Chapter – 6

Reliability analysis of the critical subsystem of the dragline using DBN

6.1 Introduction

The dragging mechanism is identified as the most critical subsystem of the dragline from the reliability aspect of the dragline system. This chapter contains detailed information about the dragging mechanism of the dragline. It also discusses reliability estimation of the dragging mechanism using DBN model, identification of the critical component of the dragging mechanism and model validation.

6.2 Dragging Mechanism

Failure analysis at chapter 5 identified that the dragging subsystem is the most critical subsystem of the dragline system. Devising suitable countermeasures against the failures of the dragging subsystem will help maximise dragline operation. Dragging subsystem mainly consists of a drag rope, motor, gearbox, brake, socket, drum, control system, pulley and chain. Drag Mechanism has two motors which help to bind the drag rope on the drag drum with the help of the gearbox. The logical interconnection relations of the components and their functions is shown in schematic form in figure 6.1.

Dragging subsystem is considered for reliability assessment using DBN to assist the maintenance engineer in adopting an apt maintenance strategy for preventing dragline failure. A DBN model for evaluating the dragging subsystem's reliability is developed based on the collect failure. Based on these collected data, all the components of dragging subsystem is only in two conditions either it may be failure condition or running(success) condition.

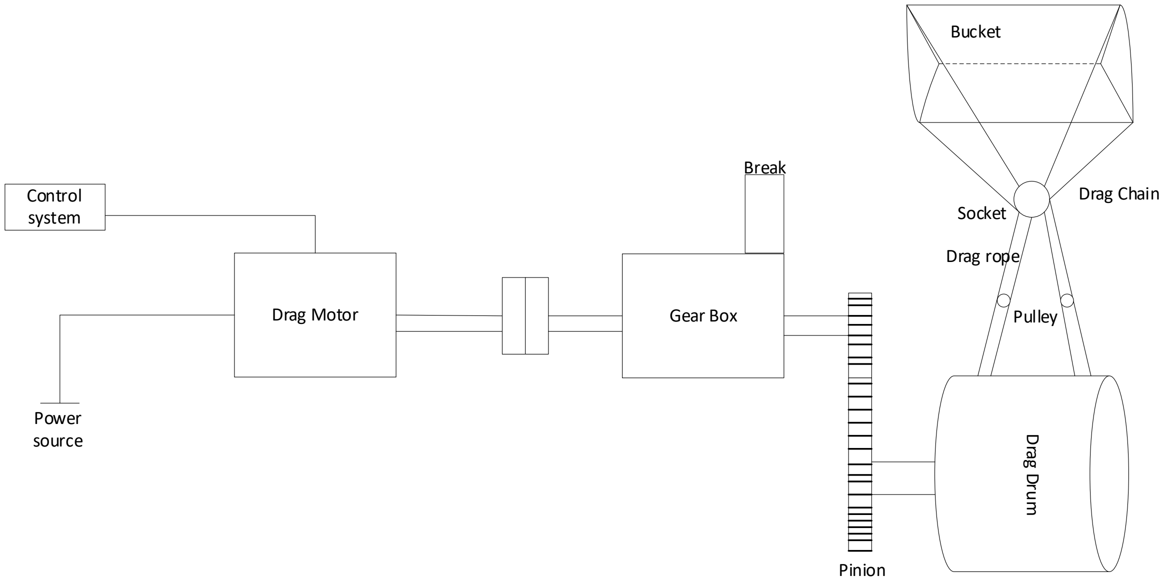

Figure 6. 1 Schematic diagram of Dragging Mechanism

Figure 6.1 displays that the external supply line feeds power to the drag motor and the control system help to run the motor accurately. The drag motor is attached to the gearbox, which helps to bind the drag rope on the drag drum. The drag drum with the help of the pinion gear arrangement and a brake, control the motor speed. Drag rope, binding on the drag drum, is used to drag the overburden into the bucket. The socket connects the drag rope and the drag chain. All the components have definite role in operating the dragging mechanism. Thus, ensuring high reliability of each component is essential to achieve high reliability of the dragging mechanism and improving the overall dragline's machine reliability.

6.3 Dynamic Bayesian Network Modelling

Conventional BNs are static in nature and unsuitable for representing dynamic relationship among process parameters. Dagum has developed the concept of dynamic networks(Dagum, Paul ; Galper, Adam ; Horvitz 1992) while Murphy has extended the dynamic networks to extending BNs to DBN(Murphy 2002). DBNs are widely used to model dynamic processes, which has propelled the pace of dynamic analysis in many fields. Weber [37] showed the suitability of DBN over the classical Markov chain technique in reliability assessment. DBN has been successfully applied in many fields like, medical science [25], availability assessment [37], safety and risk analysis [14], fault diagnosis [40] and others.

BN cannot be used to explicitly model the changes in the system over time due to the time-independent characteristic. A DBN is an extension of BN (Khakzad 2015), which is suitable for describing the dynamic behaviour of random variables by introducing relevant temporal dependencies. The extension of a static BN that links the random variables to one another's time slices is called a Dynamic Bayesian Network (DBN)(Murphy 2002; Pearl Judea 1988). The DBN is expressed by the initial and transition networks. Initial networks are defined as the prior probability of the variables. The transition network is a to-slice temporal BN (2TBN), which describes the state transition process of variables through direct edges and CPTs of inter-time-slice. In the DBN, the time dimension is discretized into multiple time slices, where every two consecutive slices constitute a transition model. Assuming that the components presented in figure 6.2(b) are time-varying, an unrolled DBN with $n(n \geq 1)$ time slice is established, as shown in figure 6.2(c). The prior probability $P(X_1(1))$ and $P(X_2(1))$ are given in the initial BN (figure 6.2(a)). In the 2TBN (Figure 6.2(b)), $X_1(t+1), X_2(t+1)$ and $Y(t+1)$ in the second slice have parent nodes, thereby generating the associated transition probability as follows:

$$
\begin{aligned}
&P(X_1(t+1), X_2(t+1), Y(t+1) \mid X_1(t), X_2(t)) \\
&= P(X_1(t+1) \mid X_1(t), X_2(t)) P(X_2(t+1) \mid X_2(t)) P(Y(t+1) \mid X_1(t+1), X_2(t+1))
\end{aligned}
\tag{6.1}
$$

Where $X_i(t+1)$ and $X_i(t)(i=1,2)$ represents components X_i at time $t+1$ and t, respectively; $Y(t+1)$ represents system Y at time t+1; $P(X_1(t+1) \mid X_1(t), X_2(t))$ is the CPT of $X_1(t+1)$ given $X_1(t)$ and $X_2(t)$; $P(X_2(t+1) \mid X_2(t))$ is the CPT of $X_2(t+1)$ given $X_2(t)$; and $P(Y(t+1) \mid X_1(t+1), X_2(t+1))$ is the CPT of $Y(t+1)$ given $X_1(t+1)$ and $X_2(t+1)$.

DBN is defined with the following two assumptions:

i. CPT of 2TBN are time-invariant, and

ii. The state of each slice is only related to that of the previous one.

Thus, the transition probability of the unrolled DBN with n time slices is expressed as:

$$
\begin{aligned}
&P(X_1(k), X_2(k), Y(k) \mid X_1(1), X_2(1), X_1(2), X_2(2), \ldots, X_1(k-1), X_2(k-1)) \\
&= P(X_1(t+1), X_2(t+1), Y(t+1) \mid X_1(t), X_2(t)), k \in [2, n]
\end{aligned}
\tag{6.2}
$$

A two-slice temporal BN(2TBN) can be defined as a product of the conditional probabilities in the 2TBN as given in equation (6.4)

$$P(X_t|X_{t-1}) = \prod_{i=1}^{N} P(X_t^i\,|P_a(X_t^i)). \tag{6.3}$$

Joint Probability distribution of DBN over the random variable $X_1, X_2, X_3, \dots \dots .. X_n$ is given below:

$$P(X_{1:T}) = \prod_{t=1}^{T} \prod_{i=1}^{N} P(X_t^i|P_a(X_t^i)) \tag{6.4}$$

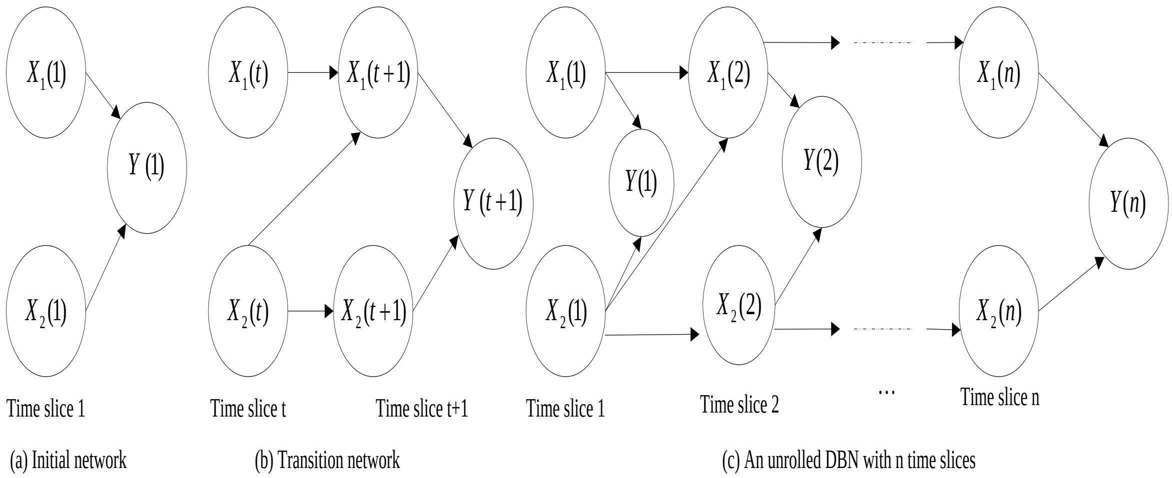

Figure 6. 2 Example of a DBN

6.4 Methodology of DBN for reliability analysis

DBN is used for the reliability modelling of the system, considering the system logical structure and dynamic behaviours of components. An established FT model can be used as the prior knowledge of DBN modelling(Bobbio, A.; Portinale, L.; Minichino, M.; Ciancamerla 2001). The graphic illustrates the transformation process, which transforms the bottom event of the FT into the parent node of the BNs and the top event into the child node of the BNs. The intra-time slice and inter-time slice conditional probability dependency models of the BN can be obtained by mapping FT gates. Figure 6.3 shows a flowchart of the methodology of the DBN.

Step 1 Map FT events into DBN nodes and define the states of the nodes.

Step 2 Establish the initial network. Create directed edges between nodes in the intra- time-slice according to their states.

Step 3 Establish the transition networks. Considering the sequential dependencies reflected by FT, directed edges are generated amongst different variables in the inner-time-slice. If a variable is time-varying, then it will also own a historical node in the previous time slice as parent.

Step 4 Populate the prior probability and CPTs of nodes. The prior probability is determined according to the observation. The CPT of each child node is defined depending on the failure probability distributions of its parent nodes and the types of gates that tie them together.

Step 5 Estimate the reliability of dragging subsystem and its components.

Step 6 Analysed the result and validate.

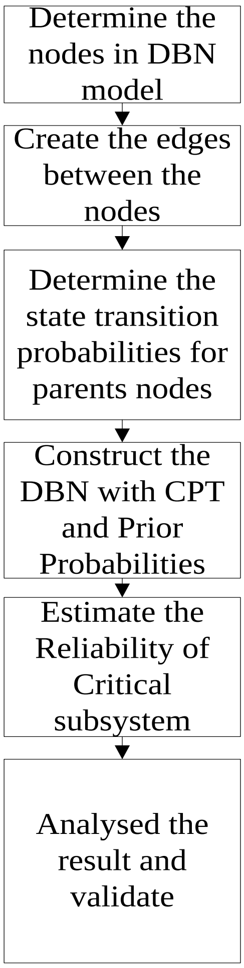

Figure 6. 3 Flowchart of the DBN model

6.5 Model Development

The mapping technique is used to convert the FT into DBN to perform the reliability analysis of the Dragging mechanism using DBN, as shown in figure 6.4. The relationship between the components and dragging subsystem has been shown in figure 6.4. The dynamic model consisting of twelve components nodes, one drag motor system node and one dragging mechanism node. All the components are subject to degradation and hence modelled with temporal nodes. These temporal relations are shown with circular arrows in figure 6.3. Failure data of the dragging mechanism has been discussed in the chapter 4 section 4.6.2 and table 4.2. Prior probability of the shaft, stator and armature have been estimated at the operating time t=1hr using the Weibull's parameters shown in the table 6.1.

Table 6. 1 Basic events and their parameters

Basic Events	Parameters	Prior Probability
Shaft failure	(0.6385191,609.3108874)	0.98347227
Stator failure	(0.4892158, 362.150)	0.985512
Armature failure	(0.575926,1904.242755)	0.98036192

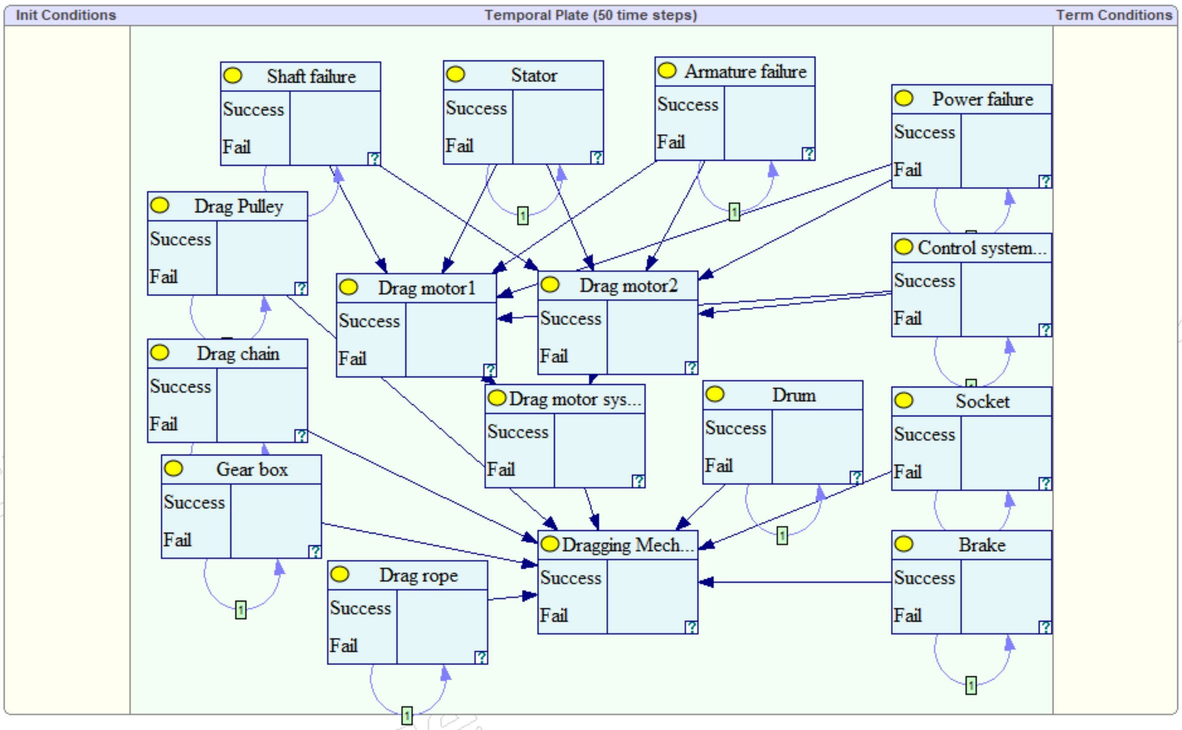

Figure 6. 4 Developed DBN model of dragging mechanism

Temporal property of component nodes are defined in the transition probabilities of components as given in Table 6.1.

Table 6. 2 Transition probabilities of various components

Shaft

Self(t)	(t-1)	
	Success	Fail
Success	0.98347227	0
Fail	0.0165273	1

Stator

Self(t)	(t-1)	
	Success	Fail
Success	0.985512	0
Fail	0.014488	1

Armature

Self(t)	(t-1)	
	Success	Fail
Success	0.980361	0
Fail	0.001963	1

Drag pulley

Self(t)	(t-1)	
	Success	Fail
Success	0.981592	0
Fail	0.018408	1

Drag rope

Self(t)	(t-1)	
	Success	Fail
Success	0.996316	0
Fail	0.003684	1

Drag Chain

Self(t)	(t-1)	
	Success	Fail
Success	0.994481	0
Fail	0.005519	1

Drag Drum

Self(t)	(t-1)	
	Success	Fail
Success	0.998133	0
Fail	0.001867	1

Drag Brake

Self(t)	(t-1)	
	Success	Fail
Success	0.971521	0
Fail	0.028479	1

Drag Socket

Self(t)	(t-1)	
	Success	Fail
Success	0.975062	0
Fail	0.024938	1

Power failure

Self(t)	(t-1)	
	Success	Fail
Success	0.967455	0
Fail	0.032545	1

Control system

Self(t)	(t-1)	
	Success	Fail
Success	0.999814	0
Fail	0.000186	1

Gearbox

Self(t)	(t-1)	
	Success	Fail
Success	0.997285	0
Fail	0.002715	1

6.6 Result & Discussion

6.6.1 Reliability analysis of dragging mechanism

DBNs are well-established extensions of regular BNs that enable the explicit modelling of changes over time. For executing the model in a DBN, two-time slices are considered for each variable while modelling the temporal evolution of a system. The symbol t denotes the current time step, and the following time step is represented by the symbol t+i. The duration t could be 1 hour, one week, one month, or even one year. The failure probability of all the components is input to evaluate the reliability, and the forward DBN analysis evaluates the dragging mechanism's reliability.

Figure 6.5 shows the DBN assessment of the dragging mechanism and interrelation between all components. The reliability of the dragging mechanism at different points of observation is obtained using the forward inference Bayesian network. Figure 6.6 displays reliability values at $t_0 \ and \ t_1$ with unroll condition of DBN. Dragline machine runs 24 hours, and daily inspection and maintenance schedule occurs in morning 9a.m -11 a.m. The overall reliability of the dragging mechanism is 84.29% at 1hr of operation, and overall dragging mechanism reliability dips to 25.48% after 8 hrs of operation. Thus, high degradation of reliability within 8 hours. This change happens due to the sharp degradation of the reliability of the drag motor system (ref figure 6.8). Therefore, the dragging mechanism needs proper care like, inspection and maintenance to maintain a good reliability figure.

Failures of the dragging mechanism can be analysed through the reliability study of the components, and the critical components, that mostly affect the reliability of the dragging mechanism, can be identified using DBN. Figure 6.7 shows the dragging sub-system's reliability curve and figure 6.8 plots the reliability curve of each component of the dragging sub-system. It shows the sharp decrease of reliability of some components. Figure 6.8 explains that rapid decrease of reliability of the dragging mechanism mainly due to the unreliability of the drag motor subsystem. Failures of power supply, motor shaft, stator and armature increases the unreliability of the drag motor. The reliability of the drag motor subsystem decreases with time, and it dips to only 13.21% within 24hrs of operation Probability that no failure will occur in power supply(45.20%), drag brake(49.98%) , socket(54.54%) and motor armature, shaft and stator within a day is only 62.12%, 67.03%, and 70.45% respectively. Furthermore, the decrease in reliability of drag chain and rope is comparative faster than other components.

For the maintenance team of the dragline, special consideration should be paid to the drag motors, power failure and drag brake, socket and pulley. For enhancing the performance of the dragline, improvements should be made to the reliability of the drag motor and reduce the power failure.

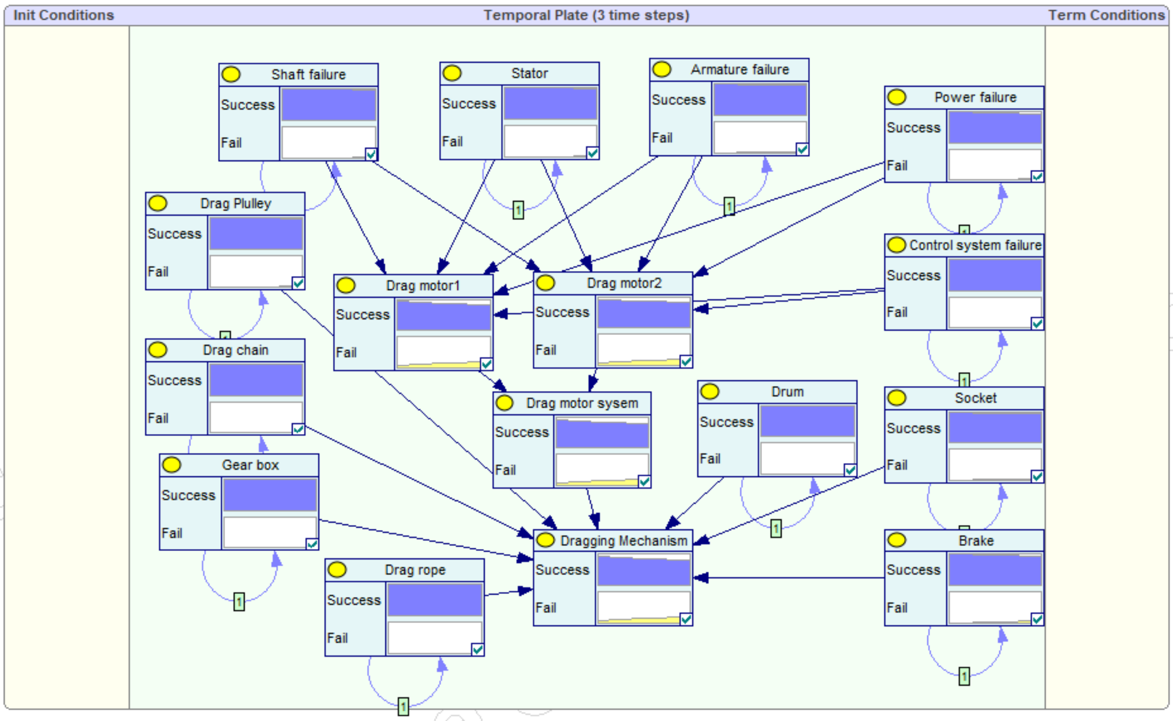

Figure 6. 5 Reliability assessment of drag Mechanism at time t_0

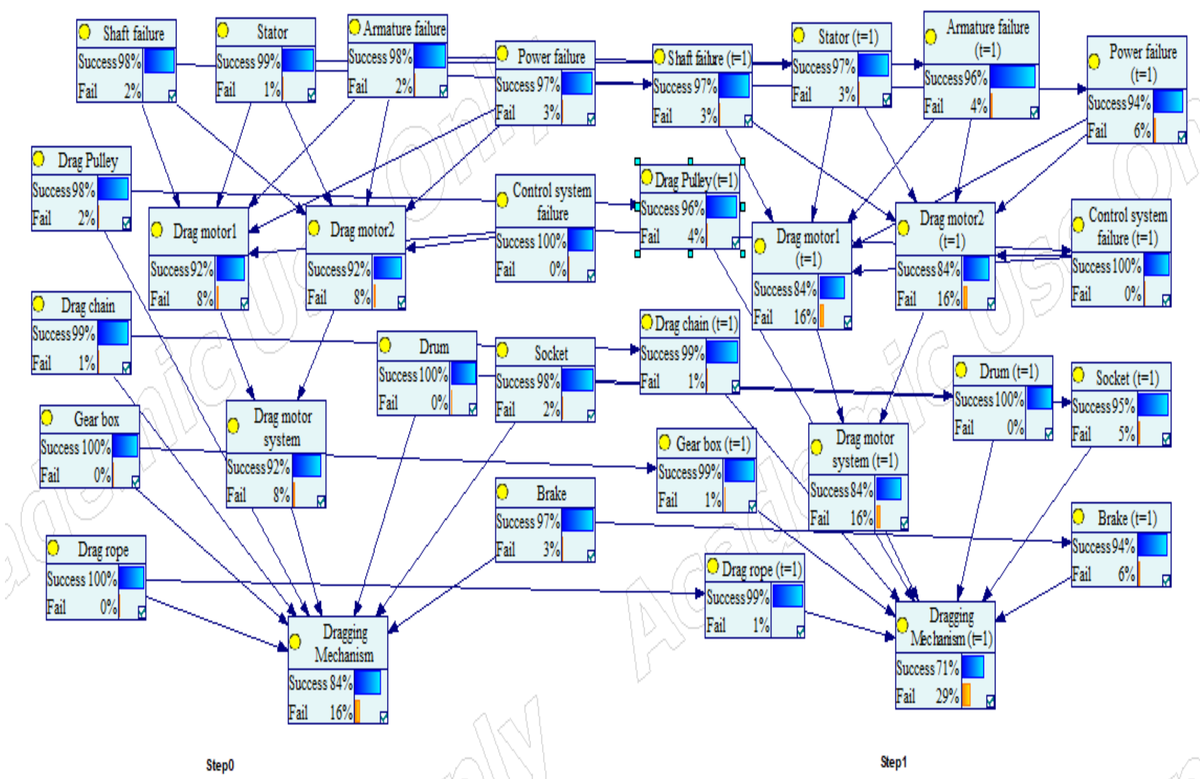

Figure 6. 6 Initial reliability and reliability at t =1 with unroll condition of DBN of dragging mechanism

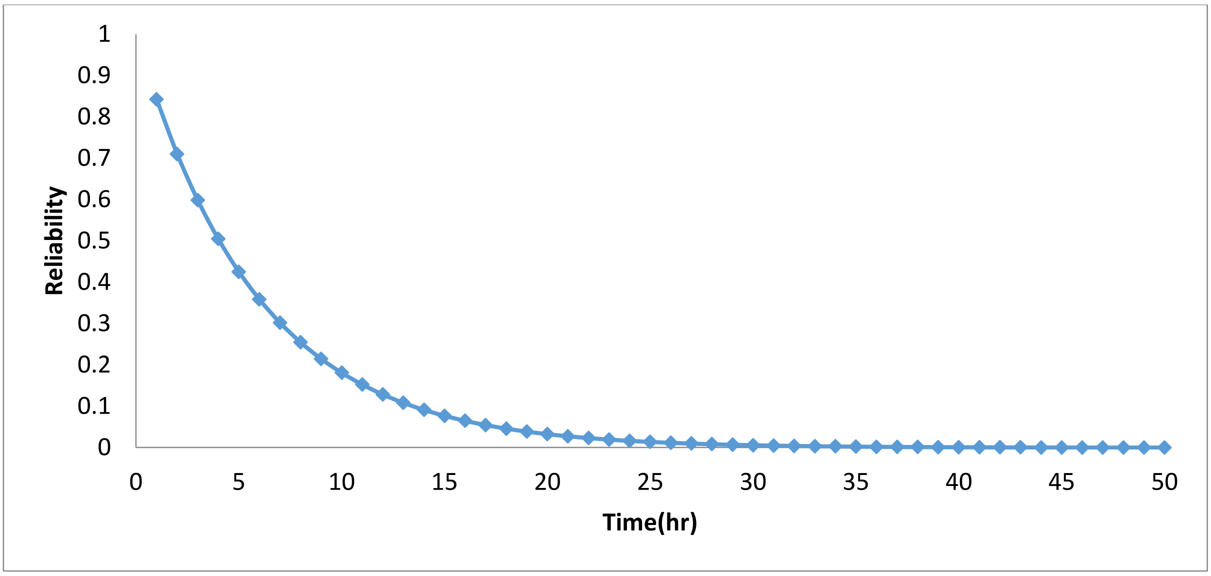

Figure 6. 7 Reliability curve of dragging mechanism using DBN

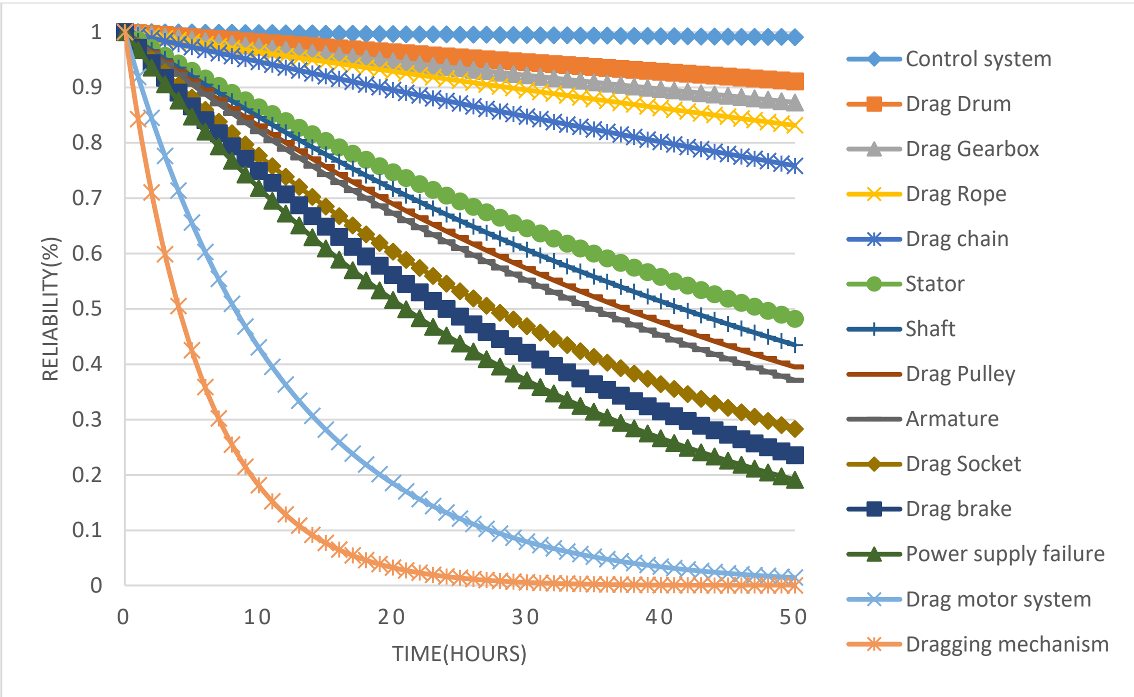

Figure 6. 8 Reliability curve of dragging mechanism including components using DBN

6.6.2 Important analysis

To identify the most critical components a sensitivity analysis has been performed assuming evidence of failure of dragging mechanism is 100% and the posterior probability of the all the root nodes of the DBN are observed. Figure 6.9 shows the unroll condition of dragging mechanism with failure probability. While figure 6.10 shows the relative increase in failure probability for all the components.

Drag motor (Armature, Shaft and Stator) has the highest increase in failure probability (26.33%) combined in the updated DBN and can be identified as the most critical component and which affects the performance of the dragline system. Power supply failure (18.04%), drag brake (15.72%) and drag socket also causes the dragline failure at greater extent. Thus, to enhance the dragging subsystem's reliability, it is necessary to improve the reliability of drag motor components, power failure, brake, and drag socket.

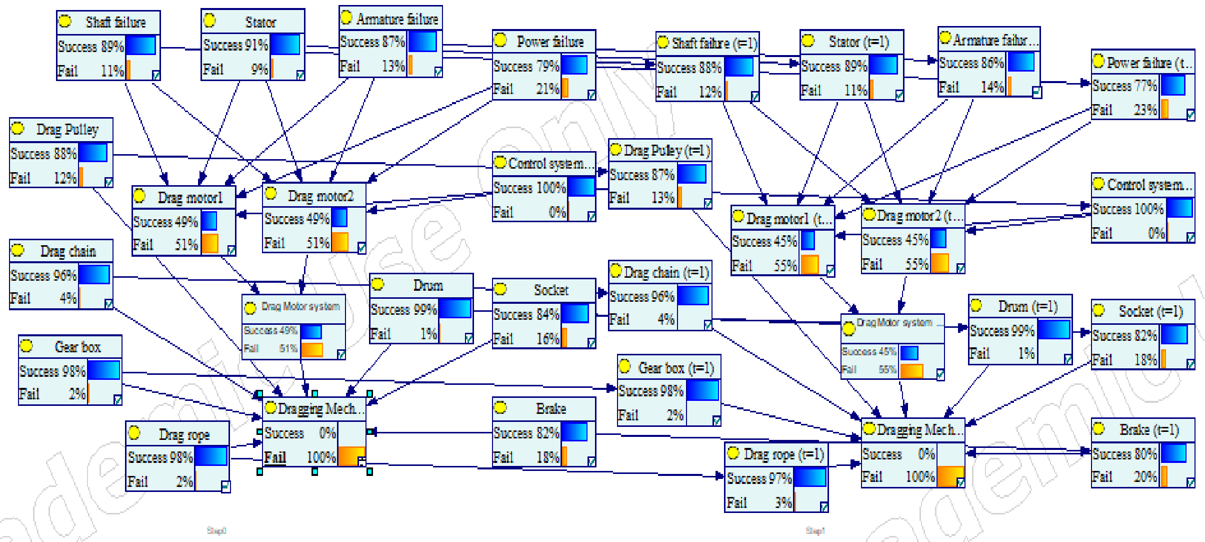

Figure 6. 9 Unroll condition of dragging mechanism with failure

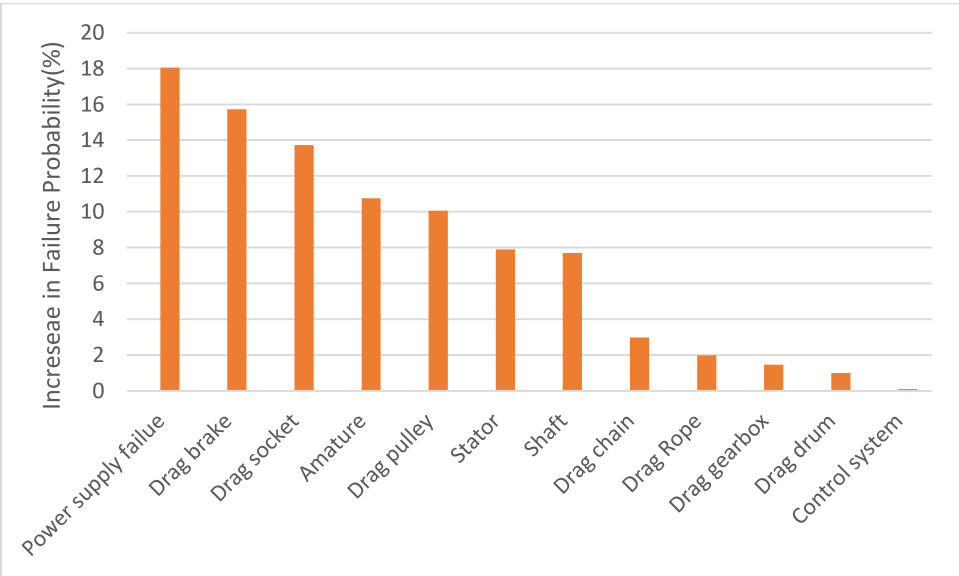

Figure 6. 10 Percentage increase in failure probability for components

6.6.3 Validation of the model

The sensitivity analysis in DBNs can be used to confirm the accuracy of parameters and determine whether greater accuracy in estimating them would be beneficial [269], [270]. In this work a one-way sensitivity analysis sensitivity analysis has been performed using the developed DBN model. The sensitivity of a parent node is quantified by changing its parameter and then resulting change in the probability of the target child node is observed [13].

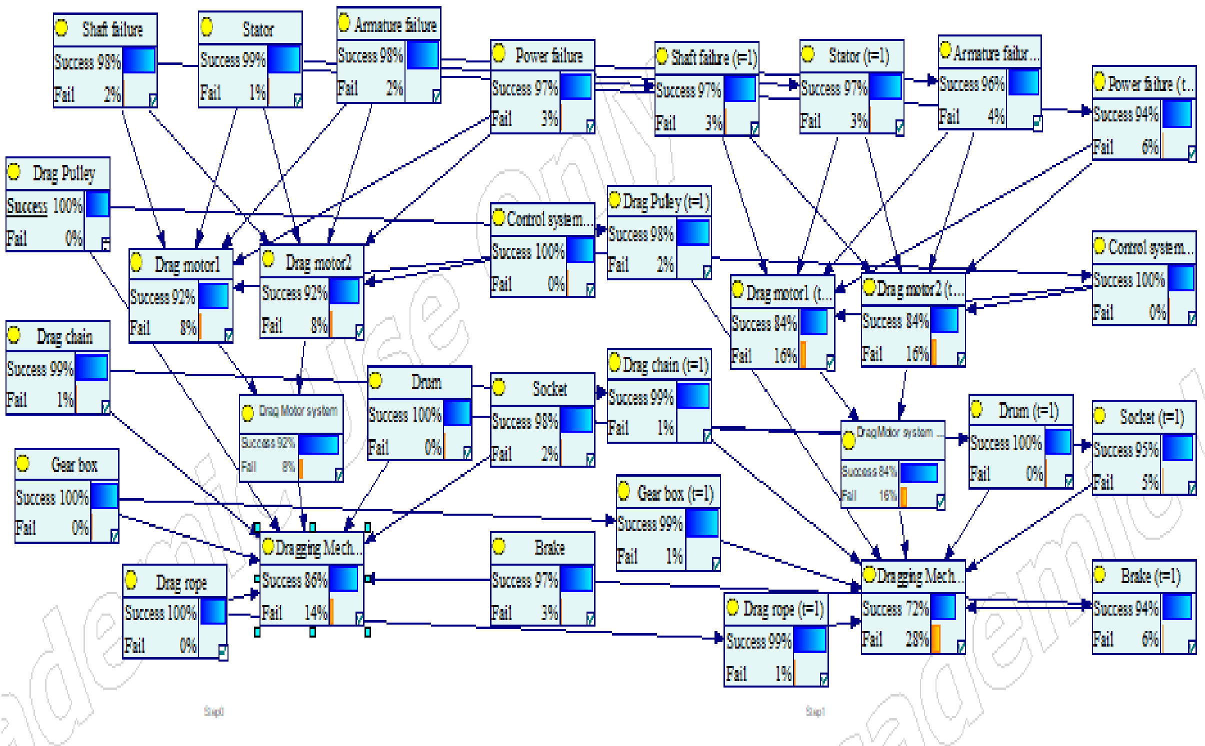

Figure 6. 11 Probability of drag pulley given 100% reliability

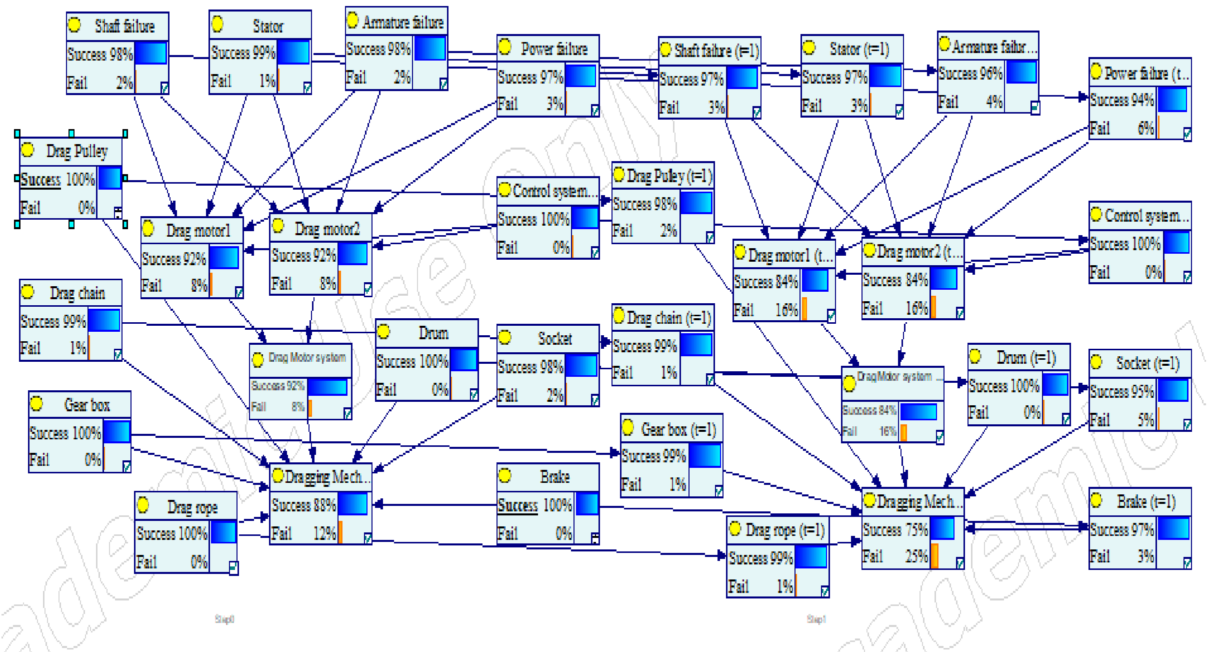

Figure 6. 12 Probability of drag pulley and brake given 100% reliability

Validation model is a one of the important aspect of this methodology because it can give users reasonable trust in the model's predictions. In the current work, the created DBNs are only partially validated using a three-axiom-based validation approach. The following are the three axioms:

(1) If the prior probability of the parent nodes is slightly increased or decreased, the posterior probabilities of the associated child nodes will also increase or drop.

(2) The change in the probability distributions of the parent nodes should not have an inconsistent impact on the child node.

(3) The overall probability fluctuations' magnitude from all the x attributes (evidence) should always have a more significant influence on the values than the set of $x - y(y \in x)$ attributes(sub-evidence).

Validation of the model, Figure 6.11 illustrated, when the state success of the drag pulley is set to 1 from 0.8 and set fail to 0 from 0.2, the system's reliability decreases from 0.86 to 0.72 in the second time slice, using the child nodes of the dragging mechanism failure as an example. Figure 6.12 has explained the system's reliability in the second part drops to 0.88 to 0.75 when both the change in the figure 6.11 and brake's state success is set to 1 from 0.9, and its fail state is set to 0 from 0.1.

The system's reliability can be found to have changed by altering the state of the parent nodes, proving the model's logicalness.

6.7 Summary

Thus, we proposed a methodology for the reliability assessment of the dragging subsystem using the Dynamic Bayesian Network (DBN). Overall reliability of the dragging mechanism is 84.29% at time $t = 1hr$. Importance analysis has been done to identify the critical components of the dragging mechanism. Drag motor system has been is identified as the most critical components. A three axiom-based validation method is applied to validate the proposed method.