Abstract: The mining production systems, both for underground and open pit extraction 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. 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.

Key-Words: reliability, simulation, modeling, mining, extraction, fuzzy, artificial intelligence

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 [1].

This system of mainly serially connected elements is characterized by the throughput (overall amount of bulk coal respectively overburden rock), 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.

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.

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, \( \lambda \) and \( \mu \), the exponential distribution associated parameters, rate of failure and rate of repair, using the Monte Carlo simulation method, we simulated the operating cycles during one month.
This kind of continuous production system is producing a variable material flow until the breakdown of an element at the moment $t_{fi}$ 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 $t_{fi+1}$.

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 $\sigma$, describing the variability of the production (fluctuations) and for $\lambda$ and $\mu$, characterizing the random behavior of the cadence of uptimes and downtimes. The simulation model was realized using MathCAD. By processing recorded data, we use the following input values:

- average monthly production
  $Q_{month\, med} = 357400\, m^3/month$;
- average hourly production
  $Q_{hour\, med} = 1117\, m^3/hour$;
- monthly production standard deviation
  $\sigma_{month} = 96998\, m^3/month$;
- hourly production standard deviation
  $\sigma_{hour} = 303\, m^3/hour$;

- average monthly operating time
  $T_{fm} = 320\, hours /month$
- working time standard deviation $\sigma_{t}=91\, hours$;
- overall available time $T= 744\, hours$;
- Breakdown rate $\lambda=1/(320/30) = 0.09375$;
- repair rate $\mu =0.071$
- Average number of breakdowns $n_{def} = 30$.

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 $Q_{mod\, hour} = 1094\, m^3/hour$ and a standard deviation of $\sigma_{hour} = 302\, t(m^3)/hour$.

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. 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.

If we realize a number high enough of iterations, by averaging, we obtain the average data 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.

3. Stress strength interference

In the literature, [3], 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 [4,8].

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 [8].

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.

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 $L \geq S$, which is the conditional failure probability, given by:

$$f(s) = \int_{-\infty}^{+\infty} f_L(s) \ast F_S(s)ds$$

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 draw 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 fig. 9 for overburden and fig.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.
4. Performance optimization model for winning machine using neural networks

Operational parameters of winning machines are strongly influenced by the random variations of strength and energetic characteristics of coal, respectively the specific resistance to cutting and specific energetic consumption at breaking.

Due to the variation of these parameters, rate of feed, torque of the drum axle and the advancement force vary randomly around an average value, which can be suddenly modified too by rapid change, for example when crossing a hard rock intrusion.

Using special transducers and processing equipment, it is possible to record the instantaneous values of torque, of the hauling (advancement) force and of the rate of feed.

Based on the above mentioned parameters, it is useful and possible to derive the values of the specific cutting resistance, \( A \) and of the specific energy consumption, \( E_s \) in order to forecast, for other conditions, expected values of the feed rate, \( v_a \), which influence the cutting capacity, of the torque on the axle, \( M_t \), which is limited by the power of the engine and of the advancement force, \( F_a \), which is also limited by the power of the hauling system.

Starting from simultaneously recorded values of the above mentioned, using a perceptron neural network (Fig.11.), the values \( F_a, M_t \) and \( v_a \) have been used, regarded as inputs for instructing the network, with the calculated values of \( E_s \) and \( A \), using dependency relations known in the technical literature.

According to the resulting structure of the neural network, the values for \( M_t, F_a \) and \( v_a \) have been determined for discrete values of \( E_s \) and \( A \).

According to these values the dependencies between the mentioned parameters have been mapped out, as in figs. 12, 13, 14, 15, 16, 17.
5. Longwall support effectiveness assessment using Fuzzy Sets

The adaptation of powered roof support, from constructive and functional point of view to the variation and specificity of geologic mining conditions, is a very actual and important research subject.

In past decades, the coal extraction technology evolved dramatically. However, the problem of the interdependence between geo/mining conditions and constructive and functional features of powered support represents a challenge which faces the specialists with huge problems to be solved and engineering sciences offer new tools for an interdisciplinary approach in this work, in order to provide to manufacturers, designers and users scientifically founded solutions.

It is difficult to obtain closed form solutions from deterministic models, historical statistical data presents a large variability, so deriving support-surrounding rocks system’s behavior is very difficult to be described using classical approaches. In the present section we try to use FUZZY modeling to obtain some qualitative results.

The support characteristics are not fix (crisp) values, they belongs to a value range. The parameters describing geo mining conditions also are difficult to be quantified, their approximation being expressed by non digital attributes.

In the mentioned diagrams, the hauling force $F_a$ has been considered as a parameter.
the FUZZY module of MATLAB, using the idea of ground response curves.

This system allows the establishment of the main parameters, the resistance and the stiffness and also setting pressure for an appropriate selection of the shield.

In Fig. 18, the ground response curves for supports with the four combination of the stiffness and yield load, with roofs of different stability are depicted.

The curves 1 to 4 (Fig.18) represent the dependence between the roof convergence and the support load, for decreasing roof stabilities. The shape of curves are determined by the empiric observation stating that at constant support load the convergence increases, when stability decreases and to maintain a given allowable convergence the support load must be higher.

The slope lines continued by horizontal lines represents the support’s loading characteristic, as the stiffness is greater, as the line is more vertical. The elevation of the horizontal segment represents the value of the yield load of the support.

The setting load is represented by the start point of slope line on the vertical axis.

The intersection between the support characteristic line and the roof characteristic curve gives the functioning point of the support-roof system at the equilibrium.

The target for a proper support of the roof is to maintain this point on the inclined line segment, for this reason the external control parameters are the setting load, the yield load and the stiffness of the support shield.

![Fig. 18 Ground response curves conceptual model](image1)

The main finding of previous research is the fact that the characteristic curve of the roof is changing in time during a working cycle, and the combination of the above mentioned parameters of the support must be selected in such a way, that the convergence be maintained under an imposed limit and the stability preserved during the entire cycle.

The roof stability, described by [7], [9] is another metric which can be used as output for the devised FUZZY model. For illustration, this concept of stability in ground response curves is presented in the Fig. 19.

In this approach, the curves represent the load-convergence dependence of the whole support-roof system. Different curves represent the system’s behavior in different operating stages of the face.

![Fig. 19 Ground response curves conceptual model according to [7](image2)]

Between these three input parameters, i.e. the setting pressure (resistance), the yield pressure (resistance) and stiffness and the output parameters, i.e. stability and convergence, the field observations and the above common sense findings allow to derive inferences for FUZZY rules [10], [11].

Based on the above considerations, we developed two FUZZY models. The FUZZY models has been developed using MATLAB’s FUZZY toolbox.

In the first model developed, we used inference rules for deriving the support load-convergence curve respectively the roof load-convergence curve. The output graphs are presented in Figs. 20 - 21.

![Fig. 20. Load-convergence curve of the support](image3)
In the second model, more sophisticated, we used stiffness, stability, yield and setting load as input variables and convergence as output variable. We obtained the spatial graphs presented in Figs. 22-24.

Interpreting the results starting from these spatial graphs may offer some practical rules about prior selection of supports, using statements from historical data and simple factual reasoning. It is possible to adjust and refine the model, comparing field data with those obtained from the model, with crisp values if applicable.

We can use the defuzzification module of the model as an interactive tool to simulate different situations by modifying some input parameters and derive crisp values for outputs, as in Fig. 25.

6. 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.

The application of neural nets to derive the dependencies between the working parameters of a shearer-loader and the cuttability metrics of the rock has been also treated.

The use of FUZZY sets to describe the operation of the roof support, starting from a qualitative conceptual model of ground response curves is presented.

The results obtained are convergent and offer the opportunity for further developments of their application.

References:


