STUDY OF THE MINING PRODUCTION SYSTEMS, PROCESSES AND COMPONENTS USING ARTIFICIAL INTELLIGENCE METHODS

Stela Dinescu, *Ph.D., Lecturer*, **Andrei Andras** *Ph.D., Lecturer, University of Petroşani ROMANIA*

ABSTRACT*: Mining production systems used in both underground and open pit mining consist of serially connected elements (winning, hauling, main conveying equipment, transfer devices and stock pile/bunker feeding equipment). The whole production system is characterized by the throughput, which depends on the functioning state of each element and it is also strongly influenced by randomness and variability of the involved processes. In order to correctly simulate and model such systems, probabilistic methods and Artificial Intelligence approaches are used - involving unit operations and equipment as well as the system as a whole - such as Neural Networks, Fuzzy Systems, Monte Carlo simulation and the Load Strength Interference method. The obtained results are convergent with real data and offer the opportunity for further developments of the wider application of mentioned methods in the study of mining production systems.*

KEYWORDS: Mining, production system, equipment, 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, and for unit operations and equipment the neural network, 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, while 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, λ and μ, 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 σ, describing the variability of the production (fluctuations) and for λ and μ, characterizing the random behavior of the cadence of uptimes and downtimes.

The simulation model was realized using MathCAD.

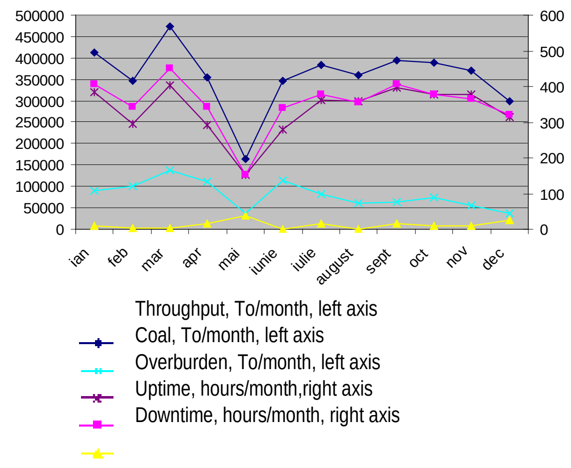


Fig. 1. Operation diagram of the Excavator no. 1

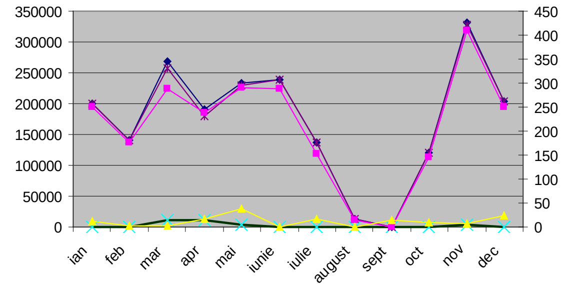
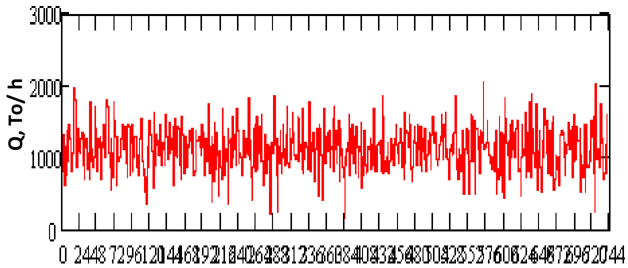


Fig. 2. Operation diagram of the Excavator no. 2



time, hours

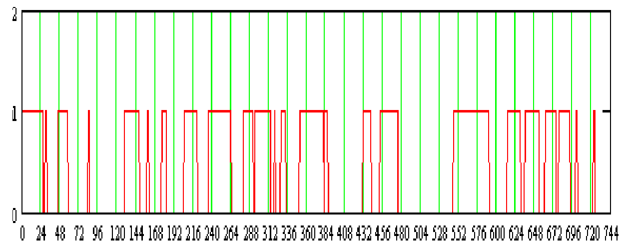
Fig. 3 The inherent production fluctuation

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

- 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.

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.

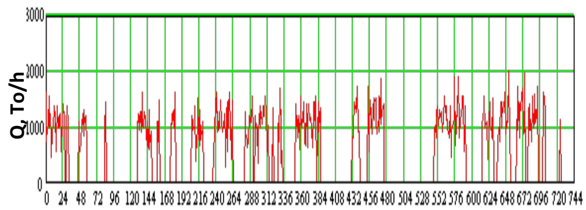
The state diagram showing the transition cadence from operating to downtimes and vice versa is presented in fig. 4.



time, hours

Fig. 4. Simulated state diagram of the system

Superposing the two diagrams (Fig. 3 and Fig. 4) we obtain the hourly production diagram which takes into account the up and downtimes, as in fig. 5.



time, hours

Fig. 5. Diagram of simulated hourly production during 1 month

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, in order to overcome 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 aging or 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, 7].

In the fig. 6 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[5] .

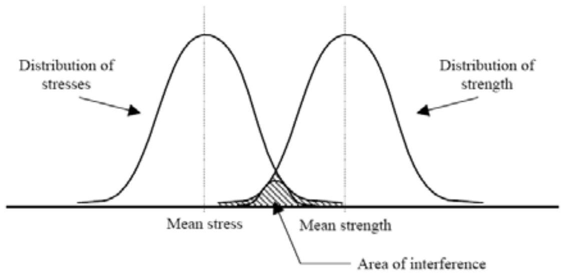


Fig. 6. Principle of the stress-strength interference

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 ≥ S, which is the conditional failure probability, given by:

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

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, 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 (available) value of the excavator's specific energy (ratio of nominal power in kW to nominal excavating capacity in m^3/hour) has been 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. 7 for overburden and fig.8 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.

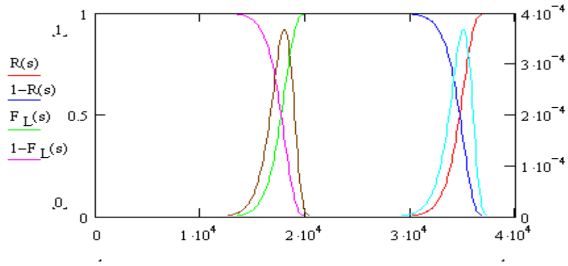


Fig. 7. The L-S interference charts for the excavator working in overburden rock (Specific energy consumption in 10^5 kWh/m^3 on x axis)

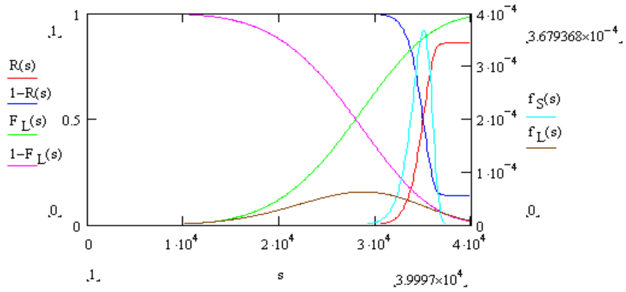


Fig. 8. . The L-S interference charts for the excavator working in lignite (Specific energy consumption in 10^5 kWh/ m^3 on x axis)

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 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.9.), 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.

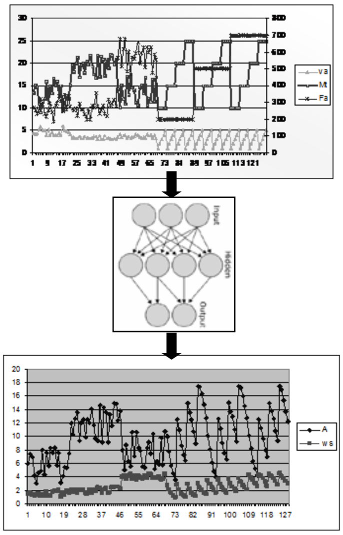


Fig.9. Inputs and outputs of the neural network

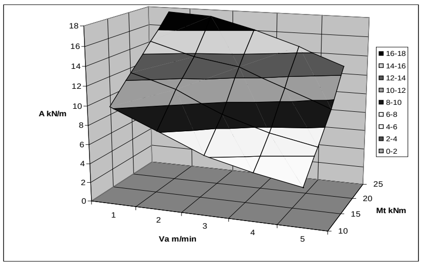


Fig. 10. Dependency of A (M_t, v_a) $\mathbf{F_a}$ **= 200 kN**

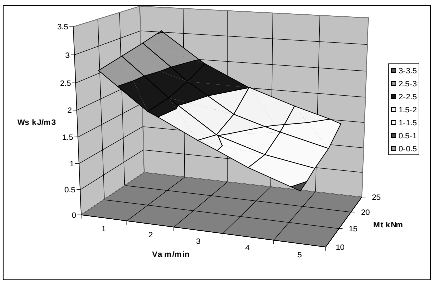


Fig. 11. Dependency of E_s (M_t, v_a) for $\mathbf{F_a}$ **= 200 kN**

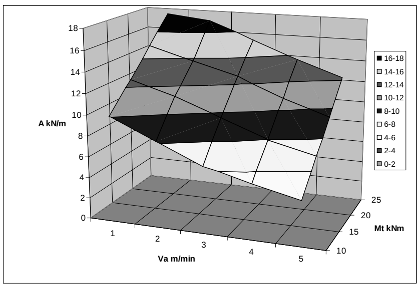


Fig. 12. Dependency of A (M_t, v_a) for $\mathbf{F_a}$ **= 500 kN**

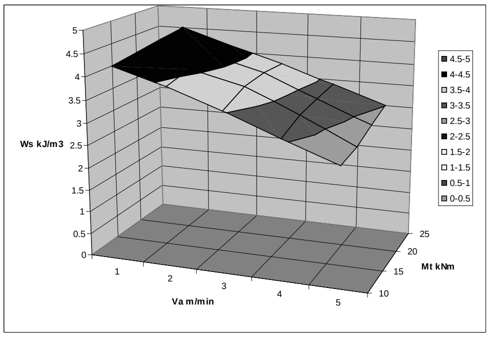


Fig. 13. Dependency of E_s (M_t, v_a) for $\mathbf{F_a}$ **= 500 kN**

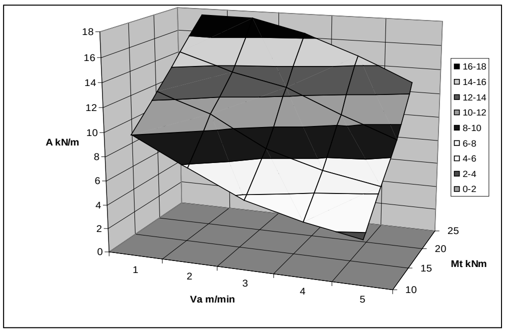


Fig. 14 . Dependency of A (M_t, v_a) for $\mathbf{F_a}$ **= 700 kN**

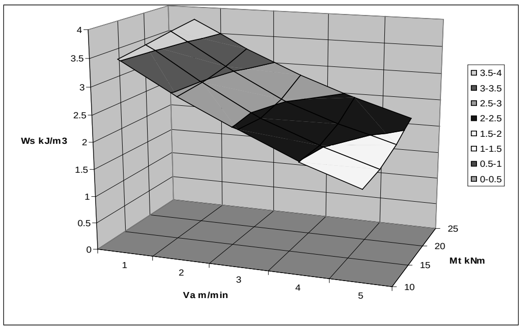


Fig. 15. Dependency of E_s (M_t, v_a) for $\mathbf{F_a}$ **= 700 kN**

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. 10, 11, 12, 13, 14, 15.

In the mentioned diagrams, the hauling force F_a has been considered as an independent parameter.

It could be possible to embed such a processing unit in the control loop of a shearer loader, in order to adaptively optimize the feed rate and/or the energy consumption.

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.

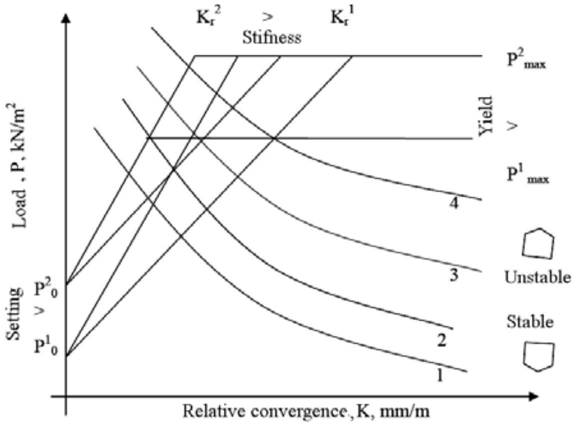


Fig.16. Ground response curves conceptual model

Hence, the decision to select a shield in order to test its compliance to given working conditions and technological factors can be made using FUZZY rules.

Starting from the idea of ground response curves. presented in [6], we have delivered an IT system based on FUZZY logic.

In Fig. 16, the ground response curves for supports

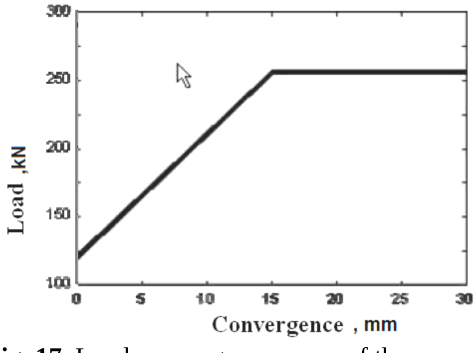


Fig. 17. Load-convergence curve of the support

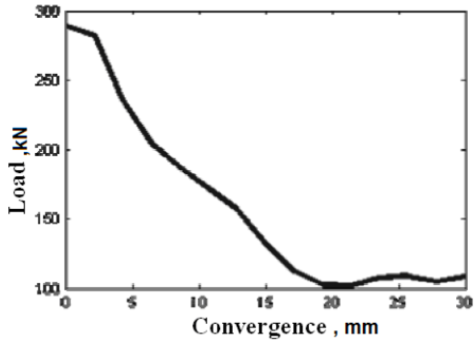


Fig. 18. Load-convergence curve of the roof

with the four combination of the stiffness and yield load, with roofs of different stability are depicted.

The curves 1 to 4 in Fig. 16 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.

The roof stability, described by [7] is another metric which can be used as output for the devised FUZZY model.

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.

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.

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. 17 - 18.

In the second model, more sophisticated, we used stiffness, stability, yield and setting load as input variables and convergence as output variable, and we obtained the 3D graphs presented in Figs. 19-21.

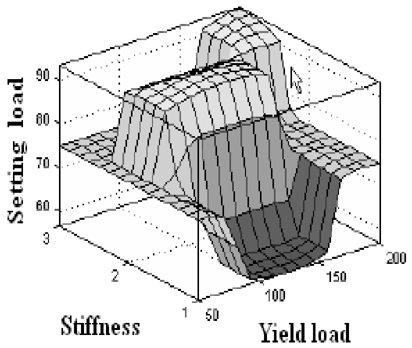


Fig. 19. Setting load as a function of stiffness and yield load

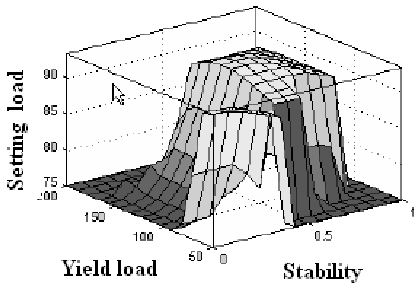


Fig.20. Setting load as a function of stability and yield load

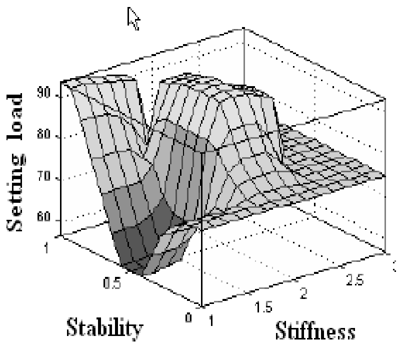


Fig.21. Setting load as a function of stability and stiffness

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.

The algorithm implemented in an expert system, may lead to a progressive optimization of existing support operation or, in the selection process – eventually by scoring and comparison – of the appropriate support parameters.

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.

We proposed and demonstrated the application of these methods to the analysis of the safety of operation of mining production systems

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 by using this method may lead to a progressive optimization of existing support operation or, in the selection process –eventually by scoring and comparison – of the appropriate support parameters.

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

7. REFERENCES:

[**1] Andras, I., Nan, M.S., Kovacs, I.** , *Research Regarding The OEE (Overall Equipment Effectiveness) Assessment Of The Coal Open Pit Mines Production System*, Annals of the University of Petroşani, Mechanical Engineering, 8 (2006), 139-146 , *ISSN 1454-9166.*

[**2] Andras, I., Dinescu, S., Andras ,A.,** Comparative Analysis Of Different Methods Of Reliability Assessment For Continuous Mining Technological Systems *Scientific Bulletin Series C: Fascicle Mechanics, Tribology, Machine Manufacturing Technology, Volume XXII, 2008, ISSN 1224-3264*

[**3] Barczak, T., M., A.,** *Retrospective Assessment of Longwall Roof Support With a Focus on Challenging Accepted Roof Support Concepts and Design Premises*. 25th International Conference on Ground Control in Mining, 2006 232, 244.

[**4] Dinescu, S. , Andras, A.**, *Modeling And Simulation of The Complex Mining Production Systems For Coal Extraction*, RECENT ADVANCES in CIVIL and MINING ENGINEERING, Proceedings of the 1st European Conference of Mining Engineering (MINENG '13).

[5] Esterhuizen, G.S., Barczak, T.M., *Development of Ground Response Curves for Longwall Tailgate Support Design* **,** Proceedings of the 41st U.S. Rock Mechanics Symposium, Golden, Colorado, June 17-21, 2006. Alexandria, VA: American Rock Mechanics Association, 2006 Jun; :1-10

[6] Nan, M.S., *Parametrii procesului de excavare la excavatoarele cu roto*r, Editura Universitas, Petroşani, 2007.

[**7]. Rao, S.S**., *Reliability-Based Design*, McGraw-Hill, Inc., New York, 1992