Bayesian Belief Networks as a Tool for Modeling Hazardous Natural Processes*

Viktoriya N. Taran[1][0000-0002-9124-0178]

[1] V.I. Vernadsky Crimean Federal University, Simferopol, Russia

victoriya_yalta@ukr.net

Abstract. The article discusses dangerous natural processes that have disastrous consequences, examples of such processes are given. The most significant factors that affect the activation of complex hazardous natural processes with catastrophic consequences are analyzed and highlighted. A model was built to predict the catastrophic consequences of dangerous natural processes using the Bayesian belief network. The vertices of the Bayesian network and the levels on which these vertices are located are determined. To determine the possible transitions in the network, an expert assessment of the values of the selected indicators was carried out. Based on expert assessments, the Bayesian network was trained. The "Investments" factor was proposed as a controlling operation on the network. The modeling and forecasting of possible scenarios for the development of complex natural processes and their catastrophic consequences were carried out. As a result of the study, a decision support system was developed for the proposed model of complex hazardous natural processes, the interface of the forecasting system, modeling and decision support was designed and programmed.

Keywords: Bayesian Belief Network, Complex Natural Systems and Processes, Modeling, Forecasting, Training Bayesian Network, Forecasting of Funds for the Rebuilding of Business Objects

1 Introduction

Various natural processes taking place on the North Black Sea Coast have a high level of unpredictability and uncertainty, which makes it difficult to study, model and forecast them. The presence of a stochastic component in the course of complex natural processes that have catastrophic consequences for the environment, the environment, and man does not allow us to obtain reliable results using traditional methods and models.

The opportunity to foresee the activation of complex natural processes on the North Black Sea Coast with catastrophic consequences allows by minimizing these consequences by carrying out special protective measures, thereby protecting human life, which will also allow using the unique coast recreation territory for the rest of tourists. Earthquakes, landslides, mudslides, natural fires, hurricanes, processing of the coastal zone of the sea, snow avalanches, extreme air temperatures [1] cause significant damage to human economic activity, do not allow the recreational territories to be fully and qualitatively used.

The northern Black Sea coast has a unique geographical location and a special medical climate and is also a recreational and well-known tourist region. Also, on the coast, there is a dense network of roads, and the population density is more than 2 times higher than the average for the Northern Black Sea region. Consequently, complex natural processes with catastrophic consequences pose a significant threat, destroying roads, buildings, and structures, causing great harm to their operation and threatening in some cases human life.

Constant changes in geological, climatic, ecological and technogenic processes negatively affect the economic objects and complex engineering structures, on which human life and health depend [3]. Complex hazardous natural processes that have catastrophic consequences, are complex random in nature, depend on many factors, contain a large proportion of uncertainty, and therefore it is very difficult to predict.

The task of studying the dynamics of complex hazardous natural processes and their modeling, as well as estimating the amount of money needed for different areas to prevent or cover material damage from the destruction of economic facilities, is a difficult task. It is due to the need to develop new approaches, methods, models, algorithms, intelligent systems that can increase the efficiency of the process of developing and making management decisions in terms of risk and various types of economic and environmental uncertainties.

Studies on modeling and forecasting complex hazardous natural processes in the Northern Black Sea region often have a narrow focus on cartographic research and geologist's expert assessment, which is based on observations, monitoring and shows the limited use of modern information technologies used in intelligent decision-making systems, and also indicates the absence systematic approach to solving the problem. The use of Bayesian belief networks will allow us to solve the task by obtaining probabilistic estimates of possible variants of the course of the events and processes under consideration.

A model based on the Bayesian belief network allows you to combine both statistical data and expert assumptions about the nature of behavior and the relationships between elements [2,3]. Bayesian networks are one of the representations of knowledge bases with uncertainty [4]

The purpose of this study is to build a Bayesian belief network form the basis of an analysis of factors and indicators as a model, which characterizing the occurrence of complex natural phenomena and processes on the North Black Sea Coast.

This information system will contain modules of expert assessments and recommendations on preventing or forestall and minimizing losses from the catastrophic consequences of complex natural processes.

2 Construction of the Bayesian belief network for modeling and forecasting complex natural processes

2.1 The Bayesian Belief Network

Bayesian networks (BNs), also known as Bayesian belief networks or Bayes nets, are a kind of probabilistic graphical model that has become very popular to practitioners mainly due to the powerful probability theory involved, which makes them able to deal with a wide range of problems. BNs have barely been used for Environmental Science and their potential is, as yet, largely unexploited [5].

Bayesian networks (BNs) are widely used as one of the most effective models in bioinformatics, artificial intelligence, text analysis, medical diagnosis, etc. Learning the structure of BNs from data can be viewed as an optimization problem [6].

Because a Bayesian network is a complete model for the variables and their relationships, it can be used to answer probabilistic queries about them. For example, the network can be used to find out updated knowledge of the state of a subset of variables when other variables (the evidence variables) are observed. This process of computing the posterior distribution of variables given evidence is called probabilistic inference. A Bayesian network can thus be considered a mechanism for automatically applying Bayes' theorem to complex problems. In the application of Bayesian networks, most of the work is related to probabilistic inferences. Any variable updating in any node of Bayesian networks might result in the evidence propagation across the Bayesian networks [7].

Bayesian networks are one of the representations of knowledge bases with uncertainty [4]. The Bayesian network was mainly employed as a statistical scheme for probabilistic forecasting that can represent the cause-effect relationships between the variables [8]. Bayesian networks have become a commonly used tool for inferring the structure of gene regulatory networks from gene expression data. In this framework, genes are mapping to nodes of a graph, and Bayesian techniques are used to determine a set of edges that best explain the data, that is, to infer the underlying structure of the network [9].

The Bayesian Belief Network is an oriented acyclic graph whose vertices are discrete random variables X with a finite number of states, and U-edges are cause-effect relations between them, characterized by a table of unconditional probabilities of transitions from one state to another under the influence of perturbations. So, the Bayesian network is a pair (G, P), where $G = \langle X, U \rangle$ is a directed acyclic graph on a finite set X whose elements are connected by a set of oriented edges U, and P is the set of conditional probability distributions [10,11].

Under uncertainty, the basis for decision-making with the help of the Bayesian belief network is the calculation of the probabilities of transition strategies from one to the other state of the system [12]. Uncertainty is uncovered by calculating the probabilities of vertex states based on available information about the value of other vertices of the network, thanks to this message, the system proceeds to the next state [13].

2.2 Building the Bayesian Belief Network

As the factors having a strong influence on the course of complex natural processes of the North Black Sea Coast, accompanied by catastrophic consequences, the following should be noted:

· precipitation (it makes sense to consider the amount of precipitation for the hydrogeological year, ie from September of the previous year to August of the current year);

· solar activity (catastrophic natural phenomena directly depend on solar activity and its 11-year cycle [13]);

· seismic activity;

· level of landslide activity during the previous period; invested funds in strengthening slopes, structures and roads [1,12].

It also makes sense to consider the intermediate and resulting indicators that will be located on the following levels of the Bayes confidence network:

· time intervals during which a catastrophic event is possible;

· the level of natural risk in probabilistic interpretation, i.e. probability of the occurrence of a particular natural process or phenomenon;

· the final level of monetary investment to eliminate the catastrophic consequences of events that have already occurred and phenomena [1,12].

So, we construct a Bayesian belief network for modeling and forecasting, based on the factors considered, as well as for predicting the level of possible consequences, which will make it possible to formulate recommendations on investing funds for protective and fortification measures.

We build a Bayesian belief network on the considered factors for modeling and forecasting, as well as for predicting the level of possible consequences. This will make it possible to formulate recommendations on investing money for protective and fortification measures.

In constructing the Bayesian belief network, we arrange the primary (initial) factors on the upper (first) level, i.e. we will place precipitation, solar activity, seismic activity, landslide activity and invested funds at the top level of the network. Each of these factors has characterized by an unconditional probability, obtained from statistical data as a result of long-term observations. Define the qualitative values of the factors in the form: Small, Average and Catastrophic (catastrophically many). The exception is the top "Invested funds", for which we choose the values: "In_Full", "Average", "Small".

Thus, the Bayesian belief network for modeling the catastrophic natural processes of the North Black Sea Coast has presented (see **Ошибка! Источник ссылки не найден.**) (using the shareware program Netica).

At the second level, we place one vertex: "Natural Risks", which will take on values similar to natural factors. At the third level - "Time limits", which will take values: two days, a week, a month and will not happen at all. As the resultant indicator, take the "Final_Amount_of_Money", i.e. the total amount spent on preventing and eliminating catastrophic consequences.

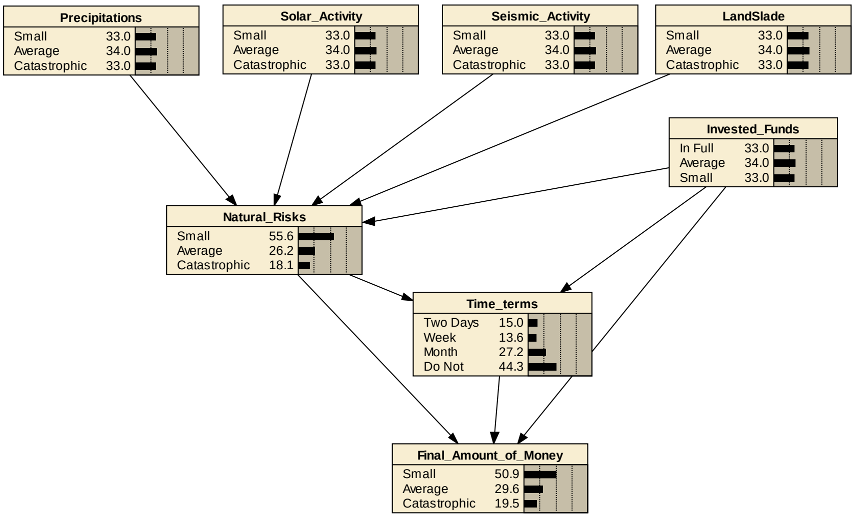
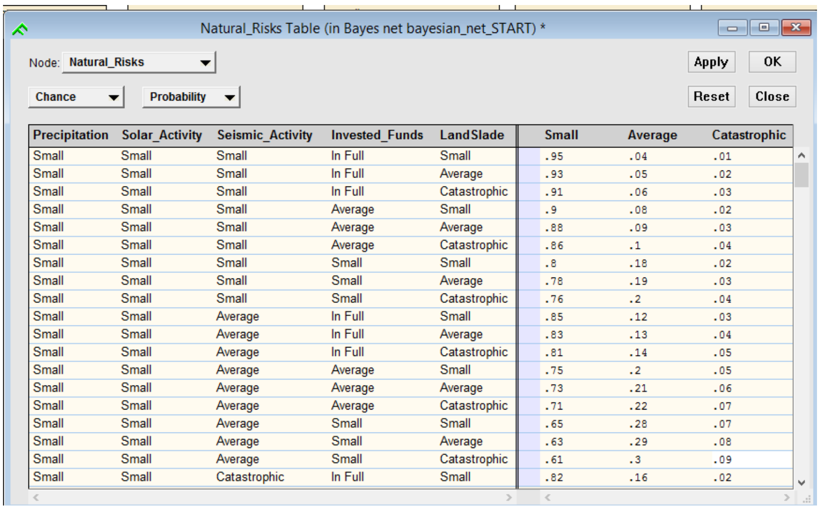


Fig. 1. The initial state of the Bayes confidence network for modeling complex natural processes that have catastrophic consequences on the southern coast of the Crimea

To train the network, fill in the tables of conditional probabilities with the help of experts for each vertex, except for the vertices of the first level. For example, the top "Natural Risks" has 35 rows of conditional probabilities (for each top-level factor) (see **Ошибка! Источник ссылки не найден.**).



Natural_Risks Table (in Bayes net bayesian_net_START) *

Node: Natural_Risks

Chance Probability

Apply OK Reset Close

Precipitation	Solar_Activity	Seismic_Activity	Invested_Funds	LandSlade	Small	Average	Catastrophic
Small	Small	Small	In Full	Small	.95	.04	.01
Small	Small	Small	In Full	Average	.93	.05	.02
Small	Small	Small	In Full	Catastrophic	.91	.06	.03
Small	Small	Small	Average	Small	.9	.08	.02
Small	Small	Small	Average	Average	.88	.09	.03
Small	Small	Small	Average	Catastrophic	.86	.1	.04
Small	Small	Small	Small	Small	.8	.18	.02
Small	Small	Small	Small	Average	.78	.19	.03
Small	Small	Small	Small	Catastrophic	.76	.2	.04
Small	Small	Average	In Full	Small	.85	.12	.03
Small	Small	Average	In Full	Average	.83	.13	.04
Small	Small	Average	In Full	Catastrophic	.81	.14	.05
Small	Small	Average	Average	Small	.75	.2	.05
Small	Small	Average	Average	Average	.73	.21	.06
Small	Small	Average	Average	Catastrophic	.71	.22	.07
Small	Small	Average	Small	Small	.65	.28	.07
Small	Small	Average	Small	Average	.63	.29	.08
Small	Small	Average	Small	Catastrophic	.61	.3	.09
Small	Small	Catastrophic	In Full	Small	.82	.16	.02

Fig. 2. Training Bayesian network (conditional probabilities for the top "Natural_Risks")

2.3 Simulation of complex natural processes using the constructed Bayesian belief network

Based on the developed Bayesian network of beliefs, we will build a forecast of the possible development of complex natural processes on the North Black Sea Coast. First, we consider catastrophic changes in only one factor, i.e. the selected factor takes the value "Catastrophic" with a probability of 100%, and the rest - the values corresponding to the average statistical observations (The following Table 1).

Table 1. Results of Modeling with the Bayesian Belief Network.

Factor values as Catastrophic (Catastrophic=100%)	Natural_Risks			
	Small	***Average***	***Catastrophic***	
Precipitation	32.4%	29.7%	37.9%	
Solar_Activity	42.2%	25.6%	32.1%	
Seismic_Activity	50.2%	27.8%	21.9%	
Landslide_Activity	55.5%	26.3%	18.2%	
All factors	4.0%	6.0%	90.0%	
Factor values as Catastrophic (Catastrophic=100%)	**Time_terms**			
	2_Day	***Week***	***Month***	***Do_Not***
Precipitation	25.1%	17.4%	23.8%	33.7%
Solar_Activity	26.1%	16.0%	24.8%	37.6%
Seismic_Activity	17.0%	14.4%	26.6%	42.0%
Landslide_Activity	15.0%	13.6%	27.1%	44.3%
All factors	64.6%	20.0%	9.4%	6.0%
Factor values as Catastrophic (Catastrophic=100%)	**Final_Amount_of_Money**			
	Small	***Average***	***Catastrophic***	
Precipitation	39.4%	31.3%	29.3%	
Solar_Activity	43.6%	30.4%	26.1%	
Seismic_Activity	48.5%	30.1%	21.4%	
Landslide_Activity	50.9%	29.6%	19.5%	
All factors	10.5%	19.5%	70.0%	

We will determine the consequences of these changes. In the next step, we consider what happens to the vertex values that are at the lower levels, if all factors simultaneously take on catastrophic values, and the top “Invested Funds” - “Small”.

As can be seen from the table, catastrophic changes of only one factor do not always lead to catastrophic destruction, which requires an immediate investment of funds to eliminate them. But at the same time, the probability of activation of any complex natural processes increases substantially, and as a result, the level of total cash flows increases.

If we assume that at the same time, the average values for all the top-level factors are significantly exceeded, the resulting indicators make a sharp jump in the direction of not only the activation of processes and investments but at the same time, there is practically no time left for preventive and strengthening measures. The result of the simulation is shown (see **Ошибка! Источник ссылки не найден.**).

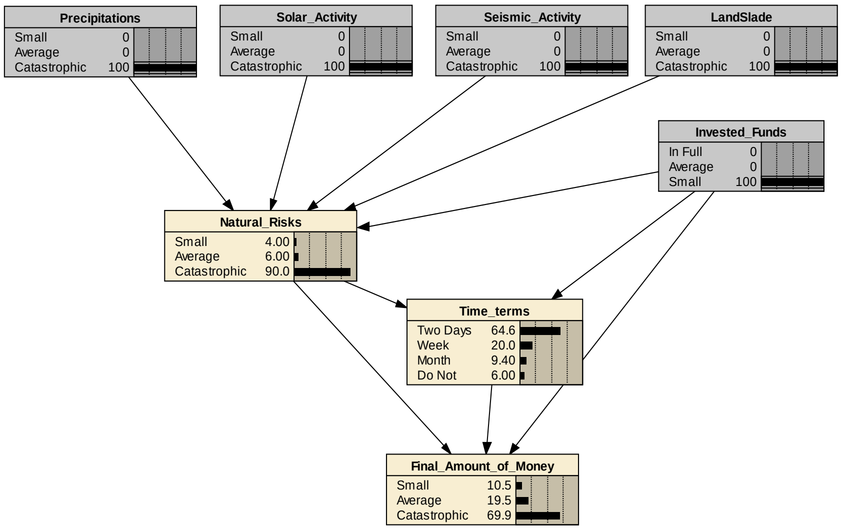


Fig. 3. Simulation of complex natural processes.

Based on the considered options for changing factors, it can be concluded that preventive measures about strengthening measures will help reduce overall costs by reducing the catastrophic consequences of the devastation resulting from the activation of complex natural processes

3 Modeling with the FCLSSCC decision support system based on the Bayesian Belief Network

To simulate catastrophic natural processes, including landslide processes that cause the greatest damage to human economic activities and threaten his life, the decision support system FCLSSCC (see **Ошибка! Источник ссылки не найден.**) was developed, which builds a long-term forecast based on classical statistical methods based on regression analysis, integration of analogs, autoregression, methods of taking into account group arguments, etc., as well as a short-term forecast based on a Bayesian network of beliefs. In this case, the system also allows you to make a short-term forecast based only on one of the selected factors listed. If, for example, there was a sharp catastrophic increase in this factor with the other values remaining unchanged.

This decision support system allows you to simulate the resulting values in the form of probabilities of the onset of alternative scenarios for the development of the process and its catastrophic consequences. For example, we choose the factor of precipitation and its value - “not active, but more than three consecutive days”, seismic activity (tremors) - “strong and short”, solar activity “high”, Landslides of the previous period - “a lot”, and previous investments in reinforcing activities were made small.

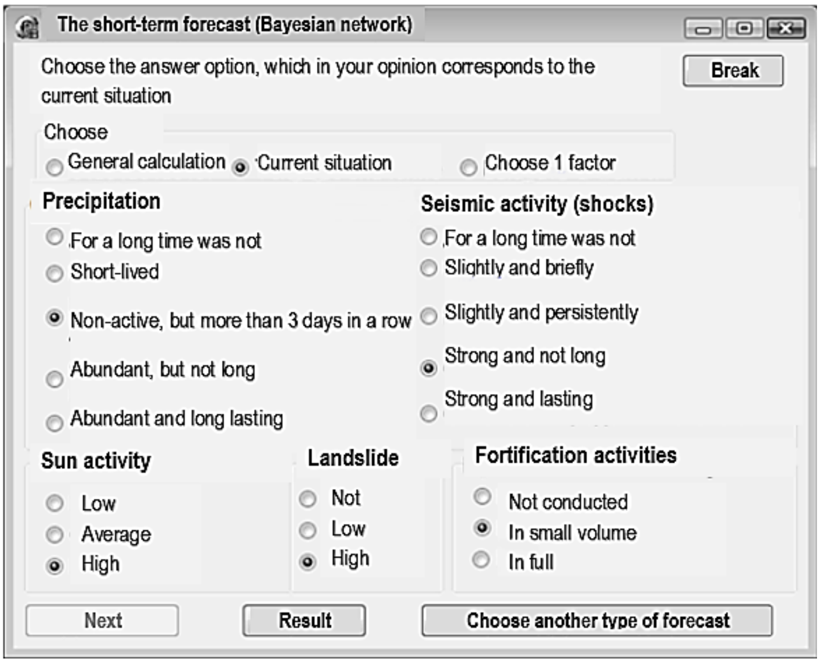
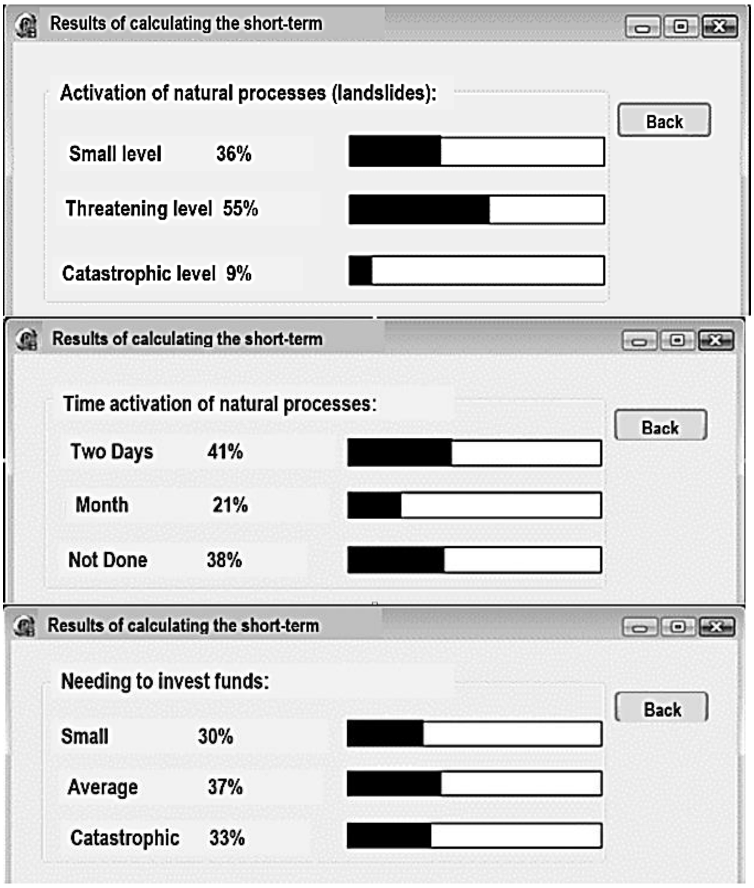


Fig. 4. Modeling with the FCLSSCC decision support system based on the Bayesian confidence network when introducing the values of the first-level factors.

If the choice of parameter values is made, then you can click on the corresponding transition and get the result, which will be presented in the form of the probability of occurrence of each of the proposed scenarios for the selected criteria or result indicators. We calculate the estimates of three criteria: the probability of manifestation of natural risks (complex natural processes - landslides with catastrophic consequences), the time during which these processes will be and the total amount of expenditures are possible. The estimates obtained are shown (see **Ошибка! Источник ссылки не найден.**).

Thus, we have the most likely outcome of "Activation of natural phenomena" Threatening = 55%, and Catastrophic = 9%; "Times_Risk" show “Two_Days” = 41% activation will occur; "Amount_Invested" Catastrophic = 33% or Average = 37%. The presented calculations show the need to invest advance funds in reinforcement measures.



a)

b)

c)

Fig. 5. Results of modeling using the Bayesian belief network: a) calculation of the possible level of active landslides; b) the time interval for the expected activation of landslides; c) the probability of total investing funds to eliminate catastrophic consequences

4 Conclusions

So, to take into account the uncertainty and randomly manifested risks of activation of complex natural processes, it is possible to use Bayes confidence networks in modeling and forecasting catastrophic consequences of natural processes [12].

The constructed Bayes confidence network and its training by filling in the tables of conditional probabilities by experts and the introduction of numerical values of factors for determining the unconditional (a priori) probabilities of the factors under consideration made it possible to obtain a forecast concerning the occurrence of catastrophic natural processes. The analysis showed that the use of the Bayesian belief network in modeling under conditions of uncertainty is becoming increasingly popular and meets the objectives. The Bayesian network is also useful when predicting processes of various origins, including complex hazardous natural processes, which allows one to take into account the structural and statistical uncertainties of the phenomena studied [1].

Thus, when using the decision support system and creating a single technical bureau for information processing and forecasting, it is possible to envisage the number and nature (i.e. consequences) of the activation of complex hazardous natural processes; the time during which they can occur, as well as optimize the costs of implementing measures to overcome the catastrophic consequences of exogenous processes taking place in the mountainous regions of the Northern Black Sea Region [14].

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