OPEN PIT LIGNITE MINING PROCESS RELIABILITY ASSESSMENT USING BAYESIAN BELIEF NETWORKS

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Abstract: In the paper the use of the Bayesian network, which may be used for the work planning of maintenance process, was presented. The paper presents a model of the machine failure based on Bayesian network. The particular attention was paid to prediction of probability of machine failure.

Key words: reliability, Bayesian networks, open pit, Pareto diagram, Bucket Wheel Excavator

1. INTRODUCTION

Process reliability may be based, for instance, on the analysis of the LCC (Life Cycle Cost) system exploitation cycle. Most of the production system operating problems may refer to the mistakes made at the very early stage of designing. The possibility of getting experience, its appropriate documentation during the system exploitation, and its application when a new investment or change of the equipment is planned, is a good way to increase the effectiveness and operating reliability, and lower the costs of maintenance process.

Another methodology managing the process reliability is based on the analysis of risk connected with failures (Risk Centered Maintenance), which consists of a detailed analysis of the production process in order to identify all possible damages in the devices, and their effects. On Referring to the collected experience, for each device several most relevant failures are chosen. Next, the frequency of the failures occurrence, their most important effects, and impact the effects have on the production process is determined. The damages of significant relevance to the production process are, then, FMEA (Failure Mode and Effects Analysis), providing that the key elements of the production process will perform on the required level of availability. Aiming at the reduction of work connected with RCM, the whole devices, and not their particular

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components, are analysed first. For this concept can be used belief network to establish probability of failure.

2. BAYESIAN NETWORK

Belief networks (also known as Bayesian networks, Bayes networks and causal probabilistic networks), provide a method to represent relationships between propositions or variables, even if the relationships involve uncertainty, unpredictability or imprecision. They may be learned automatically from data files, created by an expert, or developed by a combination of the two.

By adding decision variables (things that can be controlled), and utility variables (things we want to optimise) to the relationships of a belief network, a decision network (also known as an influence diagram) is formed. This can be used to find optimal decisions, control systems, or plans. Bayesian nets may be used in any circumstance where modelling an uncertain reality is involved (and hence probabilities are present), and, in the case of decision nets, wherever it is helpful to make intelligent, justifiable, quantifiable decisions that will maximize the chances of a desirable outcome. Since Bayes nets naturally represent causal chains, that is, the links may be cause-effect relationships between parent and child nodes, you can supply evidence of past events, and then run the Bayes net to see what the most likely future outcomes will be. Bayes nets are used for weather forecasting, stock market prediction, ecological modelling, etc., for making such predictions. Their strength is that they are very robust to missing information, and will make the best possible prediction with whatever information is present.

3. APPLICATION OF BAYESIAN NETWORK IN OPEN PIT MINING PROCESSES RELIABILITY

The open pit coal mines production system consist mainly in a string of equipment starting with winning equipment (bucket wheel excavator), on board hauling equipment, conveying equipment, transfer devices, spreaders or stackers, used alternatively for overburden removal conveying disposal and for coal winning conveying stacking. This system of mainly serially connected elements is characterized by the throughput (overall amount of bulk coal respectively overburden rock), which is strongly dependent on the functioning state of each involved equipment.

This kind of continuous production system is operating producing a variable material flow until the breakdown of an element at the moment \( t_b \) causes the stop of the system. After a certain period of time \( t_{re} \), the system is repaired and restarts, until the next breakdown is produce at the moment \( t_{b+1} \).

The production flow can be seen as weighted with a series of Heaviside functions containing binary values 1 and 0, the cadence of breakdowns, the duration of operating times and the duration of repair times being random variables.

The alternating uptimes and downtimes are cumulated until they reach the
simulation period \( T \). The simulation is repeated many times using different values for \( Q_m \) and \( \sigma \), describing the variability of the production (fluctuations) and for \( \lambda \) and \( \mu \), characterizing the random behavior of the cadence of uptimes and downtimes.

The following example refers to an open pit mine working in overburden removal in which a Bucket Wheel Excavator is excavating the rock and a haulage line with belt conveyors conveys it to a spreader which spread the rock on a waste deposit.

A simulation model was realized using MathCAD. By processing recorded data, we used the following input figures:

- average monthly production \( Q_{\text{run med}} = 357400 \text{ m}^3/\text{month} \);
- average hourly production \( Q_{\text{orar med}} = 1117 \text{ m}^3/\text{hour} \);
- monthly production standard deviation \( \sigma_{\text{run}} = 96998 \text{ m}^3/\text{month} \);
- hourly production standard deviation \( \sigma_{\text{orar}} = 303 \text{ m}^3/\text{hour} \);
- average monthly operating time \( T_{\text{run}} = 320 \text{ hours /month} \);
- working time standard deviation \( \sigma_{\text{orar}} = 96998 \text{ m}^3/\text{month} \);
- overall available time \( T = 744 \text{ hours} \);
- Breakdown rate \( \lambda = 1/(320/30) = 0.09375 \);
- repair rate \( \mu = 0.071 \);
- Average number of breakdowns \( n_{\text{def}} = 30 \).

The simulated variability of the production system, with above data, considering breakdown-safe operation ids given in figure 1. This case of simulation has realized an average hourly production \( Q_{\text{orar med}} = 1094 \text{ m}^3/\text{hour} \) and a standard deviation of \( \sigma_{\text{orar}} = 302 \text{ t(m}^3)/\text{hour} \).

Using the exponential distribution law we obtained by simulation the histograms of the distribution of operating and repair times.

The state diagram showing the transition cadence from operating to down times and vice versa is presented in figure 2.

Superposing the two diagrams (Fig. 1 and Fig. 2) we obtain the hourly production diagram which takes into account the up and downtimes, as in figure 3.

Now, we can study different scenarios changing the input parameters, as reduction of the average repair time, or reducing the fluctuation of the production rate.

Starting from recorded data we obtain Pareto distribution of breakdowns, caused by bucket wheel, conveyer and hauling system, as in figure 4.

![Fig. 1. The production fluctuation over time](image-url)
Pareto charts indicate the share between different failure modes, and the ranked frequency, without offering any information about the causal interconnection between failing elements or assemblies.

A more detailed analysis can be performed using Bayesian nets. Supposing an apriori causal connection between primary and secondary failures, we can verify the correctness using belief nets. As an example, a screenshot is presented of such an attempt using NETICA software (limited version), in figure 5.

By extending the analysis in such a way, we can highlight the causes of breakdowns in order to improve maintenance, finding out the most probable causal connection between primary and secondary failures.
CONCLUSION

Bayesian nets may be used in any circumstance where modelling an uncertain reality is involved (and hence probabilities are present), and, in the case of decision nets, wherever it is helpful to make intelligent, justifiable, quantifiable decisions that will maximize the chances of a desirable outcome.

Since Bayes nets naturally represent causal chains, that is, the links may be cause-
effect relationships between parent and child nodes, you can supply evidence of past events, and then run the Bayes net to see what the most likely future outcomes will be.

Suposing an apriori causal connection between primary and secondary failures, we can verify the correctness using belief nets. An example regarding Bucket Wheel Excavator failure is presented, using NETICA software (limited version). This paper is an example of how Bayesian nets can be used for reliability prediction.

REFERENCES

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