R_2, R_3, R_4, I_1, I_2, L_1) = P(R_1)P(R_2)P(R_3)P(R_4)P(I_1 \mid R_1R_2)P(I_2 \mid R_3R_4)P(L_1 \mid I_1I_2) \tag{5.4}$$

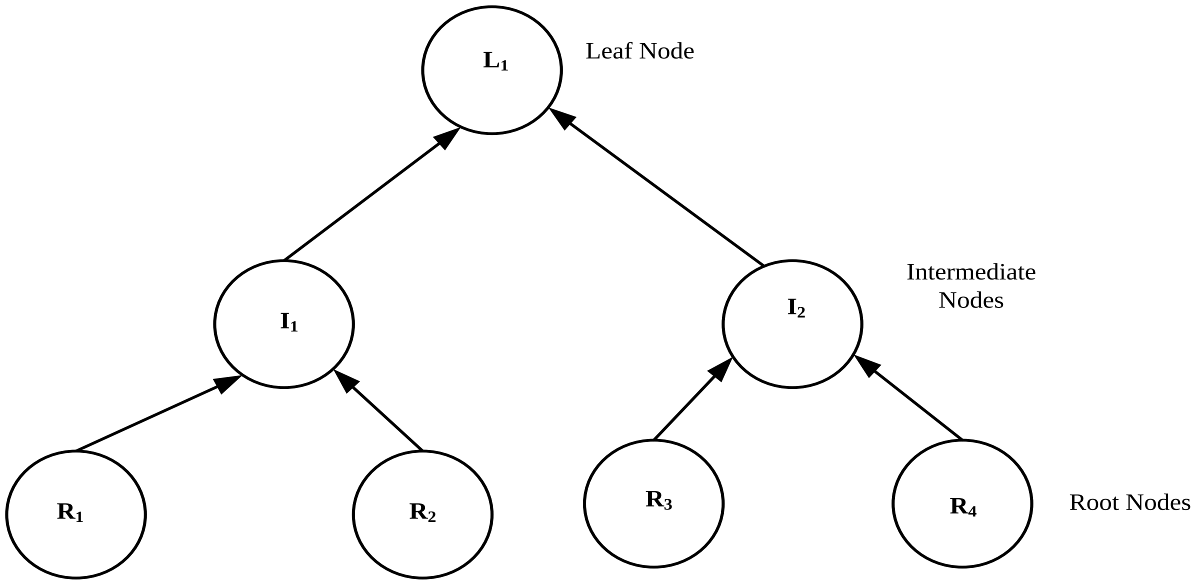

Figure 5. 5 An example BN

where R_1, R_2,R_3,R_4, I_1, I_2, L_1 are set of variables in the given BN model (Figure 5.5) where (R_1, R_2, R_3, R_4) represent the components nodes, (I_1, I_2) subsystems nodes and (L_1) system nodes, respectively and the total number of nodes are five. With the help of joint probability distribution, the probability of occurrence of the system failure can be calculated using Eq. (5.5) (refer Figure 5.5).

$$P(L_1 = 1) = \sum_{R_1 R_2 R_3 R_4 I_1 I_2} P(R_1, R_2, R_3, R_4, L_1 = 1, I_1, I_2) \tag{5.5}$$

In general, two typical information propagation procedures of BNs are top-down (predictive support reasoning) and bottom-up (diagnostic support reasoning) [96]. The joint probability distribution $P(X)$ propagates information in the top-down reasoning pattern as follows:

$$P(X_1, X_2, X_3, \ldots\ldots\ldots, X_n) = P(X_n|X_{n-1}, X_{n-2}, \ldots\ldots X_1)P(X_{n-1}|X_{n-2}, X_{n-3}, \ldots\ldots X_1) \ldots\ldots\ldots P(X_2|X_1)P(X_1) = \prod_{i=1}^{n} P(X_i|X_{i-1}, X_{i-2}, \ldots\ldots X_i) \tag{5.6}$$

However, the joint probability distribution $P(X)$ of BN follow the conditional independence and chain rule. Thus, $P(X)$ of variables $X = \{X_1, X_2, X_3, \ldots\ldots\ldots X_n\}$ is included in the network as[158].

$$P(X) = \prod_{i=1}^{n} P\left(\frac{X_i}{Pa(X_i)}\right) \tag{5.7}$$

Where $Pa(X_i)$are the parents of X_i in the BN.

The probability distribution of a given variable can be derived by marginalizing the joint probability distribution about it. This calculation is known as marginalization, and it can be used to calculate system reliability[72], [74]. The bottom-up inference procedure follows junction tree or variable elimination algorithms. The inference algorithm estimates the posterior probability distribution of a particular variable based on Bayes theorem at given evidence (set E) [19].

$$P(X/E) = \frac{P(E/X)P(X)}{P(E)} = \frac{P(X,E)}{\sum_X P(X,E)} \tag{5.8}$$

. In the BN of the case study dragline (Figure 5.6), there are forty component nodes, seven subsystems nodes, and one system node.

5.6 Result & Discussion

In this section, reliability study has been done using the FTA and BN model. Validated this method with actual reliability of the dragline. Also, discussed the BN diagnosis of the dragline and identified the critical subsystem of the dragline and validated with sensitivity analysis.

5.6.1 Reliability Analysis

In the FTA method, the reliability analysis of the dragline system has been estimated through equations (5.1) and (5.2). Figure 5.1 depicts FT of the dragline system. . In the FT, dragline failure represented as the top event, while subsystems and component failures described intermediate events and basic events respectively. Failure probabilities (Table 5.1) at the operating time t=1hr have been estimated for the basic events of the FT using the distribution parameters (Table 4.2).

The failure probability of the ‘Bucket & Accessories’ subsystem is calculated using equation 5.2

$P(S1) = 0.9590$

Similarly, failure probability for all the subsystems are calculated as:

$P(S2) = 0.8445$

$P(S3) = 0.9951$

$P(S4) = 0.9197$

$P(S5) = 0.9189$

$P(S6) = 0.8997$

$P(S7) = 0.9791$

The estimated reliability of the dragline (t=1 hr) is 59.59%

BN model has also used the failure probability of the dragline subsystem's failure events presented in table 5.1. Every major component under the defined subsystem of the dragline has been estimated for likelihood of occurrences of failure. These failure probabilities are crucial in evaluating the overall system reliability and have been taken as the prior probabilities of the BN model. The Bayesian network diagram of the dragline system mapped from the fault tree appears in figure 5.6 below, when figure 5.7 shows the details of the reliability assessment.

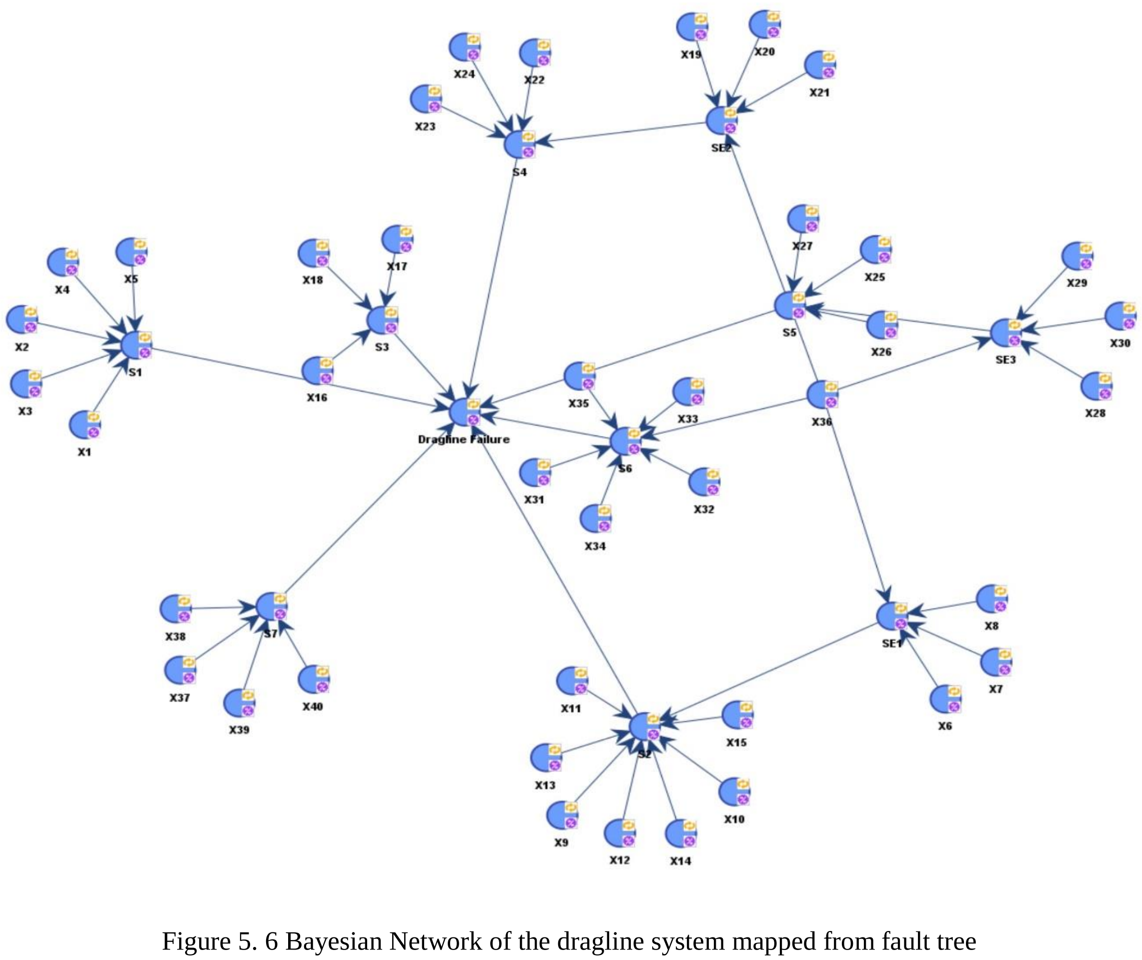

Figure 5. 6 Bayesian Network of the dragline system mapped from fault tree

CPT of every subsystem shows the causal relationship between the component and subsystem failures. Prior probabilities of the subsystems are estimated following equation (5.3). For example, Prior probability (t = 1 hr) of the 'Bucket & Accessories' subsystem

$P_{prior}(S1) = P(X1) \times P(X2) \times P(X3) \times P(X4) \times P(5)$

$= 0.9908 \times 0.9928 \times 0.9969 \times 0.9978 \times 0.9801 = 0.9544$

Similarly, the prior probability of the all the subsystems are calculated and presented in table 5.3. The BN model estimates the reliability of the dragline system based on the prior probability of the components and CPT. The estimated reliability of the dragline system is 62.03%, at t = 1 hour.

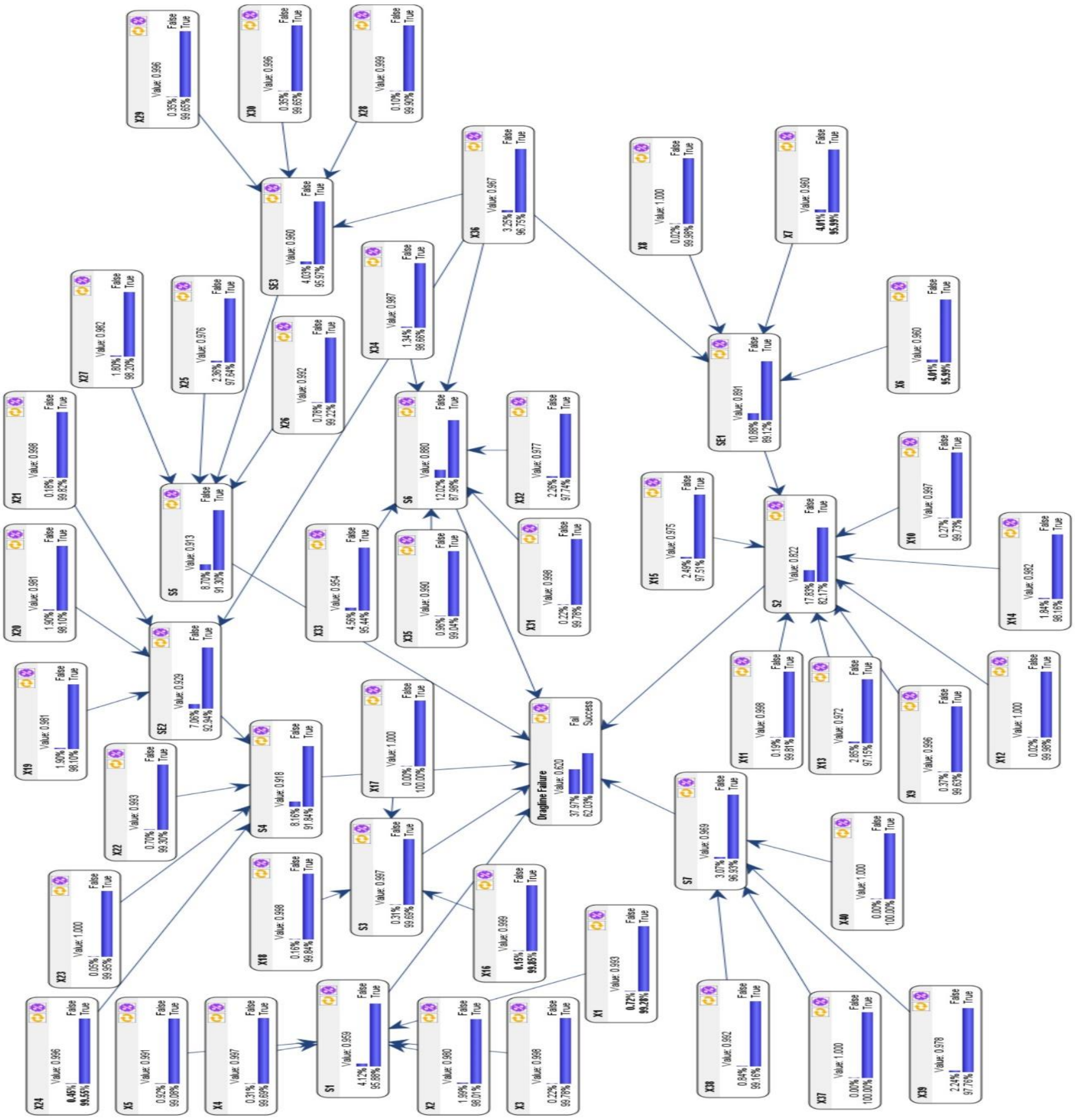

Figure 5. 7 Reliability assessment of the dragline system using BN model

5.6.2 Validation of BN model estimated reliability values

Figure 5.8 presents a comparative study of actual reliability of the dragline with the estimated reliability of the dragline using BN model and FTA. It is evident from the figure 5.8 that BN model estimates reliability much closer to actual reliability than FTA. For example: after 5 hours of operation, the actual reliability of the dragline system is 35.25% when the BN model and FTA estimate it to be 29.31% and 25.05%, respectively. This work defines error in predication as follows: Error is the difference between actual and estimated values [159] and expressed as:

$$\%error = \frac{(actual_{reliability} - estimated_{reliability})}{actual_{reliability}} * 100 \qquad (5.9)$$

Error in reliability prediction by the BN model and FTA has been calculated at different point of time as presented in the table 5.4. It is observed that the accuracy of the BN model is 83.15% when it is only 71.07% FTA. From the above discussion, it can be concluded that the developed BN model estimates the reliability of the dragline system with more than 80% precision on an average, and BN model is more precise than the FTA method.

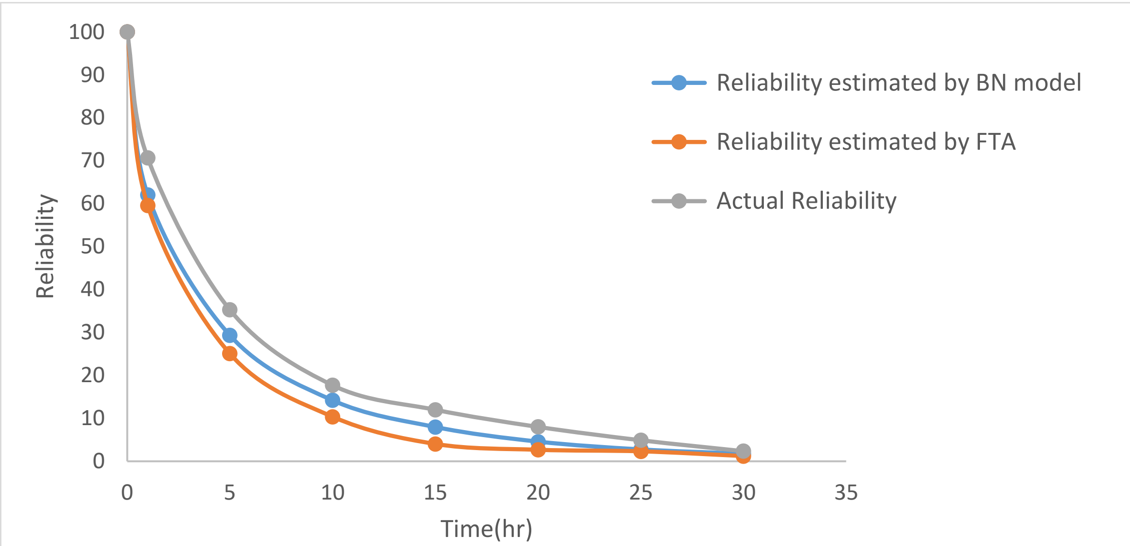

Figure 5. 8 Comparison of dragline's reliability with different models

Table 5. 4 Error in reliability prediction of dragline with different models

	BN	FTA	Actual Reliability	BN	FTA
t	R(t)	R(t)	R(t)	R(t) %Error	R(t) % Error
0	100	100	100	0	0
1	62.03	59.59	70.65	12.20	15.65
5	29.31	25.05	35.25	16.85	28.93
10	14.71	10.35	17.68	19.85	41.45
15	7.95	4.12	11.97	33.58	66.48
20	4.55	2.65	7.98	42.98	66.79
25	2.73	2.3	4.87	43.94	52.77
30	1.72	1.2	2.32	25.86	48.27

5.6.3 BN based Failure Diagnosis and importance ranking

BN helps to diagnose the failure path of a dragline as detailed below:

Path 1: Dragline → Dragging Mechanism →Drag Motor, Drag Brake and Drag Drum along with the Gearbox.

Path 2: Dragline → Electrical Auxiliary → Synchronous motor, DC motor, power system, and the MG Set.

The above diagnostic paths can be decided based on the failure diagnosis of the dragline.

The diagnosis of the dragline system failure, either due to the failure of individual subsystems or the combined subsystem failures, required updating the failure probabilities of the BN nodes (Figure 5.8). Updated probabilities of the BN nodes will help to find out the contribution of each node (from bottom to top) in the system failure events.

For assessing the contribution of each node to the system failure, the failure probability of the dragline system is set to 100%. Using this initial system probability (100%), the probability values of each node in the BN are updated as indicated in Figure 5.9. Thus, posterior probabilities are estimated from equation 5.8 using the evidence on the BN model. The prior and posterior probabilities information in table 5.3 show the significance of the dragline subsystems/components to the system failure. From Table 5.3, it can be seen that the dragging mechanism (S2) is the lowest posterior probability (reliability) of 53.04%. While the electrical auxiliary (S6) is the second lowest, and the swing mechanism is seen to be the third lowest posterior probability (reliability) subsystem with a posterior probability of 68.35% and 77.08%, respectively.

Table 5. 5 Prior and Posterior probability of the component/subsystems of the dragline

Node	Prior Probability	Posterior Probability	Node	Prior Probability	Posterior Probability
S2	0.8217	0.5304	X5	0.9908	0.9757
S6	0.8798	0.6835	X38	0.9916	0.9779
SE1	0.8912	0.7134	X26	0.9922	0.9794
S5	0.913	0.7708	X1	0.9928	0.981
S4	0.9184	0.7851	X22	0.993	0.9817
SE2	0.9294	0.8142	X24	0.9955	0.9882
X33	0.9544	0.8798	X9	0.9963	0.9903
S1	0.9544	0.8916	X29	0.9965	0.9907
SE3	0.9597	0.8938	X30	0.9965	0.9907
X6	0.9599	0.8943	X4	0.9969	0.9917
X7	0.9599	0.8943	S3	0.9969	0.9918
X36	0.9675	0.9143	X10	0.9973	0.9929
S7	0.9793	0.9193	X3	0.9978	0.9941
X13	0.9715	0.925	X31	0.9978	0.9942
X15	0.9751	0.9343	X11	0.9981	0.9951
X25	0.9764	0.9379	X21	0.9982	0.9953
X32	0.9774	0.9404	X18	0.9984	0.9957
X39	0.9776	0.9409	X16	0.9985	0.9961
X2	0.9801	0.9475	X28	0.999	0.9974
X19	0.981	0.9501	X23	0.9995	0.9987
X20	0.981	0.9501	X12	0.9998	0.9995
X14	0.9816	0.9515	X8	0.9998	0.9995
X27	0.982	0.9525	X40	1	1
X34	0.9866	0.9647	X37	1	1
X35	0.9904	0.9748	X17	1	1

Dragline failure following path 1: The updated BN model as presented in figure 5.9, shows that the drag motor is one of the significant contributors to failure with a failure probability of 28.66%. This is followed by the drag brake failure with a probability of 15.97%.

Dragline failure following path 2: The Electrical subsystem has five major components; the synchronous motor is attributed to having a failure probability of 12.02%, and thus, makes a significant contribution towards the reliability of the dragline system. The Bayesian network in figure 5.10, shows the joint failure probability of the overall dragline and dragging mechanism subsystem, when both the dragline system and the dragging mechanism subsystem have failed.

A similar investigation on the overall dragline and the electrical auxiliary subsystem is shown in figure 5.11. The major failed components in the Electrical subsystem are the synchronous motor, power supply, DC system and the MG set with a failure probability of 11.17%, 37.98%, 27.08% and 18.83%, respectively.

Based on the relative change in probability (prior and posterior probability), subsystems/components of the dragline have been ranked as shown in the table 5.4 and table 5.5

Table 5. 6 Criticality ranking of the subsystems of the dragline

Node	Prior Probability	Posterior Probability	% change in Reliability	Criticality Ranking
S2	0.8217	0.5304	0.35451	1
S6	0.8798	0.6835	0.22312	2
S5	0.913	0.7708	0.15575	3
S4	0.9184	0.7851	0.14514	4
S1	0.9544	0.8916	0.0658	5
S7	0.9793	0.9193	0.06127	6
S3	0.9969	0.9918	0.005116	7

Table 5. 7 Criticality ranking of the components of the dragline

Node	%Reliability difference	Criticality Ranking	Node	%Reliability difference	Criticality Ranking
SE1	0.19950628	1	X1	0.011886	23
SE2	0.12395094	2	X22	0.01138	24
X33	0.07816429	3	X24	0.007333	25
SE3	0.06866729	4	X9	0.006022	26
X6	0.06834045	5	X29	0.00582	27
X7	0.06834045	6	X30	0.00582	28
X36	0.05498708	7	X4	0.005216	29
X13	0.04786413	8	X10	0.004412	30
X15	0.04184186	9	X3	0.003708	31
X25	0.03943056	10	X31	0.003608	32
X32	0.03785554	11	X11	0.003006	33
X39	0.03754092	12	X21	0.002905	34
X2	0.03326191	13	X18	0.002704	35
X19	0.03149847	14	X16	0.002404	36
X20	0.03149847	15	X28	0.001602	37
X14	0.03066422	16	X23	0.0008	38
X27	0.03004073	17	X12	0.0003	39
X34	0.02219745	18	X8	0.0003	40
X35	0.01575121	19	X40	0	41
X5	0.01524	20	X37	0	42
X38	0.013816	21	X17	0	43
X26	0.012901	22			

Table 5.4, depicts that dragging mechanism (S2) is the most critical subsystem of the dragline system followed by S6, S5, S4, S7, S1 and S3 respectively. Four subsystems namely, (S2, S6, S5, and S4) contributes 80 % of dragline failures and are the critical subsystems of the dragline system.

Similarly, it is also evident from table 5.5 that failure of drag motor system (SE1) is the most critical for dragline operation and dump rope failure (X17) has limited impact on dragline failure. Failures of SE1, SE2, X33, SE3, X6, X7 and X33 shares 80% of the dragline failures and are critical components of the dragline.

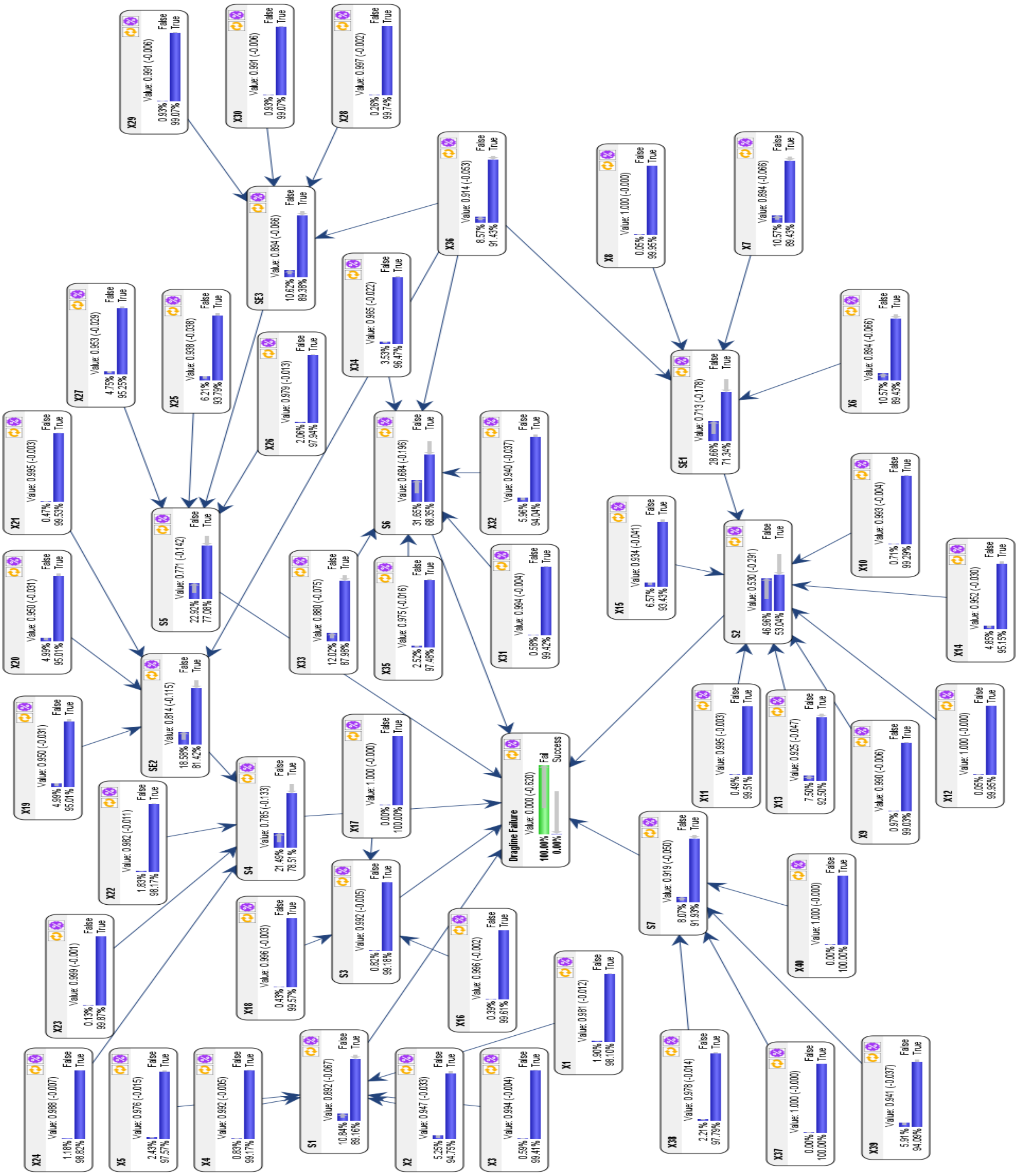

Figure 5. 9 Updated Bayesian network with Dragline failure

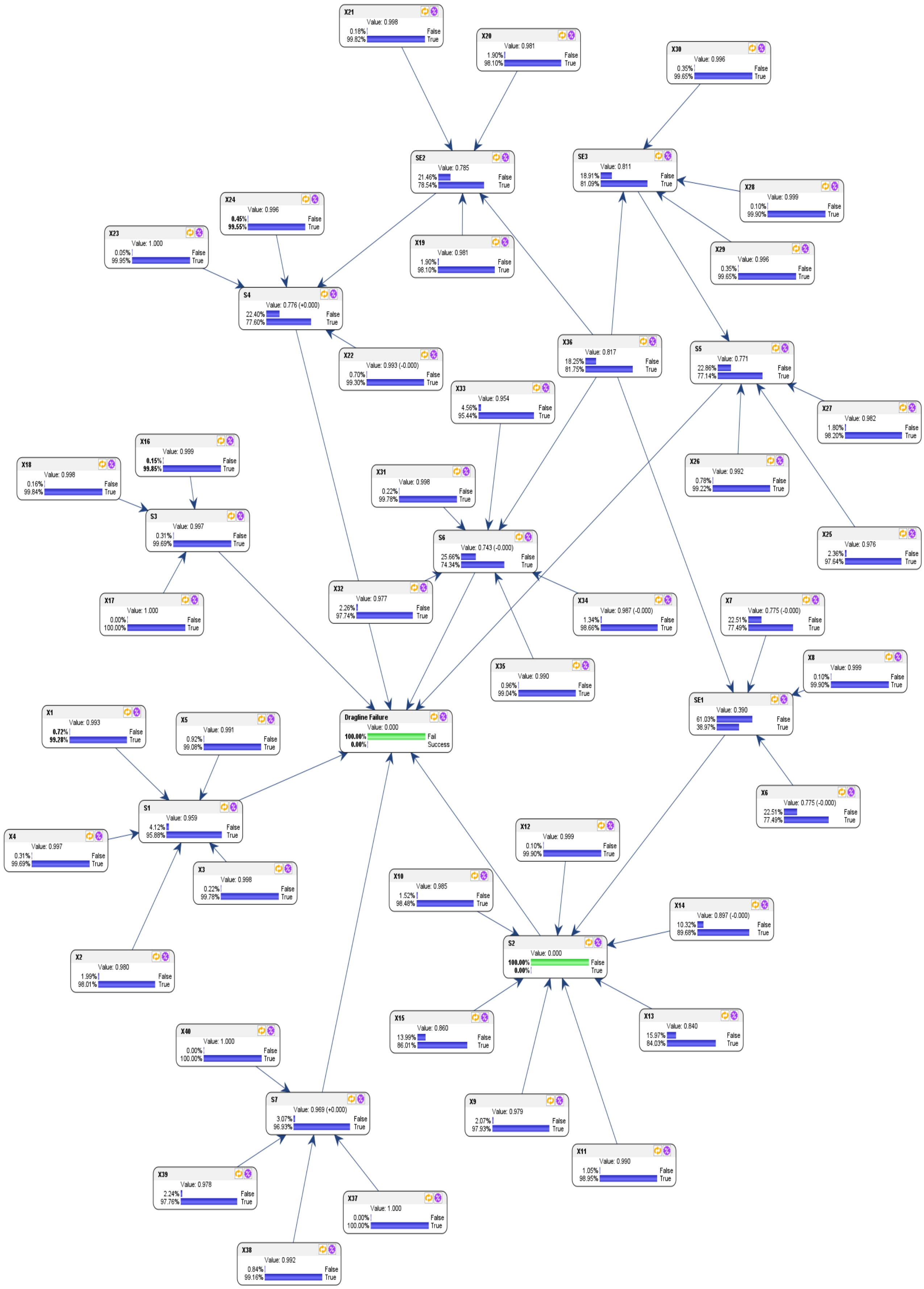

Figure 5. 10 Updated Bayesian network with the dragline and Dragging Mechanism failure

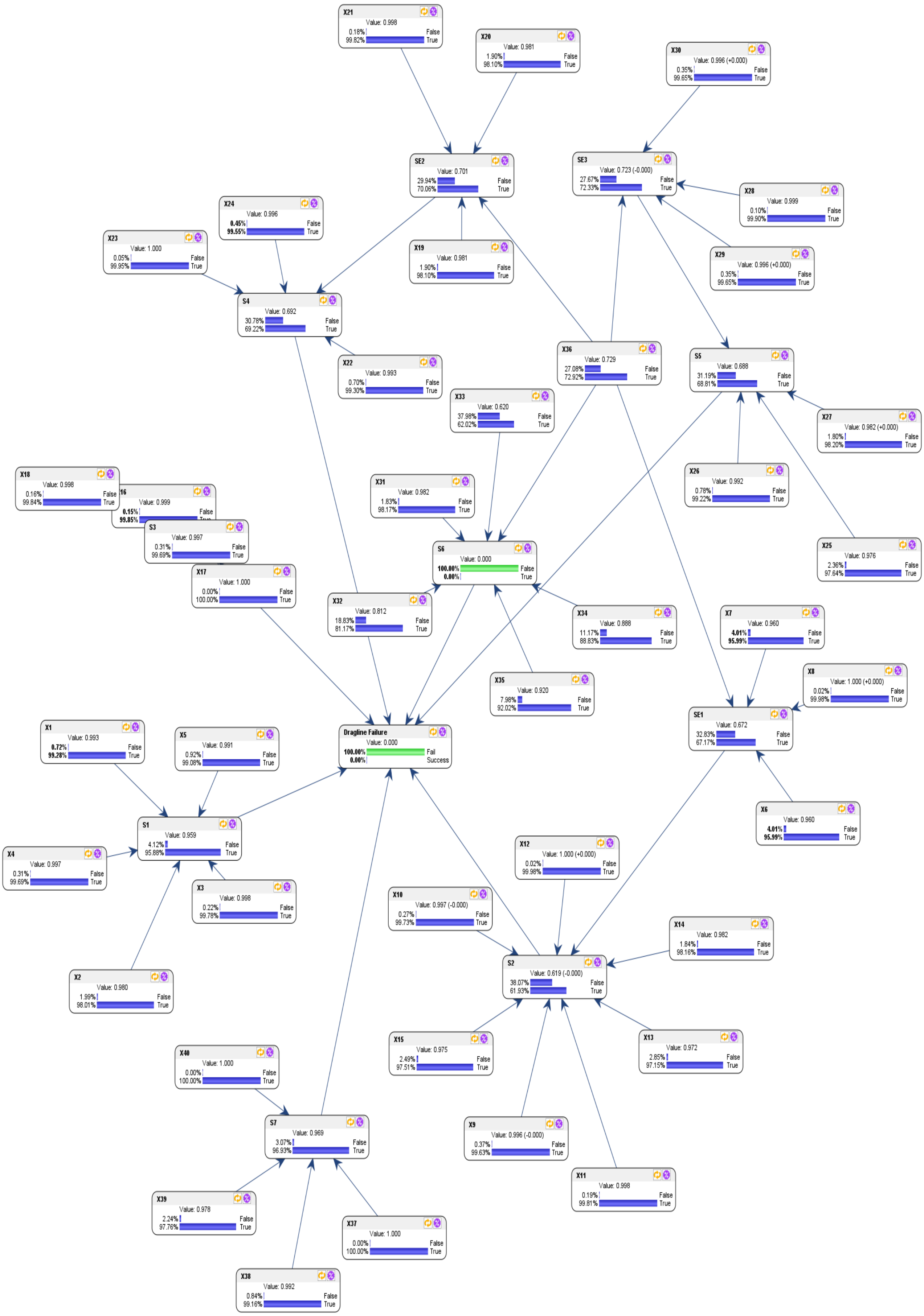

Figure 5. 11 Updated Bayesian network with the Dragline system and Electrical Auxiliary Failure

5.6.4 Validation of critically ranking using Sensitivity analysis

In BNs, the sensitivity analysis can be used for verifying the correctness of parameters, and to understand whether more precision in estimating them would be useful [160], [161]. To study the importance of root nodes, a sensitivity analysis in BN model has been conducted.

It is a standard practice to study the correlation and covariance between variables to determine their relative importance, particularly the target variable. Here a different approach based on information theory has been utilized for the sensitivity study. Instead of computing the correlation coefficient, how observing a predictor variable affects the states' uncertainty of a to-be-predicted variable has been considered. Evaluating Mutual Information (MI) values between pairs of random variables reveal the degree of dependence between two random variables. The reasoning behind this approach is that the state of one node provides a lot of information about the state of another node if they are connected. In other words, these variables are more dependent on one another than any other nodes in the network[162].

MI between two random variables X and Y is denoted by $I(X;Y)$, and mathematically defined as follows[163]:

$$I(X;Y) = H(X) - H(X|Y) \tag{5.10}$$

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:

$$H(X) = -\sum_{i=1}^{n} P(X_i)\log(P(X_i)) \tag{5.11}$$

$$H(X|Y) = -\sum_{i=1}^{n}\sum_{j=1}^{m} P(X = x_i, Y = y_i) * \log(P(X = x_i|Y = y_i)) \tag{5.12}$$

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

Using the concept of Mutual Information (MI) theory the contribution of individual nodes into failure of target node has been estimated using equation (5.12). From figure 5.12 it is clear that, the

Dragging mechanism (S2) contributes maximum to the overall failure of the Dragline and is the most critical subsystem in Dragline. This result supports the result obtained through BN analysis. . In comparison, electrical auxiliary subsystem (S6) and swing mechanism contributed around 18.79% and 13.16% to overall dragline failure. Figure 5.13 shows the top 10 critical components and their contribution to dragline failure. It is observed that the drag motor system contributes the most with around 16.82% of the dragline failure, followed by the hoist motor system, synchronous motor and swing motor system with 10.5%, 6.64% and 5.83%, respectively. This result complies with the results obtained in the present study using BN.

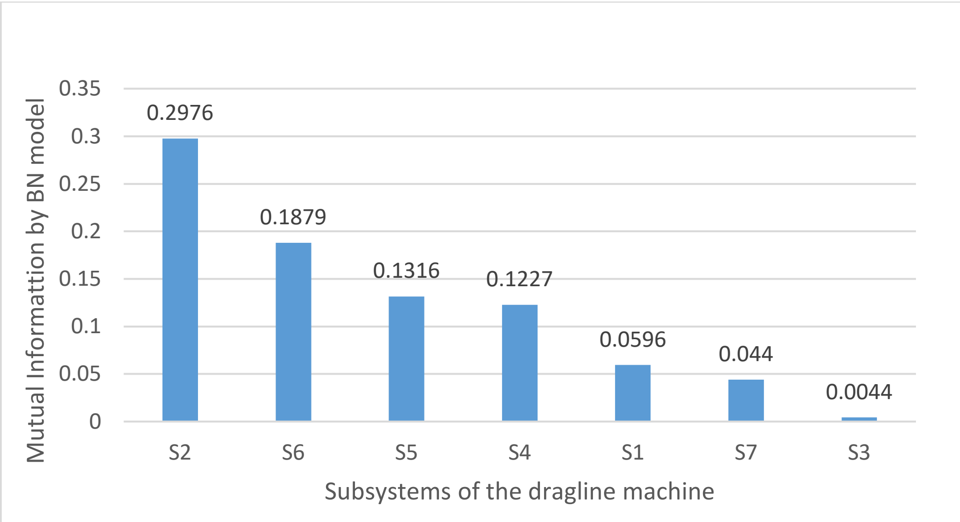

Figure 5. 12 Importance of subsystems of dragline

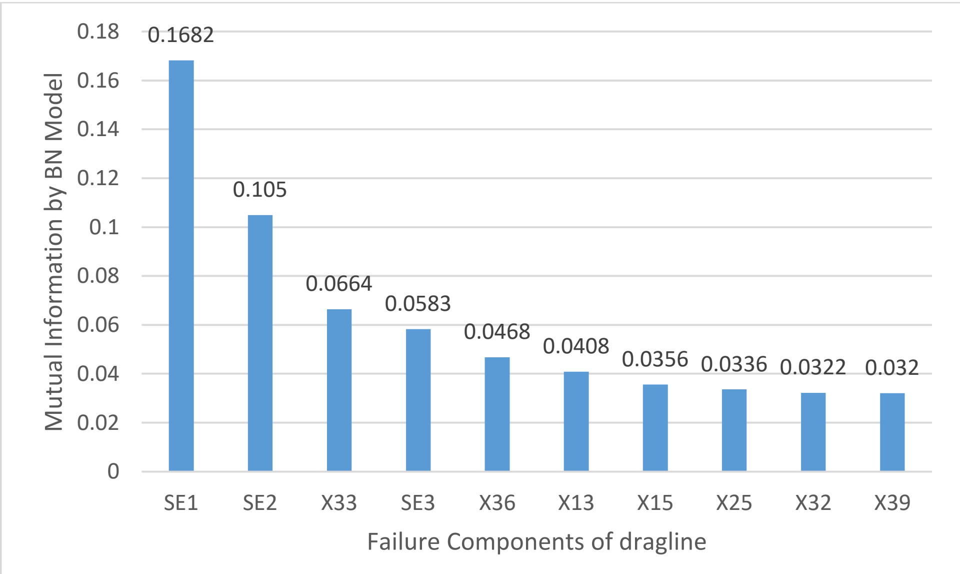

Figure 5. 13 Importance of failure components of Dragline

To improve the reliability of the dragline, it is necessary to improve the reliability of the dragging mechanism, electrical auxiliary subsystem and swing mechanism. Thus, the quality enhancement of Dragline depends on the reliability improvement of the components of the subsystems mentioned above. Therefore, it should be highlighted that the maintenance methods of various components/subsystems vary from one another.

5.7 Summary

In this chapter, reliability study has been done on the case study dragline using traditional FTA method and BN model. Validated the studied model with actual reliability of the dragline which was based on the traditional non-parametric model using the operational failure data of the dragline. Estimated reliability of the dragline through BN model much precise to the actual reliability of the dragline as compared to the FTA. Dragging mechanism has been identified as the most critical subsystem of the dragline.