Chapter 1

Introduction

1.1 Introduction

Unidentified and undetected faults in heavy earthmoving machinery (HEMM) can lead to unwanted failures. The occurrence of failures causes permanent damage to the components of a system, and the system may not perform its required functions. Failures are also associated with reduced availability, reliability, and increased downtime and maintenance cost. Since coal mining is cyclic in nature, it is always intended to make the equipment operational and available in a production cycle to achieve the targeted production. Demand of coal is increasing continuously, and India wants to double its coal production to 1100 MT by 2025 [1], and opencast coal mining produces about 93% of coal in India [2]. In mechanized coal mines, several HEMMs such as dumper, shovel, drill machine, bulldozer, and dragline with various capacities are deployed to achieve the production requirements of the mine. In India, most of the large surface coal mines have been switching over from shovel mining to dragline mining for removal of overburden due to high rate of overburden removal and subsequently, high production rate with low cost of production [3].

Dragline is a capital-intensive HEMM used in coal mines for removal of overburden, and its failure has major consequence on productivity of the mines. The productivity of large draglines in Australian coal mining industry is around $8000 per hour [4]. Apart from a high degree of flexibility, utilization of a dragline results in an entirely low cost per cubic meter of overburden removal and subsequent low cost per ton of the desired mineral [5], [6]. Dragline can be used to remove a large volume of overburden lying above the coal seam and to dump them into the de-coaled area in the shortest possible time at low costs [7], [8]. The removal of overburden using dragline saves up to 30–50% of the cost as compared to the shovel-truck method [9]. Therefore, deployment of draglines in opencast coal mines is highly desirable to achieve the targeted production in the mines. The performance of dragline degrades over time due to ageing, wear, unpredicted fault and failure, which also decreases the availability and reliability [10].

The occurrence of the unpredicted faults of HEMM increases the likelihood of failure and downtime losses, which eventually reduces the performance, decreases production and increases the maintenance cost [11], [12]. Therefore, identification of important failure modes of various components of dragline is highly desirable. Although prediction of faults in a complex system is a challenging task, fault analysis provides in-depth understanding of the occurrence of faults and helps in identifying their root causes. Dragline is a capital-intensive HEMM, and hence its failure is highly undesirable. The occurrence of failure of the dragline system causes permanent damage to the system/component and the system is unable to perform its required function. On the other hand, a fault occurs when at least one characteristic property of the system or equipment is unacceptable. The presence of a fault is normally detected through the sensor feedbacks, or sometimes through visual inspection or through opinion of experts. If the value of a parameter observed through sensor feedback exceeds the predefined threshold limit value, it is realized that a fault has occurred. In addition, the inspection of the dragline system to identify the root causes of fault occurrence is not always possible since the dragline is very large, complex, and constituted by many subsystems and components.

Therefore, advanced artificial intelligence tools are used for fault analysis of dragline using real-time monitoring data, historical data and experts' opinion that can predict the fault and give some indication to identify the root causes of the occurrence of the fault. The real-time fault diagnostic model, in general, is developed to detect, isolate and identify the fault types and to make a decision support system to undertake timely maintenance. In the decision support system, the types of faults can decide the maintenance action, whether to continue operating the dragline or discontinue the dragline operation to undertake suitable condition-based maintenance (CBM) policy.

1.2 Statement of the Problem

The occurrence of unpredicted fault of HEMMs increases the likelihood of occurrence of failure and downtime losses, which eventually reduces the performance, production loss and increases the maintenance cost of the system [11], [12]. Since mining is cycle in nature, the failure of one HEMM affects the whole operation of the industry, as these are mostly dependent on one another for achieving the desired production. Depending on the industries, the maintenance costs accounted for 15–60% of the total production cost for plant equipment due to occurrence of failure [13]. It is reported that the US industries spend more than $200 billion annually on maintaining plant equipment and facilities [14]. The case study on dragline reported that occurrence of unwanted failure significantly impacts the machinery performance, productivity and maintenance cost which accounts for about 40–50% of the total operating cost [6]. Hence, it is necessary to put all efforts to make the HEMM operational so that production can be achieved continuously with improved reliability and availability and to prevent the catastrophic failure of the equipment.

For analysis of failure, the draglines working in a coal mine located in northern India were selected. It was observed from the annual maintenance worksheet (April 2016 to March 2017) of a group of three draglines of the coal mine that about 3234 hours were lost due to failure of the drag systems of the draglines. These downtime hours accounted for 49% of the total breakdown hours of the draglines (Figure 1.1). The frequency of failure of the drag system of three draglines was 26 during the above-mentioned period.

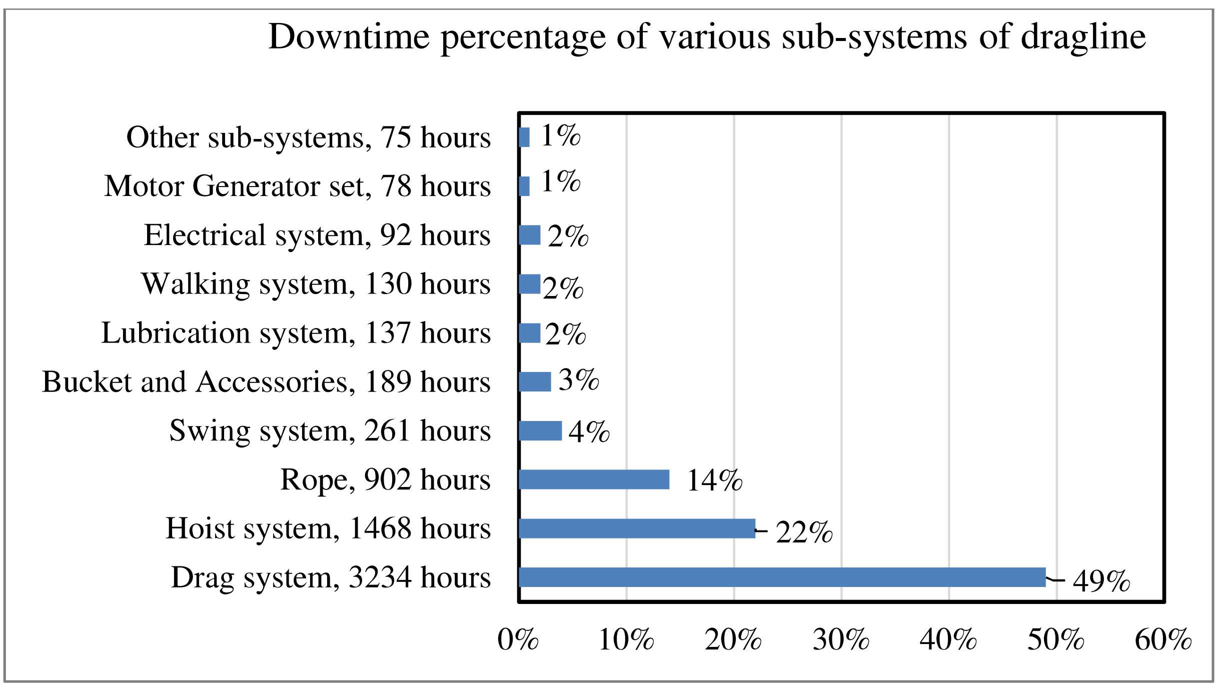

Figure 1.1 Downtimes of various subsystems of three draglines deployed in the coal mine.

1.3 Significance and Novelty of the Research

Since dragline is a costly equipment, research works on dragline are focused on reducing the occurrence of unwanted failure, downtime, overall maintenance cost and improve the productivity of draglines. Most of the research works are based on the time to failure and time to repair data of failure components of dragline to compute the reliability and make a preventive maintenance policy [5], [9], [15], [16]. The preventive replacement interval of dragline component is optimized using a lifetime parameter and failure mechanism using a reliability evaluation method and age-replacement model [5]. Moreover, the reliability assessment and age-replacement model is developed for two draglines working in the mines by considering cost factors to investigate optimum preventive replacement policy of wear-out components of the draglines [17]. The replacement interval of a cluster of the critical components of dragline is optimized using failure mode effects analysis and reliability-centered maintenance policy [9]. The criticality and sensitivity of the subsystems of draglines are identified using failure mode effects analysis by calculating the risk priority number to prepare the maintenance planning to reduce the maintenance cost and production loss [18]. The downtime of dragline is optimized to identify the component with low reliability and maintainability to identify the cause of the failure by critically analyzing the inherent availability, reliability and maintainability using time to failure and time to repair data [15]. The downtime of dragline is optimized using cost-effective time counter algorithm to optimize the inspection interval of the components based on uptime, downtime, lifetime, repair time, and financial values of the dragline components and minimizing the maintenance cost up to 5–6% [6]. Another research work developed an algorithm to evaluate the random uptime/downtime characteristics of the two active draglines, and the optimized values of inspection interval and found the decrease in the maintenance costs of dragline between 5.9–6.2% [19].

The research works conducted on various components/subsystems of dragline to reduce the downtime and to improve the performance of draglines are presented in Table 1.1.

Table 1.1 Literature on the failure mechanism of various components of dragline

Assessment of dragline component	Methodology	Authors
Failure mechanism of a swing pinion shaft	Chemical analysis of materials from the tooth another shaft by using atomic absorption spectroscopy.	Ranganath et al. [20]
Failure mechanism of bucket	Finite element analysis	Ridley and Algra [21], Azam and Rai [22]
Fracture mechanics of booms	Stress analysis	Dayawansa et al. [4]
Fatigue cracking of dragline boom support strands	Visual examination and electromagnetic testing	Metcalfe and Costanzi [23]
Stress concentration factors of main chord tubular joint of dragline	Weld profile and weld root gaps are measured using silicon imprint technique and feeler gauges.	Pang et al. [24]
3D dynamic modelling to investigate the performance and front-end structure strength of dragline.	Lagrange equations and finite element analysis.	Li and Liu [25]
Failure analysis of dragline cluster	Using ultrasonic waves by studying both the diffraction pattern and the reflected waves	Jones et al. [26]
Dragline cluster	Comparative study on the application of several existing design codes for prediction of the fatigue life of a typical four-member dragline cluster.	Joshi and Price [27]

It can be observed from Table 1.1 that most of the research works conducted on draglines are mainly focused on failure analysis of the swing pinion shaft [20], bucket [21], [22], boom [4], boom support [23], main chord tabular joint [24], front-end structure [25], and cluster [27], [28] of the dragline. Therefore, in this research work, one of the most critical subsystems of the dragline, i.e., drag system—responsible for 49% of the total downtime of dragline—is considered for the fault analysis.

In the literature, fault diagnosis of the dragline expert system is developed to diagnose faults in 18 components of a dragline by considering the descriptions of the problem, dialogue to acquire dragline conditions and its own knowledge to propose a solution [29]. The research works on predictive fault analysis is also limited. Therefore, in this research work, the cause, symptom and fault data of the dragline system is considered to construct the model to analyze the fault. Hence data based fault analysis approach using artificial intelligence tools can be an effective alternative to predict the occurrence of faults in the dragline system. Moreover, in fault analysis literature, it is mentioned that degree of fault detection is fixed considering the combined response of judgement of experts and sequential trial and error. However, the process of the degree of fault detection limit is demonstrated in this thesis.

1.4 Objectives of the Research

The objectives of this research are to overcome the challenges to prevent the dragline failure through the development of reliable, cost-effective, and real-time fault analysis methodology. It is expected that the proposed methodology will help in better understanding the occurrence of faults and to prevent subsequent failures of the dragline system.

The elements of the main objectives are outlined below:

i. Identification of the critical components of the dragline using failure mode, effects and criticality analysis (FMECA).

ii. Development of the fault analysis model of the dragline system using Bayesian Network (BN) to identify the fault types and their root causes.

  - Development of reasoning to identify various fault types (e.g., degraded fault, catastrophic fault or intermittent fault) using the CPT.
  - Evaluation of presence of conflicts among the pieces of evidences observed and validation of the BN model using conflict analysis.
  - Identification of the most critical parameters which are responsible for occurrence of fault and validation of the model using sensitivity analysis.

iii. Prediction of the occurrence of fault and identification of responsible causes of the dragline system using cause to symptom and symptom to fault model using artificial neural network (ANN).

1.5 Research Methodology

Dragline is a complex system consisting of many mechanical and electrical components. For fault analysis of dragline, one of the critical subsystems of dragline leading to the majority of the downtimes is considered for fault analysis. In this research work, BN and ANN are used for fault analysis. The BN is the most powerful fault analysis method to explain the structure of the problems which uses probability statistics in complex fields in reasons the uncertainty [30], [31]. The ANN is a non-statistical quantitative-based approach used in fault analysis of both process monitoring and pattern recognition of the linear and nonlinear system for industrial application [32]–[36].

The drag system is a large complex and more complicated system because one fault can be linked to multiple symptoms or multiple causes, and one cause can be responsible for the occurrence of multiple symptoms or multiple faults. Most of the artificial intelligence tools such as fault tree, fuzzy logic and Bayesian network are used in the inference based fault analysis to make the causal relationships between dependent and independent variables [37]. Although the fuzzy logic and fault tree analysis are mostly used to handle the two-layer such as cause-effect relationship or symptom-fault relationship, it is difficult to update the model when the real-time evidence is observed [38], [39]. However, for drawing an inference, BN is a powerful artificial intelligence tool in the area of probabilistic knowledge to explain the multi-layer structure problems to establish the causal relationships between multiple causes, multiple symptoms, and multiple faults [13], [40], and it can be updated when new evidence is available. The BNs are still attractive for modeling and investigating machine learning applications using small data sets [41], [42]. Moreover, a three-layer cause, symptom and fault relationship was developed in the BN model suitable for deriving the inference and handling complex cases under conditions of uncertainty, unpredictability or imprecision [13], [43].

The artificial intelligence tools used for the fault prediction are support vector machine [44], [45], hidden Markov model [46], [47], principal component analysis [48], [49], independent component analysis [50]–[52], K-means cluster algorithm [53], [54], and ANN [11], [55]. Among these, the ANN is a very powerful artificial intelligence tool for identifying the faulty pattern and classification of fault by pattern recognition [56]. The ANN models are also used to make a relationship between the dependent and independent linear or nonlinear variable with high prediction accuracy, computational efficiency and its flexibility in use [57], [58]. Therefore, ANN based fault analysis is used to improve the predictive accuracy of the fault and to identify the root cause of the system so that catastrophic failures of the dragline system can be prevented. Subsequently, the combination of both models can be used in real-time application to predict the occurrence of a fault which is expected to minimize the downtime of dragline and can help in preparing the suitable maintenance policy of dragline.

1.6 Outline of the Thesis

The present thesis comprises eight chapters, and the structure of the thesis is shown in Figure 1.2.

Chapter 1: Introduction

The first chapter presents the general introduction of HEMM, basic terminology of fault analysis, a background of the statement of the problem, significance of the research, objectives of the research work, and finally outlined the structure of the thesis.

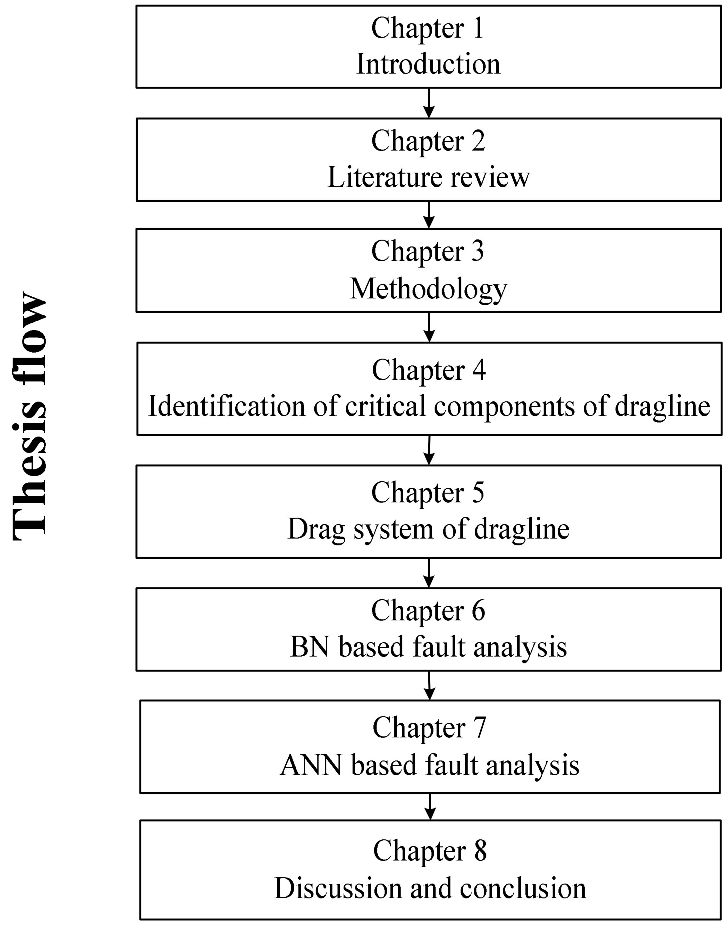

Figure 1.2 Structure of the thesis

Chapter 2: Literature review

The second chapter represents the comprehensive literature survey of dragline, FMECA, and various fault analysis approaches available in the literature. A brief description of various fault analysis methodologies is also explained along with their industrial applications.

Chapter 3: Methodology

The third chapter presents the methodology to fulfill the various objectives of the research works. The tools used for fault analysis of the drag system are FMECA, BN and ANN. The validation of BN using conflict analysis and sensitivity analysis is also described in this chapter.

Chapter 4: Identification of critical components of dragline

The fourth chapter contains a detailed description of dragline located in the northern India. This chapter also includes the detailed process of fault and failure data of various components of dragline. The most critical components of dragline are identified using FMECA by calculating the risk priority number (RPN) is also described.

Chapter 5: Drag system of dragline

The fifth chapter contains the detailed information about the drag system of dragline. This chapter also describes the parameters of cause, symptom and fault of the drag system and their threshold values. Finally, the process of data collection of cause, symptom and fault of the drag system is described.

Chapter 6: Bayesian Network based fault analysis

The sixth chapter of the thesis contains description of fault analysis of drag system using BN model. The BN and its topology to establish the causal relationship between cause, symptom, and fault using CPT are also explained. The methodology of BN based fault analysis consists of fault inference, fault type identification, conflict analysis, and sensitivity analysis. Finally, the processes of model validation, result and discussion of some cases to identify the fault and sensitivity analysis of the BN model are described.

Chapter 7: Artificial Neural Network based fault analysis

The seventh chapter of the thesis contains description of the fault analysis of the drag system using ANN model. This chapter describes ANN and its architecture to make the relationships between cause to symptom and symptom to fault. Finally, the processes of model validation, result and discussion of some cases to identify the fault are also described.

Chapter 8: Discussion and conclusion

The eighth chapter of the thesis presents the discussion and conclusion and findings drawn from the present research work. The industrial applications, limitations and suggestions for future research scope are also highlighted.