Preface

Unidentified and undetected faults in heavy earthmoving machinery (HEMM) can lead to unwanted failures. The occurrence of failure can cause permanent damage to the components of a system, and reduces the productivity and performance of the system. Since coal mining is cyclic in nature, it is always intended to make the equipment operational in order to maintain the production cycle to achieve the targeted production. Dragline is a capital-intensive HEMM used in coal mines for removal of overburden. The productivity of large draglines reported in Australian coal mining industry is around $8000 per hour, and its failure has a major consequence on productivity of the mines.

Till date, most of the research works conducted on draglines are mainly based on failure data and research works on predictive fault analysis of capital-intensive draglines are still limited. The maintenance worksheet 2016-17 of the coal mine for a group of three draglines reported that 49% of total downtime was contributed by the drag system alone. Moreover, the failure mode, effects and criticality analysis (FMECA) of 30 components of dragline identified three components based on the acceptable risk criterion. The drag system was identified as the most critical failure component of dragline, followed by the hoist system and dump rope. Therefore, in this thesis, 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 using artificial intelligence tools so that frequency of failure and downtimes of dragline can be reduced to an acceptable level.

The fault analysis of drag system is complex 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 used in data-driven based fault analysis such as fault tree, fuzzy logic and Bayesian Network (BN) are used in the inference based fault analysis to analyze the causal relationships between dependent and independent variables. Although the fuzzy logic and fault tree analysis is preferred to handle the two-layer causal relationship; however, BN is a powerful artificial intelligence tool in the area of probabilistic knowledge to explain the multi-layer structure problems to establish causal relationship between multiple causes, symptoms and faults. In addition, the BN model offers flexibility in updating the fault database when new evidence is observed. Therefore, a three-layer BN model for drag system is developed with six cause, six symptom and four fault nodes for deriving the fault inference.

For fault analysis, the fault and failure data of a dragline for 28-month (2014-16) period, deployed in a coal mine in northern India, was collected. The cause, symptom, and fault data of the drag system of dragline from its commissioning to 7267:30 EHMR (Engine Hourly Machine Rate) during the May 2014 to September 2016 were collected from historical recorded sensor data, maintenance worksheet, and visual inspection. The collected data were divided into 15 min interval and were converted into categorical data. A total of 29070 data were recorded. When the symptom crossed the predefined threshold limit, the faults and their root causes were recorded using the maintenance record and experts' judgment. Collected cause, symptom and fault data have been converted into categorical data (1 or 0): '1' refers that the symptom exceeded the threshold limit, and '0' signifies that the data was within the threshold limit. Similar classifications were made for fault (present =1 and absent = 0) and cause (identified =1, not identified = 0).

Subsequently, for BN analysis, the dataset was divided into the testing dataset and validation dataset. The test dataset is used for building the 16-node three-layer BN model to establish the causal relationships between cause, symptom, and fault. Based on the set of observed evidence, the fault inference of the BN model is used to make reasoning to categorize the faults into catastrophic fault, degraded fault or intermittent fault. The conflict among the observed set of evidences is measured through the conflict analysis. The experts' opinion helped to deciding the degree of detection limit of faults such as α, β, and ε and it is further validated using BN through the demonstration of 10 specific fault cases. The identified fault types can help in designing the decision support system. The proposed BN model was also validated using the conflict analysis considering six active cases of fault diagnosis that measured negative conflict values revealing correctness of the model. The sensitivity analysis of the BN model is used to identify the root causes that mostly influence the occurrence of fault for a given evidence. The prediction accuracy of the BN model is validated using validation dataset for the most effective parameter of the occurrence of fault for given evidence(s). In addition, three-axiom-based sensitivity analysis is also used to validate the model. Finally, case-based reasoning discussed in the decision support system can provide in-depth understanding of fault occurrence for developing maintenance policy.

Rather than the inference based fault diagnosis using BN, the classification based data-driven fault analysis model is also proposed using the multi-layer layer perceptron (MLP) in artificial neural network (ANN). Out of 29070 generated data, there were 452 instances when the symptoms exceeded the threshold limit, which resulted into 199 faults that led to 16 failures in the drag system. Two ANN models have been developed to understand the fault occurrence using seven causes, seven symptoms and five fault parameters of drag system. The data classification is similar to BN, with an addition of nodes for unidentified fault, unidentified symptom, and unidentified cause. When the cause or fault occurs without giving any symptom is defined as unidentified symptom and it occurs mainly due to the effect of other subsystems of the dragline (i.e., sudden fall of the bucket, boom that affects the drag system) and these faults are categorized as unidentified faults. When the cause of the occurrence of fault is unknown, they are categorized into unidentified cause. In this research work, the cause to symptom model is used to identify the sequence of responsible root causes when the symptom exceeds the threshold limit. In addition, the symptom to fault model is used to predict the occurrence of possible faults to prevent a catastrophic failure of the drag system. In the ANN model, the prediction accuracy symptom using cause was 94.2%, and that of fault using the symptoms was 97.1%. The sensitivity of causes and symptoms were ranked for individual faults which is expected to help the maintenance engineer to predict the faults and to make the sequence of preventive maintenance action plan in real-time condition to minimize the unwanted downtime and maintenance cost of the dragline.

Therefore the industrial application of this research work is that the results of real-time fault diagnosis using BN and ANN models can be incorporated in the decision support system to prepare a suitable maintenance policy. The result of fault type identification of BN model can help to categorize the occurrence of fault as catastrophic fault, degradation fault, or intermittent fault type, which will direct the decision support system to decide whether to continue to operate the dragline or to discontinue the operation. Based on the fault type, the maintenance action can be undertaken, e.g., urgent maintenance or maintenance is to be done during scheduled inspection interval or during P-F interval. The results of the sensitivity analysis of the BN model can be used to identify the most influencing parameter of the occurrence of fault, which can help to initiate the maintenance of the dragline. On the other hand, the result of the ANN based fault analysis will facilitate to prepare the sequence of maintenance action plan based on identified root causes of the fault. Hence, the decision support system can be a guiding tool for the maintenance engineer to preparing suitable condition-based maintenance (CBM) policy to optimize the downtime and maintenance cost of dragline.

Finally, the novelty of the research work is to demonstrate the procedure to determine the degree of fault detection α, β and ε. Through the literature shows an indication of determining these values through experts' opinion and sequential trial and error, 10 such specific fault occurrence cases of the maintenance worksheet have been validated through the BN and experts' opinion. Secondly, a plethora of works have been conducted on failure analysis of dragline and the research work on fault analysis of dragline is still limited. Many dragline components (e.g., bucket, boom, swing shaft, front-end structure) have been analyzed in the literature; however, research works on drag system which is responsible of 49% of downtime have not been conducted. Therefore the research work explained in this thesis would direct the researchers to analyze fault in HEMMs using artificial intelligence tools. The results of the research work are expected to enhance the knowledgebase of the maintenance engineer to formulate a suitable maintenance policy.