Available online at www.aucjc.ro
Annals of the University of Craiova for
Journalism, Communication and Management

2, 56-64, 2016 *ISSN 2501-3513*

Mining Technological System's Performance Analysis

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Abstract. The mining production systems, both for underground and open pit extraction consist mainly in a string of equipment starting with the winning equipment (shearer loader, in case of underground longwall mining or bucket wheel excavator in case of open pit mining), hauling equipment (armored face conveyor in longwall mining or the on-board belt conveyor in case of excavators), main conveying equipment (belt conveyor in both cases), transfer devices, stock pile or bunker feeding equipment. This system of mainly serially connected elements is characterized by the throughput (overall amount of bulk coal respectively overburden rock produced), which is dependent on the functioning state of each involved equipment, and is strongly affected also by the process inherent variability due to the randomness of the involved processes (e.g. the cutting properties of the rock). In order to model and simulate such production systems, some probabilistic methods are applied arising from the artificial intelligence approach, involving unit operations and equipment, as the overall system as a whole, namely the Monte Carlo simulation, neural networks, fuzzy systems, and the Load Strength Interference methods. The results obtained are convergent and offer the opportunity for further developments of their application in the study of mining production systems.

Keywords: mining, technology, system, analysis, performance
JEL: A19, Q40

1. Introduction

The continuous mining production systems consist mainly in a string of equipment starting with winning equipment (shearer loader, in case of underground longwall mining or bucket wheel excavator in case of open pit mining), hauling equipment (armored face conveyor in longwall mining or the on-board belt conveyor in case of excavators), main conveying equipment (belt conveyor in both cases), transfer devices, stock pile or bunker feeding equipment (Kovacs, Iliaş & Nan, 2000).

This system of mainly serially connected elements is characterized by the throughput (overall amount of bulk coal respectively overburden rock), excavated, conveyed and sent to stock pile or next user, which is dependent on the functioning state of each involved equipment, and is affected also by the process inherent variability due to the randomness of the cutting properties of the rock (Andras, Nan, Kovacs, Cristea & Tomescu, 2006; Andraş, Nan& Kovacs, 2007 ; Teodorescu, 2015).

The functioning state of the involved elements is also randomly switching between uptime/downtime, having different probabilities of occurrence and duration. In order to model and simulate such production systems, some probabilistic methods are applied arising from the artificial intelligence approach, involving unit operations and equipment, as the overall system as a whole, namely the Monte Carlo simulation, neural networks, fuzzy systems, and the Load Strength Interference methods. For the performance assessment, new reliability tools can be used, as AMSAA-CROW or Douanne charts. Some of these methods will be exemplified on data obtained from long time observation of Bucket Wheel Excavators from Romanian open pit coal mines in order to demonstrate the viability of such new analysis tools in the monitoring and diagnosing mining production systems.

2. Reliability analysis by simulation

In Fig. 1 the diagram of the monthly production of a bucket wheel excavator based production system operating in a Romanian open pit mine (Nan, 2007) is presented, in comparison with another, presented in Fig. 2.

The first one has a more intensive operating regime (throughput larger with about 50% then the second one, due to the smaller ratio coal/ overburden produced). Also we can see the breakdown total hours are greater for the first one then the second one, working mainly in overburden rock. Starting from the main reliability parameters determined on the basis of these recorded data, such as MTBF and MTTR, respectively the exponential distribution associated parameters, the rate of failure l and the rate of repair m , using the Monte Carlo simulation method, we simulated the operating cycles during one month.

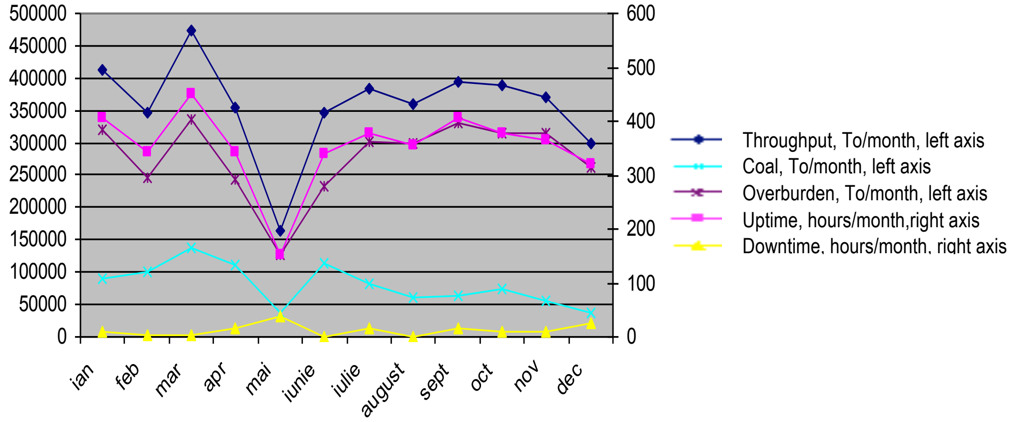

Fig. 1. Operation diagram of the Excavator no. 1

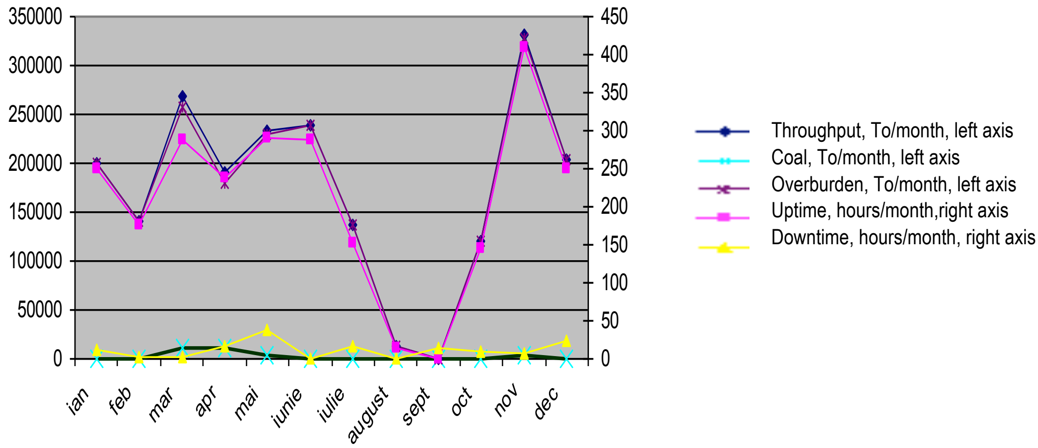

Fig. 2. Operation diagram of the Excavator no. 2

This kind of continuous production system is producing a variable material flow until the breakdown of an element at the moment tf_i which causes the stop of the system. After a certain period of time t_{ru}, the system is repaired and restarts, until the next breakdown is produce at the moment tf_{i+1}.

In order to perform simulation, 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 σ, describing the inherent variability (fluctuation) of the production and for λ and μ, characterizing the random behavior of the cadence of uptimes and downtimes. The simulation model was realized using MathCAD.

By processing recorded data, we use the following input values:

- average monthly production: $Q_{month\ med}$ = 357 400 m^3/month;
- average hourly production: $Q_{hour\ med}$ = 1117 m^3/hour;
- monthly production standard deviation: σ_{month} = 96 998 m^3/month;
- hourly production standard deviation : σ_{hour} = 303 m^3/hour;
- average monthly operating time: T_{fm} = 320 hours /month
- working time standard deviation: σ_{tf}=91 hours;
- overall available time: T= 744 hours ;
- Breakdown rate : λ=1/(320/30) = 0,09375;
- repair rate: μ =0.071
- Average number of breakdowns: n_{def} = 30.

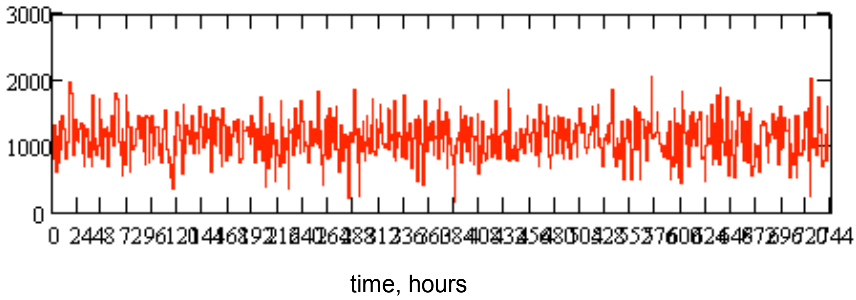

Fig. 3 The inherent production fluctuation

The simulated variability of the production system, with above data, considering breakdown-safe operation is given in figure 3.

This case of simulation has been realized an average hourly production $Q_{med\ hour}$ = 1094 m^3/hour and a standard deviation of σ_{hour} = 302 t(m^3)/hour

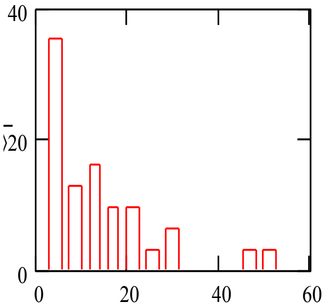

Fig.4 Histogram of uptimes

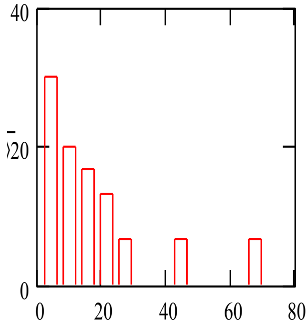

Fig.5 Histogram of downtimes

Using the exponential distribution law, we obtained by simulation the histograms of the distribution of operating and repair times shown in figures 4 and 5.

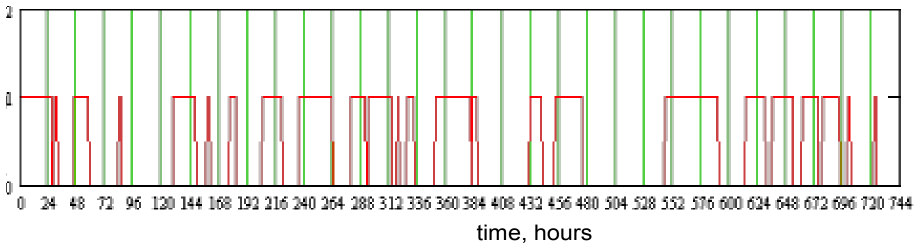

Fig. 6 Simulated state diagram of the system

The state diagram showing the transition cadence from operating to downtimes and vice versa is presented in fig. 6.

Superposing the two diagrams (Fig. 3 and Fig. 6) we obtain the hourly production diagram which takes into account the up and downtimes, as in fig. 7.

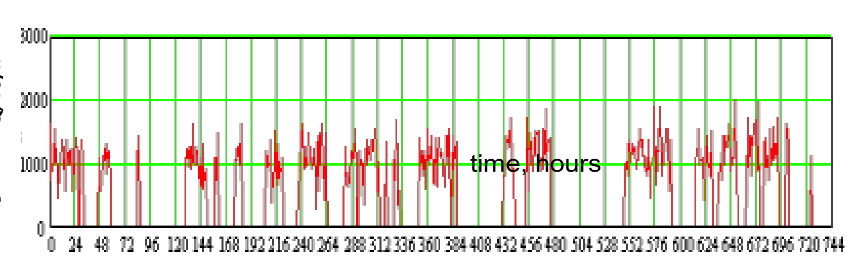

Fig. 7

Diagram of simulated hourly production during 1 month

If we realize a number high enough of iterations, by averaging, we obtain in the average results near to start input data considered. In this way, we calibrate the model to reflect the actual situation. 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 (Ferencová, Jeleňová & Kakalejčík, 2015).

3. Stress strength interference

In the literature (Rao, 1992), the influence of operating regime, load, stress, requirement, as independent variables, on the safety of work, reliability, probability of failure, and degree of damage of the failure as dependent variables are considered in the conditional reliability theory using the stress-strength interference method.

The method is originated in the sizing methods based on probability of the variable loaded systems, as a response to the limits of classical sizing procedures.

In the frame of the classical method, the yield value of strength S and the estimated value of load L are defined. It is presumed that L is always less than S, the difference S-L being called safety range while the ratio S/L is called safety factor. By designing a system based on this theory, the reliability of a system is considered infinity, and the probability of failure is equal to zero. The failure occurrence after a time period is considered due to the decrease of S over time due to the fatigue, or the occurrence of an accidental load greater than L. Mining equipment is facing both causes of probability of failure due to the randomness of the sources of load, accidental overloads and fatigue due to wear of components. We propose and demonstrate the application of this method to the analysis of the safety of operation of mining production systems (Andra, Nan &Kovacs, 2006; Andras, Nan & Kovacs, 2008).

In the fig. 8 the principle of the method is presented. The strength S, in general meaning, is a metric of the capacity of a component to resist to loads without damaging, and has not a constant value, being a random variable (Andras, Dinescu & Andras, 2008). On the horizontal axis we have compatible meanings, such as load, requirement, capacity, flow rate, in physical values, at yield values. On the vertical axis we have probabilities or probability densities, of the occurrence of the given values.

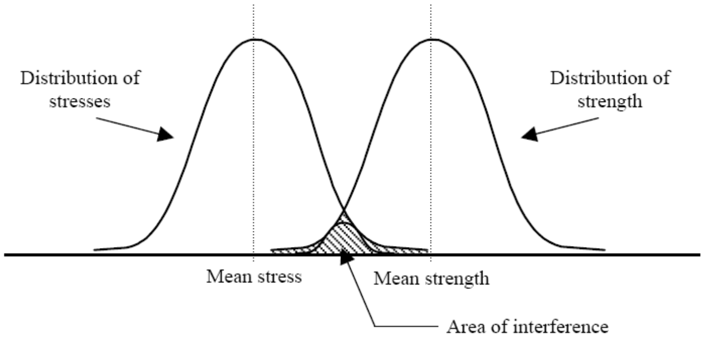

Fig. 8. Principle of the stress-strength interference

Similarly to strength, the load has also a random variation, so we can represent both distributions on the same picture.

As it can be seen, the two probability fields present an area of interference, which signify that it is possible to occur situations in which the load is greater than the strength. From here it results a third distribution, the probability of the event L ≥ S, which is the conditional failure probability, given by:

$$P_f(s) = \int_{-\infty}^{+\infty} f_L(s) * F_S(s) ds. \quad (1)$$

Where: $f_L(s)$ is the probability density of load and $F_S(s)$ is the cumulative probability of strength.

As an example, using a MathCAD program, we drawn up the Load Strength interference diagrams for the Bucket Wheel Excavators discussed before.

In our study, we consider as load the specific cutting energy is considered, which is between 0,08 and 0,4 kWh/m^3 for lignite, with a larger spread of values, respectively 0.18 and 0,2 kWh/ m^3 for overburden rock, with narrower spread.

As strength, the nominal value of the excavator was considered, as 0.35 kWh/m^3, with a normally distributed variability, due to variability of working conditions.

With these values, the Load-Strength interference diagrams were drawn up for the two cases, presented in figs. 9 for overburden and 10 for lignite.

As it can be noticed, the degree of non-reliability is greater for the excavator operating in lignite, about 15%, then for the excavator working in overburden, where is practically zero.

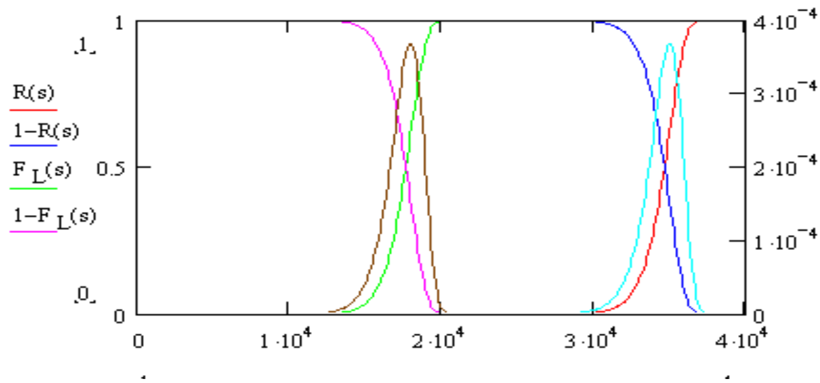

Fig. 9. The L-S interference charts for the excavator working in overburden rock (Specific energy consumption in 10^5 kWh/m^3 on x axis)

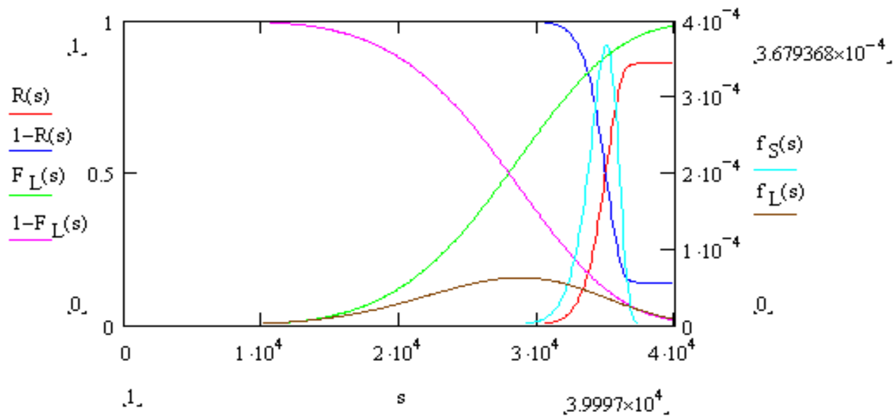

Fig. 10 . The L-S interference charts for the excavator working in lignite (Specific energy consumption in 10^5 kWh/ m^3 on x axis)

4. Conclusion

In order to find out new methods for the quick assessment of large production systems used in coal mining, we presented and tested by real world examples two alternative–complementary methods of reliability analysis, namely the Monte Carlo simulation and the Load Strength Interference methods.

These methods are useful for the retro analysis of the production systems, characterized by two kind of uncertainty, i.e. the inherent random variability of continuous operation, due to the in-situ characteristics of the mined-out rock, and by the uptime/downtime random alternation in the equipment chain state. The results obtained are convergent one with the other, and offers the opportunity for further developments of their application in creation of an intelligent system of performance prediction.

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