Fault Analysis of Dragline using Bayesian Network and Artificial Neural Network

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Doctor of Philosophy

By

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Chapter 8

Discussions and Conclusion

8.1 Introduction

This chapter of thesis presents the discussions on the results of the failure mode, effects and criticality analysis, BN based fault analysis and ANN based fault analysis. The results of the fault analysis can be used to prepare an appropriate CBM policy to optimize downtime. Finally, the limitations of the research and its future scope have also been highlighted.

8.2 Discussions

Dragline is a capital-intensive equipment used in opencast coal mines for stripping overburden. The occurrence of failure of dragline components increases the downtime and reduces its performance. The risk of various failure components of dragline is identified using FMECA and the higher risk components are selected for fault analysis. Three critical components are identified such as drag system, hoist system, and dump rope. Among the three, FMECA identified drag system of dragline as the most critical subsystem of the dragline. The fault analysis of the drag system should identify the probability of occurrence of fault, and its responsible root causes. Most of the research works on draglines emphasize on minimizing the downtime and unwanted failure using either time counter algorithm [6], [19] or reliability based analysis [5], [16] mostly used failure data to suggest the maintenance policy. One of the critical subsystems of dragline has been identified for fault analysis in order to reduce the downtime and frequency of failures of dragline. The RPN of thirty various failure components of dragline is identified. It is observed that the drag system is the most critical subsystem of the dragline. The components having lower RPN requires less attention during preventive maintenance and the preventive maintenance interval of the components can be increased. On the other hand, the components having higher RPN require more attention during preventive maintenance and the preventive maintenance interval can be decreased. Therefore, drag system having higher RPN is considered for fault analysis in order to reduce the overall downtime of dragline.

After identifying the critical components and the subsystems of the dragline using FMECA, the fault analysis of the drag system was carried out using artificial intelligence tools. In this thesis, real-time fault analysis of the drag system is carried out using BN model through the development of causal relationship between cause, symptom, and fault. The result of real-time fault analysis was used to identify the fault type and best combination three parameters (e.g., interesting fault, evidence, and parameter under study) that mostly influence the targeted fault has been analyzed using sensitivity analysis. The ANN based fault analysis approach was used to predict the occurrence of fault and sequence of responsible root causes. Hence combination of both fault analysis approaches is proposed to be used in the decision support system to develop the suitable CBM policy.

In the literature, the expert system is developed considering the human judgment to fault diagnosis of 18 components of dragline [29]. In present research work, the historical cause, symptom, and fault data that generated continuously for every 15 min are collected from the sensor feedback, maintenance worksheet, and visual inspection. The collected data are categorized based on the threshold limit value and a BN model is constructed. The CPT of the BN model makes a causal relationship between causes to symptoms to faults of the drag system. Six cause nodes, six symptom nodes, and four fault nodes are identified. The conflict analysis is used to measure the conflict among the observed set of evidence as well as to validate the BN model. The fault inference used to make reasoning to categories fault such as no fault, catastrophic fault, degraded fault or intermittent fault based on the observed evidence and the degree of detection limit of fault such as α, β, and ε. After identification of fault type, the decision support system can help to make a decision either to continue to operate the dragline or to discontinue the operation to prevent a major failure. There are six cases that have been explained for given evidence to identify the occurrence of fault and suggest the suitable maintenance action. The maintenance types e.g., urgent maintenance or maintenance is done during schedule inspection interval or during P-F interval of fault is designated based on fault type.

When the maintenance action of targeted fault (interesting parameter) is planned for given evidence, it is required to know the most influencing parameter (cause or symptom) that mostly affect the occurrence of fault. When the new evidence is observed, the sensitivity analysis also identifies the most influencing parameter of the targeted fault. In addition, the three axioms based sensitivity analysis is used to validate the model and accuracy of the BN model is identified in terms of percentage of error between the developed model using validation data set for most effective parameter.

Finally, case-based reasoning used in the decision support system to prepare the suitable CBM policy.

In this research work, the case-based reasoning is preferred based on the observed evidence using cause, symptom and fault data. The ANN based fault analysis is used to predict the occurrence of fault when the symptom exceeds the predefined threshold limit value. The cause to symptom model is used to make a relationship between multiple causes to multiple symptoms and to identify the sequence of responsible root causes when the symptom exceeds the predefined threshold limit value. The symptom to fault model is used to predict the occurrence of possible fault to avoid the catastrophic failure of the drag system when the symptom exceeds the predefined threshold limits value. Hence a proper sequence of maintenance action can optimize the downtime and identify the responsible root causes quickly.

8.3 Conclusion

From the research work conducted on dragline subsystem, the following conclusions can be drawn:

(i). In this research work, it was identified that 30 components belonging to seven subsystems were responsible for dragline failure. It was identified using the failure data of dragline of 28 months during 2014–16. The RPN helped to quantitatively estimate the risk scores of the critical components of the dragline. From the FMECA (Figure 4.4), the drag system of dragline was ranked with highest risk priority number (RPN = 80). The RPNs of the hoist

system (RPN = 40) and that of dump rope (RPN = 36) were also above the acceptable risk score of dragline.

(ii). During the afore-mentioned period, drag system of the considered dragline contributed to 50% of the total downtime of the dragline (Figure 4.2). Therefore, the drag system was selected for further fault analysis in order to reduce the failure frequency and the downtime of dragline.

(iii). For real-time fault analysis of the drag system, the developed BN model of the drag system through six cause nodes, six symptom nodes and four fault nodes is used. The causal links between cause-symptom-fault have been established using a set of qualitative state to compute the CPT of the BN (Figure 6.5). The degree of detection limit of fault (α, β and ε), which were fixed with the help of experts' opinion, were validated through some fault occurrence cases of available maintenance record using the BN (Table 6.2). The acceptable values of degree of fault detection, as decided for fault analysis, are $\alpha = 0.55$, $\beta = 0.25$ and $\varepsilon = 0.30$, which fulfilled the criteria of identified fault types (Table 6.2).

(iv). The occurrence of fault is categorized as catastrophic fault, degradation fault or intermittent fault based on the observed set of evidences and reasoning of fault identification. After identification of fault type, a decision support system can be developed to decide whether to continue to operate the dragline or discontinue the operation. Based on the fault type, the maintenance action is to

be performed, e.g., urgent maintenance or maintenance is to be done during schedule inspection interval or during P-F interval of fault.

(v). In order to measure the conflict among the set of observed evidences, the conflict analysis is done. Notably, a conflict occurs when two or more pieces of evidences are put into the BN model simultaneously. In this research work, six fault occurrence cases from the collected data have been demonstrated, and the conflict measure is found to be negative for the cases, which reveals that the proposed BN model is appropriate for diagnosing the faults in the drag system.

(vi). The sensitivity analysis is used in the BN model to identify the best combination of three parameters (evidence, target variable, and investigating variables) that mostly influence the occurrence of fault for given evidence and observed new evidence. The three axioms based sensitivity analysis is used to validate the model. The accuracy of the BN model is also identified in terms of percentage of error for the most effective parameter identified using validation dataset. After finding fault types and the most effective parameter, necessary CBM action can be undertaken by the maintenance engineer.

(vii). The ANN model is used to make a relationship between cause to symptom and symptom to fault with high prediction accuracy. The prediction accuracy of symptoms using the cause was 94.2% and that of fault using symptom was 97.1%. Hence the high accuracy of the model gives the significant aspect to the fault diagnosis and provides reasonable confidence to diagnostic results.

(viii). The sensitivity analysis of ANN model is used to identify how sensitive the model is for the change of each cause and ranked the causes based on their percentage contribution. Based on the observed symptoms, the maintenance engineer can make effective preventive maintenance action plan of the cause. Similar observations were recorded from the symptom to fault relationship to prevent the fault before the failure of dragline. Therefore, the accuracy of predicted symptoms/faults and prioritization of the causes/symptoms can help the maintenance engineer in preparing a real-time monitoring action plan of the drag system so as to minimize the failure frequency and downtime of dragline. In addition, the average time to inspect one parameter takes about 5–20 min, as reported by the dragline maintenance staff. If the causes or the symptoms are identified in the proper sequence, most of the responsible causes can be identified after one or two steps, thus reducing the downtime.

(ix). The inference based fault analysis of BN model and results of classification based fault analysis of ANN model can assist the maintenance engineer to undertake necessary maintenance action to eliminate the root causes to avoid the catastrophic failures of the dragline. Therefore, the combination of both models can be used in real-time application to predict the occurrence of fault and prepare appropriate CBM policy. Thus fault analysis can be used as a guiding tool for the maintenance engineer to undertake necessary CBM action in order to reduce the failure frequency and downtime losses; simultaneously increasing its safety, reliability and productivity.

8.4 Future Scope of Research Work

In this research, the historical data of cause, symptom and fault of the drag system was collected as hard evidences. For future analysis of the drag system, the soft evidence such as the statistical distributions of the nodes can be incorporated in the model for deeper understanding of faults, which in turn can also help in preparing a suitable maintenance strategy for minimizing failure and downtimes of the dragline. The use of embedded sensors and artificial intelligence in every unit operation of mining is expected in future, which will generate a continuous stream of data for further analysis. Therefore optimized sensor data and time-variant parameters (age of the HEMM), cost of labour and inventory can be used to create the dynamic BN and ANN to detect and diagnose the fault and develop an effective decision support system to prepare the condition-based maintenance policy.

The fault analysis explained in this thesis is limited to the drag system only. The remaining two critical components of dragline (e.g., hoist system and dump rope) identified by the FMECA can also be considered for fault analysis using artificial intelligence tools. Further, the methodology explained in thesis can equally be applicable to remaining subsystems of dragline such as hoisting system, swing system, walking system of the dragline and can be extended to the other sophisticated and capital-intensive HEMMs used in mines and other industries.