INTELIGENT COMPUTER SYSTEM FOR CONTINUOUS RISK EVALUATION AND DECISION SUPPORT OF SAFETY MANAGEMENT IN MINING

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ABSTRACT

The structure and the theoretical basis of Bayesian network - Mine Accident Risk dot Net (MAR.NET) for decision support in mining safety are presented. The network is composed from 22 nodes described with specific states designed for description of mining risk factors. In the heart of the network is conditional probability distribution of the chance node "Type of the accident" containing 37800 state configurations. A new formula for evaluation of safety risk level is proposed. For the purpose of decision making the network is extended to influence diagram. The possibilities of learning and adoption of MAR.NET to specific object in uncertainty and some application of simulated safety cases are discussed.

INTRODUCTION

The information support of the safety management required processing of a large amount of data both of quantity and quality type. It is well known from the practice that taking into account only quantificators of safety risk like coefficients and indexes of frequency and weight are not sufficient for characterizing and control of safety level. The quality system for risk evaluation is needed. The new generic ISO 18000 series devoted to quality safety management is an eloquent fact about the importance of the problem.

Today the investigation and registering of an accident are documented in minimum 60 data fields of different formats. The scrutinize of safety risks in the large mining companies ordinary includes more than 3000 massive of data for description of 50 and more accidents per year. Every one accident is classified in 21 indicators (tab. 1) any of which described with 2 up to 26 characteristics (states) (Michaylov and Petrov (1997), Michaylov and collective (2002)).

The psychology and cognitive science are ascertain the fact that the human mind cannot effectively manipulate such kind of data structures and meet serious difficulties to make an inference when the possible decisions have more than 3 alternatives. Such informational overload of the consciousness leads to ignorance of information and heuristic deciding of variants. The risk of bad decisions increasing and the safety become pursuit rather than achieved purpose. The problem is of particular interest in time critical decision-making.

Another important feature of safety management is the probability and fuzzy uncertainty attending decision-making. In practice this mean that the expected effects of actions for risk reducing also will be connected with some likelihood. What is the degree of certainty that one of the expected effects is most likely is the correct question. Rendering the expert opinions is everyday activity in safety management. The successive implementing of acquired data and expert experience in decision-making is of vital importance. A typical approach for safety risks investigation by separately studying of the impact of isolated factor groups inevitably relevant to loses of information about the mutuality in the safety system. In terms of information such a "disjoint" is irreversible process. In other words the model we use to support our decisions those not reflect the real world because the interdependences in the safety system are very diligence removed since on methodological level.

New synergetic approach should apply for the purposes of risk investigation and decision support for improvement of safety. A model representing the mutual influence of dangers, human and control over the safety is needed.

The structure of intelligent computer system MAR.NET (My Accident Risk dot Net) for information fusion of databases and expert opinion is presented. The system is designed for practical use from safety managers in mining companies.

INDICATORS OF SAFETY RISKS IN MAR.NET

In the best practice exist pursuit of an integrated system of indicators characterizing safety risks. An integrated system of safety indicators for mining industry was developed in University of Mining and Geology "St. Ivan Rilsky" in the beginning of 90 and last updated in Michaylov and collective (2002) (tab. 1). Every indicator has a set of characteristics structured in hierarchical groups. The number of groups in stets are between 2 and 26. Because of lack of space the characteristic sets are not present in this paper.

The defined indicators in table 1 can be used for quality investigation of safety risks in any other industrial branch. The characteristic sets of some of the indicators will be different. But the principle of studying and data manipulation remains the same. This is great advantage for implementation in practice and for software development.

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The shown indicator system can be used for risk investigation in all industries. The worldwide practice shows that successive computer systems using artificial intelligence methodologies are developed for a local domain irrespective of some universality. MAR.NET is developed for investigation of safety risks in mining industry. The sub domains in knowledge base for mining branches - coal mining, metal and nonmetal mining both for underground and open pit, required different sets of characteristics for some indicators.

Name	Short label
Time of occurrence	01.Hour
Occupation groups	02.Occupation
Degree of education	03.Education
Length of service	04.Practice
Length of service in entertainment	05.Practice_Co
Length of service in profession	06.Practice_Pro
Day after last rest (weekend)	07.Day_after
Hours after start of job	08.Hour_after
Place of accident	09.Place
Kind of job during the incident	10.Job
Kind of incident leading the accident	11.Incident
Human factor in cause of accident	12.Human_Factor
Material factor in cause of accident	13.Material_Factor
The dangers of the environment	14.Environment
Deviation from ordinary actions and conditions	15.1.Deviation_A 15.2.Deviation_C
Severity of the accident	16.Severity
Harmed parts of body	17.Body
Kind of injury	18.Injury
Period of health restore	19.Recover_Period
Safety precautions (risk redusing measures)	20.Measure
Machines related with the accident	21.Machinery

Place of accident is a typical indicator for which the characteristic set needs to be overwritten for the different mining objects. On the other hand the learning of MAR.NET system will be much more adequate for specific branch and adoption – for specific objects. The convergence of the systems is the next step.

DRAWING OF INFERENCE FOR SAFETY RISKS LEVEL

Reporting the safety risk level is the important end result of risk evaluation. It is hard to define all the different aspects of risks in notion of one safety level. For the purpose the following definitions are accepted:

The drawing of inference for safety risk level is a process of statistical conclusion for synergetic influence of the risk factors on the accident severity in uncertainty. The risk factors under review are shown in table 1.

In the terms of safety a classical definition for risk is the production:

RISK = PROBABILITY x CONSIQUENCES

In the description of safety level all risks must be take into account. After execution of safety programs the object of evaluation is the remaining (current) risk. - R_c . The level of safety can be useful quantificator for comparison of objects and branches with one value. But the dimension of risk is specified from the dimension of consequences. Usually the consequences are classified as economical and human and social. In capacity of quantitative link can be used the count of loosed working hours. It is not necessary to be human-hours. The indicator 19.Recover_Period described the consequences of the accidents with 10 discrete intervals – "A. Up to 3 days", "B. 4 to 17 days", ..., "J. 6000 days (means irrecoverable accidents)".

The following expression for calculating the safety risk level are proposed:

If we accept that the threshold for sensitivity of risk evaluation is in probability of $1/10^8$ and 3 loosed working days as a consequence, than the minimal safety risk is evaluated on $R_0 = 3_x 10^{-8}$. In that case the level of safety risk L_s can be calculated as a function of current risk - R_c and the threshold risk - R_0 by (1).

$$L_s = \log\left(R_c/R_0\right) \tag{1}$$

The L_s posses some properties which makes it useful for calculating of risk level. First, since the risks are always positive quantity and $R_c \ge R_0 > 0$ the value of level will be always calculable and $L_s > 0$. Second, when the current risk aligns with the threshold $R_c = R_0$, the safety risks level $L_{\rm s}=0$. And last but not least the human perceptions are determined from logarithmic levels as stated of generalized psychophysical low of Veber-Fehner. Take into these considerations the 10th basis of logarithm is recommended. Besides the one-value quantification of safety risk the management is needed of detailed quality investigation based on the available knowledge. The data collection for risks and safety level of a specific object is made by excerption (registry of accidents, failures, protocols of inspections etc.). It leads inexorable to statistical evaluation of excerpted conclusion for the real state of the safety system, which obviously is richer of properties (Вентцель (2001)). Nonlinear dynamics of manifestation of the incidents with possibility the safety system to pass in chaotic regime (Guastello (1997); Stengers and Prigogine (1997); Petrov (1999)) puts the question outside of the application range of well-developed methodologies for reducing of the problem dimension like deterministic factor analysis and classical statistical averages. (Трухаев, Горшков (1985)).

Bayesian approach for statistical inference

The frequency interpretation of probability is called objective ore classical point of view in statistic theory. In the statistical decision theory the Bayesian approach is used to draw of conclusions in uncertainty. The approach offers a different interpretation of probability called subjective point of view. The idea of conditional probability takes a main place in Bayesian approach. From the investigator is required to use subjective probability as a measure of belief for the state of observed object (*Hines, (2000)*). This is more intuitive perception of probability, which means rather than chance than frequency. The level of belief is specified with the probability distribution for a given unknown parameter. This procedure is completely different of any other statistical approaches, where the uncertain parameters are treated as unknown constants. The Bayes approach required from investigator to think for unknown parameters as random variables.

The low for complete probability and Bayes Theorem

The evaluation of impact of co incidents on the accidents is in the base of detailed risk investigation. The mathematical fundament of the MAR.NET model is based on the following major dependencies:

Let A_i , A_2 , ... is an enumerated collection of events sharing a space of realization – *S*. The events in collection are mutually independent with union *S*. Let *B* is another event. If the probabilities $P(A_i)$ and $P(B | A_i)$ are known for $i \in I$ (*I* is the set of indexes of events) than it can be shown that:

$$P(B) = P(B | A_1)P(A_1) + P(B | A_2)P(A_2) + \dots,$$
(2)

a result known as low for complete probability;

$$P(A_j | B) = \frac{P(B | A_j)P(A_j)}{P(B | A_1)P(A_1) + P(B | A_2)P(A_2) + \dots},$$
 (3)

a result known as Bayes Theorem and;

$$P(A_1, A_2, ..., A_n) = P(A_1 | A_2, A_3, ..., A_n) P(A_2 | A_3, A_4, ..., A_n), (4)$$

....P(A_{n-1} | A_n) P(A_n)

a result known as chain rule, with significant importance in Bayesian networks.

Bayesian belief network - BBN

The Bayesian network is presented with directed acyclic graph with the following elements: the chance nodes representing random variables and the edges – probability independencies between the variables. The nodes have conditional probability tables assigned to describe the independencies. The nodes without the parent have unconditional (marginal) distribution.

One of most powerful feature of Bayesian network is the global treatment of local uncertainty. In other words – the changes in probability distribution in one chance node are propagated to all the nodes linked with edges following the directions in the network. The propagation of probability against the directions is possible due to Bayes Theorem. For statistical description of net and propagation of probability the results (2, 3 and 4) are used.

Unlike of classical statistical inferences (which work rather than with confidence intervals than statement of probability) is, that the Bayesian inference completely described the fact, that the expectation alone cannot predict the probability of unexpected events. Prior information for unexpected events is needed. The necessity of prior opinion is the key part of Bayesian inference. Of course, this requirement is a weakness. Not always is easy to obtain the prior information, except of experts. But in lack of data for safety in an entertainment (newly created or thinly proficient) the opportunity to use experience from similar objects and from experts is great advantage. A well-learned Bayesian network can be of great benefit for newly appointed safety personnel. In objects with complicated behavior of safety system, even not large, the advantages of such technology will stay clear for a short time.

Drawing of inference in Bayesian network

Drawing of inference or making conclusions in Bayesian networks means calculating of conditional probability for some variables to be given information from the others. It is ease when all indications are lead from predecessors (parents) to child variables (nodes) of interests ($B_i \rightarrow A$, fig. 1). But when an indication is gived from child to parent, the network must draw a conclusion against the direction of edges. The Bayes Theorem (3) is used for such a back propagation of probability.

Decision-making and Influence diagram

Computer models for decision support can be developed on the base of pure BBN, but the conceptions of utility functions and the decisions are not clearly formulated and fully cover. The extension of BBN with two tapes of nodes represents an influence diagram (fig. 1). The influence diagrams are used fore evaluation of different variants of decisions by calculating of expected utility of launched actions.



Figure 1. An example of Bayesian network extended to influence diagram with node "Decision" and node "Utility"

The decision nodes must be linked in chain in the logical consequence of independency between variables in the model. The nodes from which the decision is depend, must be with known state before the decision is made.

STRUCTURE OF MAR.NET

MAR.NET is designed as Bayesian belief network extended to influence diagram (fig. 2). The main purpose of MAR.NET is to support decisions for increasing of safety level in industrial objects, entertainment and whole branch. Currently the states of the nodes are adapted for the specific of coal mining. The nodes in the model correspond with the indicator variables described in tab.1. The states of indicators are labeled like the characteristics of the indicators. The conditional dependency between the variables can directly be read from the graph on fig. 2. The probability of different configurations of states in the net described the subjective point of view to happen an accident according to conditions given by states of parent nodes.

Marginal nodes in the root of the net are 14.Environment, 10.Job and 02.Occupation. The initial state of MAR.NET are uniform distribution of probability of the state configurations. The zero probability assigned to a state or configuration of states means striking off the possibility of occurrence of this state. The probability tables assigned to the marginal nodes are shown in table 2.

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Social-human severity of accidents is evaluated of 16.Sevirity node. Economical risk of accident consequences is evaluated from utility node "Loses". The risk measured in loosed working days is evaluated from chance node 19.Recover_Period. All the 3 nodes are child of parent nodes and have conditional probability distributions. Every state configuration (column) is an independent group with complete probability of 1.

In the heart of the MAR.NET is a chance node 11.Incident – "Kind of incident leading the accident". In current realization the node is a child of five predecessors – four chance nodes and one decision node respectively 12,13, 15.1, 15.2 μ 20 (see tab.1 for full names). The conditional probability table of node



Figure 2. MAR.NET decision support system for improvement of safety level

Table 2. Initial	probability	rtable of	chance	node 10.Job),
raioro Er minar	p: 0.0 a.o	10.010 01	0		

State	Probability
A. Transport and load	0.2
B. Ordinary exploatation	0.2
E. Other	0.2

The impact of nodes 01.Hower, 07.Day_after and, 08.Hower_after (tab. 1) are object of additional study and not connected in the MAR.NET model on the present stage of development. The rest of the nodes have conditional probability distributions of their states (tab. 3).

Table 3. Initial conditional probability table P(17.Body/18.Injure)

/	18.Injure 17.Body	A	В		Z
	A. Head	0.25	0.25	0.25	0.25
	B. Hands	0.25	0.25	0.25	0.25
	C. Legs	0.25	0.25	0.25	0.25
	D. Others	0.25	0.25	0.25	0.25
	Total	1	1	1	1

11.Incident is a multidimensional massive given by probability distribution (5).

The massive dimension is 18*14*15*5*2 = 37800. It is clear why for the experts is impossible to take into account all known configurations of conditional states.

The looses caused by the accident are described in utility node "Loses" (tab. 4)

The decision node 20.Measure – "Safety precautions (risk redusing measures)" is used for continuous evaluation of actions provided in safety programs.

Table 4. Utility table of node "Loses"

Body		А			
Injure	А		Р	А	
Loses	-90		-100000	-150	

The effects of actions are propagated in MAR.NET through chance node 11.Incident. A simple question can be given by defining of two states of decision node 20.Measure: Action 0 and Safety Program. It means to do nothing or to execute a safety program. The cost of actions are specified in utility node

"M.Cost" (tab. 5). The conditional independency of the nodes 09.Place and 20.Measure can be read of the graph in fig. 2.

Place		А		В		
Measure	Action 0	Safety Program	Action 0	Safety Program		
M.Cost	0	-5000	0	-10000		

Table 5. Utility table of the node "M.Cost"

With the decision node "RISK EVALUATION" the expected utility of risk evaluation procedures are evaluated. For example if two state "Yes" and "No" are assigned as the decision the utility function will calculate expected utility of both actions. The pressure for starting of risk evaluation renders the increasing of loosed working days – node 19. The expenses related with the procedures of evaluation are given from utility function by node "RE.Cost" as conditional distribution determined of predecessor nodes "RISK EVALUATION" \varkappa "09.Place" (see fig. 2 and tab. 6).

The choice of alternative decision is make on principle of maximal expected utility. The global utility function U is a total of all expected local utility (5).

Table 6. Utility table of the node "RE.Cost"

Place				С	
Risk Evaluation	YES	NO	YES	NO	
RE.Cost	-1000	0	-2500	0	

$$U = \sum u_i \tag{5}$$

$$u_i = \sum_j^i p_j u_j \tag{6}$$

where p_i is the conditional probability for occurrence of state

configuration c_j , and u_j - is the value of utility related with this realization. For example the distribution of utility node Loses contains j = 104 probability. But in calculation of U the local utility expected in nodes RE.Cost and M.Cost are taking into account, i.e. i = 3.

INFERENCE OF SAFETY LEVEL WITH MAR.NET

If a new prior information is available the procedure for statistical inference must be started in order to update the probability distributions in the net. The propagation of known probability according to the independency between the variable (given by the edges) is executed. The posterior probability distribution for all the nodes is as a result. The expert can see the probability of any configuration of the node states and evaluated utility of alternative decision actions.

An example for node 10.Job -" Kind of job during the incident" is given on figure 3.



Figure 3. Posterior probability distribution of node 10. Job.

LEARNINIG OF MAR.NET

The learning of the model can be done by 6 different ways. The first – imputing the known probability by hand for given configurations of states. According to dimensions of distributions this is a hard task. For the purpose of machine learning the special algorithms are developed. When the database for safety in the object is accessible, union of SQL queries can prepare the initialization of probability distributions. For the purpose of learning, the structure of MAR.NET is described in manner of (5) from the roots of network to the end child nodes. The SQL queries in the union follow described consequence. As a result the probability tables are formed.

Learning from data cases

This type of learning is appropriate for initializing of probability distribution after structure defining of the net. A set of variables for which the prior information is available is specified. For any of the nodes related to the specified set the experience table is assigned. The experience tables count the number of realization of any specified configuration of states in the set. Learning set of variables (nodes) in MAR.NET envelope all indicators (tab. 7).

N01	N02	N03	N04	N05	N06		N21
А	А	D	Q	Α	В		N/A
С		D	D	N/A	С		С

Table 7. Example of learning data cases for MAR.NET

Where N01..N21 is the internal name of the nodes.

When thee is no information about manifestation of some variable in the case the missing data is marked with "N/A" symbol. The codes A, B etc. corresponding with the labels of states of variables. The nodes represent the indicators (tab.1). The states are the characteristics of the indicators. The nodes and states of MAR.NET are compatible with databases of the software product for registering and analyzing of accidents Mine Accident Risk version 2002 (MAR). The product Mine Accident Risk are developed since 1995 in the department of "Mine Ventilation and Labour Safety" in MGU "St Ivan Rilsky". The learning metod of MAR.NET is known as EM-algorithm commonly used in Bayesian network for graphical associated models with missing data (Cowell and Dawid, 1992; Lauritzen, 1995). The target of algorithm is enriching of conditional probability tables assigned to the nodes of network. For this purpose the algorithm performed a number of iteration. In any iteration logarithm of probability the given example to produce the current probability distribution is calculated. The EMalgorithm tries to maximize this log-probability. The iterations

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stop when the deferens between log-probabilities obtained of two successive iterations became sufficiently small (for example of the order of 10⁻⁴). The EM-algorithm cannot learn the conditional distributions for continuous nodes. In MAR.NET there are no continuous nodes.

Learning adoption from data cases

Learning adoption of MAR.NET is necessary when a new accident is registered or new information from inspection, investigation or observation is available. The adoption of knowledge about the safety through consequtively updating of probability distributions in the net on the base of available experience is performed. The experience about a given discrete node is present as a set of counts for evidence $Alpha_0,...,Alpha_{n-1}$, where *n* is a count of configurations of the parent nodes. Alpha_i means the number of times a parent node to fail in *i*th state configuration конфигурация. The count has a sense of frequency and is a nonnegative real number. Alpha_i is stored in experience table assigned of the nodes determined for learning adoption. The nodes for which there are no experiences are adopted according the rules of probability propagation in the net as discussed above.

Entering expert opinions

The notion of experience in Bayesian networks can be introduced as a quantitative memory which can be based both on quantitative expert judgment and past cases. *Dissemination of experience* refers to the process of computing prior conditional distributions for the variables in the network. *Retrieval of experience* refers to the process of computing updated distributions for the parameters that determine the conditional distributions for the variables in the network (*Spiegelhalter and. Lauritzen, (1990)*).

The used in MAR.NET algorithm for entering the expert opinions allows control of the actuality of learned experience through special fading tables for reducing the impact of past. The fading factor *Deltai* is used for reducing the experience count *Alphai*. The fading factor *Deltai*, is a nonnegative real number between 0 and 1 but typically close to 1. The detailed description of the algorithm is given in *Spiegelhalter and*. *Lauritzen*, (1990).

Structure learning

A possibility to extract structure of the net from data cases is an exceptionally interesting feature of BBN. The data cases are structured in manner shown in tab. 7. The algorithms for structure learning of BBN are known as PC-algorithms (*Spirtes, C. Glymour and. Scheines (2000); Pearl (2000)*). The independency tests for variables in the model is performed. The test statistic is approximately χ^2 distributed and allows conditional independency. The recommended value of level of confidence in which the zero hypothesis for independence is rejected is *LC* = 0.05.

Some interesting results were obtained in structure learning of MAR.NEY with 122 data cases for registered accidents in coal mine of "Babino". The conditional dependency of following variables where accepted in LC = 0.05: Occupation \rightarrow Time of accident occurrence, Length of service \rightarrow Human factor, Education level \rightarrow Day after weekend \rightarrow Deviation from ordinary actions. In LC=0.1 new dependence between Time of accident occurrence \rightarrow Length of service in entertainment is accepted".

The structure learning gives an alternative way the experts to reconsider his conceptions for safety in given object using artificial intelligence. When the understanding of safety risks manifestation is changed, the model of MAR.NET on structural level also can be changed.

Simulation

Three approaches for obtaining simulated experience will be discussed. The first is by generating of simulated data cases and learning MAR.NET with EM-algorithm. The simulations are based on variations of the current prior distribution. The result of simulations must be in the format given in tab.7 in order to be useful from the learning algorithm. The simulation can be set to give a percent of missing data. The missing data imitate unknown probabilities for configuration of variable states and simulate uncertainty in the safety system. A more efficient approach is generating data cases by simulation models of real subsystems of the object. In both approaches the fixedness of safety system in case of occurrence of unregistered cases.

The third way of simulation is based on the powerful feature of Bayesian networks to derive conclusion against the direction of the edges. It can be simulate increasing of severity of accidents and after propagation of probability according Byes Theorem to obtain posterior distribution of the predecessor nodes of interest.

CONCLUSIONS

A system for decision support in mining safety MAR.NET is proposed. The system can be adopted for other branches saving the type nodes and the proposed structure. The states of the part the nodes can be different. It is recommended the learning of MAR.NET to realize on different copy of the system for open pit and underground coal mining and for metal and non-metal mining and quarries. Adoption of MAR.NET is adequate to realize for different objects on the learned instances of branch models.

There are not hidden layers in the MAR.NET. The structure is clear and ease to modify according to changes of expert opinions. The inference of safety level can be done in uncertainty, which is the usual case in safety management.

The well learned MAR.NET model can be used for education and training. The contemporary technologies allow the .NET models learned and adopted for different objects to communicate each other including via the Internet. Such a super-BBN in which the nodes are other BBNs can constitute intelligent net with distributed calculation and possibilities of knowledge exchange.

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