Modeling of Complex Systems over Bayesian Belief Network

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Abstract. The article analyzes the factors that have an impact on the activation of complex natural processes and their catastrophic consequences. Solar activity, precipitation and seismic activity have chosen as the most significant factors, a sharp increase in which leads to activation of natural processes such as landslides, mudflows, natural and forest fires, snow avalanches, hurricanes, tornados, squalls, volcanic eruptions, etc. Intermediate and resulting indicators have chosen to describe and evaluate the course of the processes under consideration: Natural Hazards, Time Frame and Cash. The construction of the Bayesian Belief Network for modeling of complex natural processes on the Northern Mountainous Coast of Black Sea, its structure and training by filling in probability tables are considered. Experts fill conditional probabilities for dependent or intermediate vertices. The values of unconditional probabilities have filled according to observation data for top-level vertices. The managing or controlling factor is determined as Funds Invested and its importance has discussed. Simulation of various scenarios of the course of natural processes has carried out, for which the probability of occurrence of certain states of the resulting outcome indicators is calculated.

Keywords: Modeling · Forecasting · Complex systems · Catastrophic consequences of complex natural processes · Landslide processes · Bayesian Belief Network

1 Introduction

The Northern Coast of the Black Sea, with its unique climate conditions, historical, natural and economic resources, is the region most often affected by natural disasters and exogenous processes. In addition, this narrow strip of the coast has more than 50% of all peninsula roads, and the urbanization density is more than double that of the average for the Northern Mountainous Coast of Black Sea [1]. Thus, complex natural processes pose a significant threat; they destroy not only roads, but also buildings and all kinds of structures, and cause great damage to their operation [2]. Despite the development of modeling and forecasting methods, the prediction of the natural processes activation, which can entail catastrophic destructive consequences, detrimental to economic activity, is one of the main problems of the modern scientific world. The identification of all factors, the determination of the degree of their influence on the course and activation of

V. Sukhomlin and E. Zubareva (Eds.): SITITO 2017, CCIS 1204, pp. 192–202, 2021.
https://doi.org/10.1007/978-3-030-78273-3_19

catastrophic processes and the forecasting of possible consequences remain an ongoing challenge and an actual task, and, moreover, the work is made more complex by the risk that there are some unforeseen situations in the system, which is also a complex task of analyzing the random dynamic processes [3].

There is a narrow focus of research on the forecasting of complex natural processes in the Northern Mountainous Coast of Black Sea, observation, monitoring, cartographic studies and expert evaluation of a specialist. The weak link in this area is the limited use of modern information technologies and intellectual decision-making systems, the lack of a systematic approach [4, 5].

This Article seeks to analyze the factors having a direct impact on the activation of complex natural processes, the modeling of these processes with the help of the Bayesian Belief Network, and building a forecast model.

2 Identification of Factors Affecting the Activation of Catastrophic Natural Processes

Complex natural processes taking place on the Northern Mountainous Coast of Black Sea and in other regions are of a complex random nature. They depend on many factors, have considerable uncertainty, and therefore are very difficult to forecast [5].

Let us highlight the complex natural processes leading to catastrophic consequences:

- hydrometeorological hazards;
- flooding;
- low water;
- landslips;
- processing of shores of seas and reservoirs;
- natural fires;
- mud flows;
- snow avalanches;
- earthquakes;
- tsunami;
- hurricanes, tornadoes, squalls;
- volcanic eruptions;
- extreme air temperatures [6].

It was been revealed that the occurrence of any catastrophic natural phenomena, as well as landslide processes, directly depends on the solar activity and its 11-year cycle. Thus, we name the solar activity as the first and the main factor [1, 5].

In addition to the solar activity, rainfalls of two opposite types have a great influence:

- summer showers, as a result of which the land is not soaked, and large streams of water rushing from the mountains carry the top layer of the soil to the sea, washing away its organic component and eroding ravines;

- winter drizzling rain, which moisten the soil abundantly, deeply soaking it and filling the underground karst cavities – in that way natural water reservoirs for the summer appear; they create soil strains, resulting in land movements - spring land-slides, downfalls and mud flows.

Another factor to be consider is seismic activity. The Northern Mountains of Black Sea are relatively young mountains, and they react to earthquakes. But we will only consider earthquakes with epicenters, located not more than 200 km from the Coast and with a magnitude not exceeding 8,5 K, i.e. the level of released energy in the epicenter corresponds to 8.5 K.

As a factor of the so-called regulation of natural processes or management, consider the following factor: investing in fortification and protective structures. All these factors are attributing to the primary or most significantly affecting the activation of catastrophic natural processes, a drastic change of which leads to a change in the course of these processes and their activation.

There are a large number of observation stations for monitoring the natural conditions on the Black Sea's northern mountain coast, such as: meteorological stations, a seismic station, observatories and research institutes. Meteorological stations are equipped with modern instruments for collecting weather data. The seismic station is equipped with accurate and sensitive sensors, which have no analogues on the North Coast of the Black Sea. The hydrogeological research department examines landslide processes from the geological point of view, monitors and keeps records of these processes since 1945. Observatories conduct observations of solar activity, have a large set of monitoring data since 1900. The branch of the Institute of Marine Geology and Geophysics is engaged in studying and monitoring the states of the earth's surface, sea currents and changes in the relief of the seabed.

Therefore, we chose such factors as precipitation, solar activity, seismic activity for modeling and forecasting complex natural processes. Many scientists use these factors to build their models and make calculations for the forecast.

All these indicators are processing independently of each other, although the single center for the study of natural phenomena of the Northern Mountainous Coast of Black Sea could solve the problems of forecasting and predicting natural processes that entail catastrophic consequences. In this case it is not possible to apply classical regression analysis or autoregressive models, which are used most often in the field, since the error of such calculations is too great, in addition, the forecast interval is often too large or whether, on the contrary, too small for timely decision-making and implementation of the decision.

3 Building a Bayesian Belief Networks

The logical-probabilistic approach, in which the propositional formulas (given over a certain alphabet) are the model of the statement, is of particular interest from the point of view of modeling the reasoning process of the expert. This is traditional for formal logic and the degree of confidence in the truth (or stochastic uncertainty of the truth) of these propositional formulas and the bond strength between them are characterizing by probability estimates: both scalar (point) and interval [7]. Due to their high transparency, the ability to combine empirical data with expert knowledge and their apparent relevance to uncertainty, Bayesian Belief Networks can make a significant contribution to the study and modeling of complex systems of a different nature [11].

A Bayesian Belief Network (BBN) is represented by a pair (G, P), where $G = \langle X, E \rangle$ is a directed acyclic graph on a finite set X (its vertices are the listed factors and the expected intermediate and result indicators) connected by a set of oriented edges E, set of conditional probability distributions. Thus, Bayesian Networks are a convenient tool for describing complex processes and events with uncertainties. To describe the Bayesian Network, it is necessary to determine the structure of the graph and the parameters of each node. This information can be obtaining directly from data or from expert estimates [8]. A graph has written as a set of conditions for independence, as each variable is independent of its parents G. The second component of the pair is a set of parameters that defines the network. From a mathematical point of view, BBN is a model for representing probabilistic dependencies, as well as the absence of these dependencies. At the same time, the link $A \rightarrow B$ is the cause, when the event A is the cause of the occurrence of B, affects the value accepted by V. BBN is called the cause (causal), when all links are causal [9].

To make decisions using a Bayesian Belief Network in conditions of uncertainty, the basis is the calculation of the probabilities of the transition strategies from one to the other state of the system. Evaluation of indeterminate forms in the BBN has performed by calculating the probabilities of the states of vertices based on available information about the value of other vertices of the network, thanks to these messages, the system proceeds to the next state [10].

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 [11, 12]. Bayesian networks are one of the representations of knowledge bases with uncertainty [13].

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 [14, 15].

We construct the graph of the Bayesian Belief Network in the form of a "tree", where the top-level contains the vertex-factors with unconditional probabilities, which are determined at the beginning of the simulation from experiments or observation results. These are the factors listed above: Solar activity, Seismic activity and Precipitation and Invested funds. We will work with the *Netica* program, which is a shareware product. At the second level, we place one vertex: "Natural risks", i.e. we can expect the activation of natural processes and the risk of causing catastrophic destruction. The next level will also consist of only one vertex: "Time Terms" - the forecast of the time interval, during which the catastrophic consequences of the course of natural processes will manifest (or not manifest).

The last fourth level is the result of modeling "Total Cash", i.e. the final amount of funds that will be required to eliminate catastrophic consequences, including the funds invested in reinforcement measures.

Each of the listed vertices, except for "Investment" and "Time Terms", will have three types of values: Few, Medium and Catastrophic. "Investment" will contain such values: "In Full", "Medium", "Few". For the vertex "Time Terms", we define the following possible values: "Two days", "Week", "Month", "Do Not". The Bayesian network, taking into account all the above, is shown in Fig. 1.

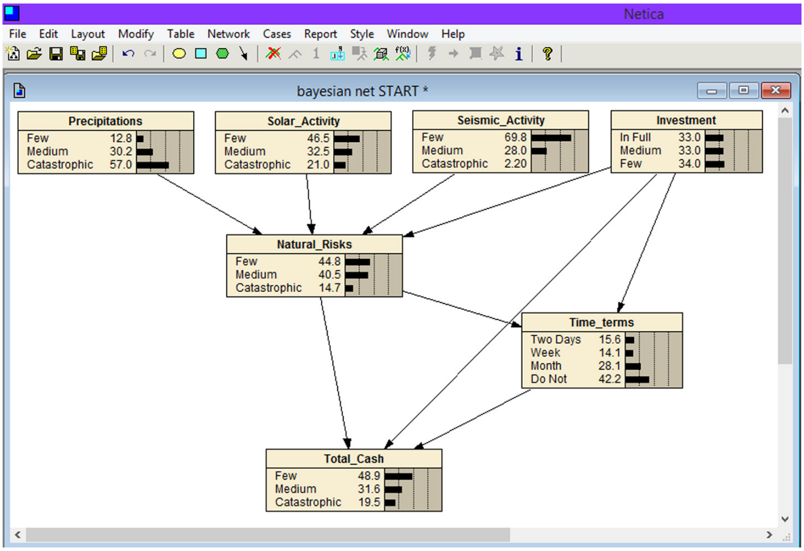
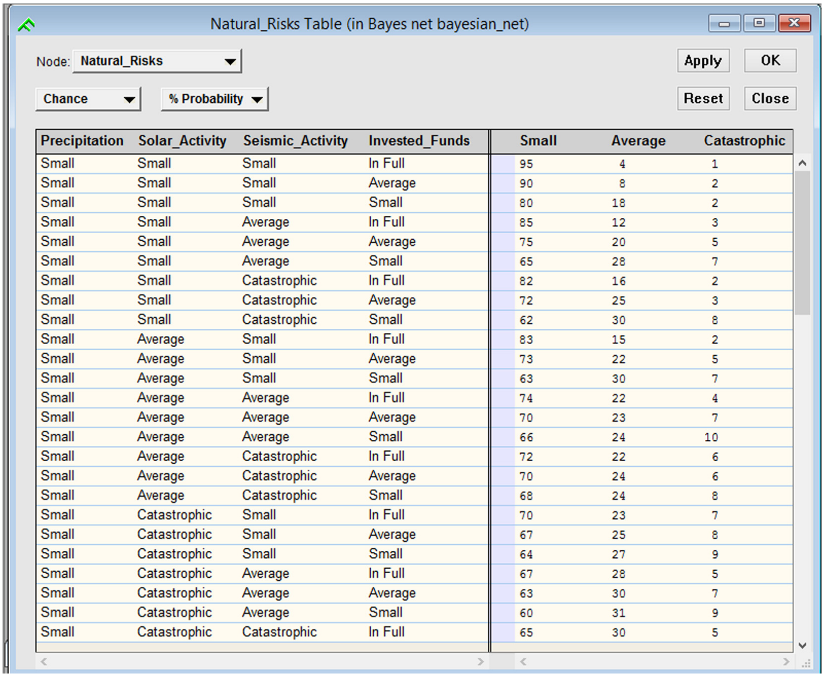


Fig. 1. Bayesian Belief Network for complex natural processes modeling.

The Bayesian network training is done by filling in conditional probability tables for the vertices of the middle and lower levels and unconditional probabilities for the vertex-factors that lie at the upper level (from the results of observations). Tables are filled using expert evaluations, exhibited by experts (Fig. 2). At the same time, if the vertex has three variants of values, then the training table will include $3n+1$ conditional probabilities, for which the condition should be fulfilled: the sum in the line is 100 (100%). For example, the probability table for the "Natural Risks" vertex has $3n$ lines, i.e. $3^4 = 81$ lines, and each line has three probability values, the total number of probability values is 243. The main distinguishing feature of the proposed model is the distribution of all values for each graph node into three groups, and for the vertex "Temporary risks" – there are even by four, while the classical Bayesian networks operate with only two values of the variables: 0 and 1. By increasing the number of values that can take by graph nodes (the vertex) the size of the tables of conditional probabilities increases dramatically. This concerns the vertices of the second, third and fourth levels. We will perform simulations with the help of the shareware pro-gram Netica.



Precipitation	Solar_Activity	Seismic_Activity	Invested_Funds	Small	Average	Catastrophic
Small	Small	Small	In Full	95	4	1
Small	Small	Small	Average	90	8	2
Small	Small	Small	Small	80	18	2
Small	Small	Average	In Full	85	12	3
Small	Small	Average	Average	75	20	5
Small	Small	Average	Small	65	28	7
Small	Small	Catastrophic	In Full	82	16	2
Small	Small	Catastrophic	Average	72	25	3
Small	Small	Catastrophic	Small	62	30	8
Small	Average	Small	In Full	83	15	2
Small	Average	Small	Average	73	22	5
Small	Average	Small	Small	63	30	7
Small	Average	Average	In Full	74	22	4
Small	Average	Average	Average	70	23	7
Small	Average	Average	Small	66	24	10
Small	Average	Catastrophic	In Full	72	22	6
Small	Average	Catastrophic	Average	70	24	6
Small	Average	Catastrophic	Small	68	24	8
Small	Catastrophic	Small	In Full	70	23	7
Small	Catastrophic	Small	Average	67	25	8
Small	Catastrophic	Small	Small	64	27	9
Small	Catastrophic	Average	In Full	67	28	5
Small	Catastrophic	Average	Average	63	30	7
Small	Catastrophic	Average	Small	60	31	9
Small	Catastrophic	Catastrophic	In Full	65	30	5

Fig. 2. Filling in the conditional probabilities tables of the Bayesian Belief Network.

After filling all the tables of conditional and unconditional probabilities, we get this result. The probabilities for the vertices are distributed as follows:

- "Natural risks": "Few" - 44.8%, "Medium" - 40.5%, "Catastrophic" - 14.7%;
- "Time Terms": "Two Days" - 16.6%, "Do Not" - 42.2%;
- "Total cash": "Not much" - 48.9%, "Medium" - 31.6%, "Catastrophic" - 19.5%.

This indicates that with generalized input data, sharp catastrophic destruction from natural processes is not expected. The investment is at an average level, no special costs are required to eliminate the consequences of complex natural processes.

4 Simulation of Complex Natural Processes Using the Bayesian Belief Network

To construct an operational forecast, after filling in all tables of conditional probabilities, you must enter new input values. We set the initial conditions for the upper level for operational (short-term) modeling.

Let, for example, there have been strong (catastrophic) atmospheric precipitation against the background of sharply increased solar activity, while the seismic activity is medium, and the investments have been at a low level. The result of the forecast shows that the activation will take place at a catastrophic level "Natural Risk" (65%), with the probability of small and averages disruptions of 10% and 25%, respectively, and it should be expected within the next two days (52.1%), the greatest probability of destruction requiring additional large scale investments (56.0%), as shown in Fig. 3.

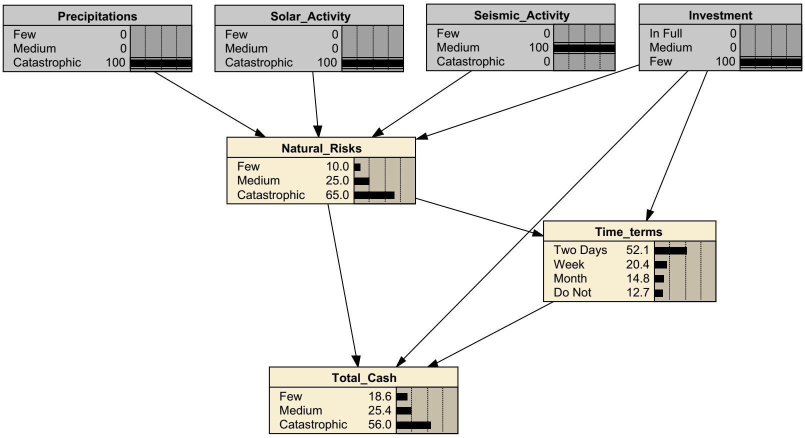


Fig. 3. The Bayesian Belief Network for predicting the course of complex natural processes and their consequences.

Let's consider three scenarios:

– funds are invested in small (insufficient) volume (Few);
– funds are invested in average volume, but, maybe, at the wrong time (Medium);
– funds are fully invested (In Full).

Let's consider the probabilities of the three remaining nodes of the Bayesian network: "Natural Risks", "Time Terms" and "Total Cash". The obtained results are tabulating in the constructed Table 1, which reflects the changes in the control factor and its influence on the vertices of the lower levels. We leave the previously selected values for the first level vertices. Let's construct the forecast for the received model, we will change only values of the controlling factor.

Thus, we can see from the table that with a small investment of funds, the level of "Natural Risks" is threateningly increasing to 65%, i.e. the probability of catastrophic destructions caused by natural processes increases to 65%. At the same time, natural processes with catastrophic consequences are expecting to occur within two days with a probability of 52.1%, within one week – 20.4%, which indicates the necessity of mandatory preventive measures, and possibly the need to prepare and mobilize forces for future elimination of such consequences. The total amount of cash will be required at the same time in a catastrophic amount with a probability of 56.0%, and only slightly more than 20% the probability of an average cost level.

With medium-sized investments, (i.e. funds are providing, but maybe not always on time and not always in full), the reviewed indicators are less threatening. The probability of catastrophic consequences is reducing to 54%, the waiting period for the manifestation

Table 1. The results of the forecast when the managing factor “Investment” changes.

Investment		Few (100%)	Medium 100%)	In_Full (100%)
Natural risk, %	Few	2	14	20
	Medium	25	32	38
	Catastrophic	65	54	42
Time frame, %	2 days	52.1	32.1	16.6
	Week	20.4	22.1	17.2
	Month	14.8	20.8	27.6
	Do Not	12.7	25.0	38.6
Cash, %	Few	18.6	30.3	42.3
	Medium	25.4	34.2	36.5
	Catastrophic	56.0	35.5	21.2

of these processes is up to 32.1% and 22.1%, and the catastrophic total costs are reducing to 35.5% (Fig. 4).

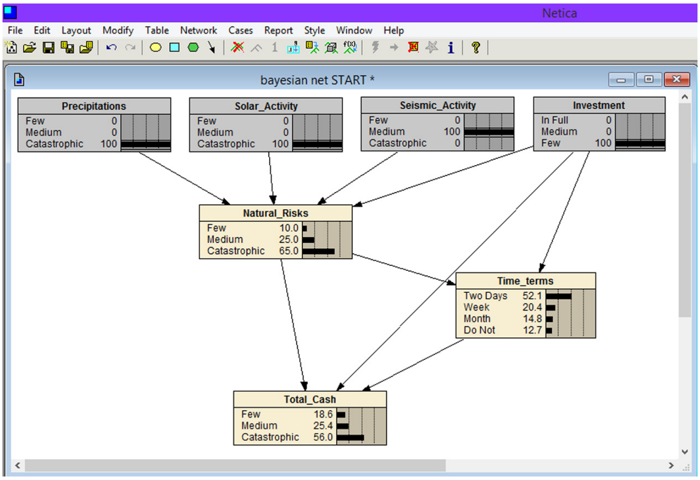


Fig. 4. Modeling Bayesian Belief Network

These values of the considered graph vertices depend not only on the controlling factor “Invested funds”, but also on the current state of nature, which is describing by rest of the vertices of the first level.

The table shows that atmospheric precipitation and solar activity necessarily lead to activation of complex natural processes, but the level of destruction and cata-strophic consequences can will been significantly reduced if the strengthening measures have been taken place in advance, i.e. funds investment, strengthening the most dangerous sections of roads, communications, retaining walls, structures, etc.

If we set a goal: to find out what possible characteristics we get, if we want to minimize total costs, then the Bayesian networks allow us to recalculate the probability of the graph state even for top-level vertices, i.e. in the opposite direction. Figure 5 shows the result of the simulation. Yes, indeed, preliminary investments must be made in a much larger volume, but at the same time, the natural risks of activating natural processes that have catastrophic consequences are reduced up to 22.5%, and the occurrence time of catastrophic consequences is delayed by a month (28.6%), or such natural disasters won't even occur (43.0%).

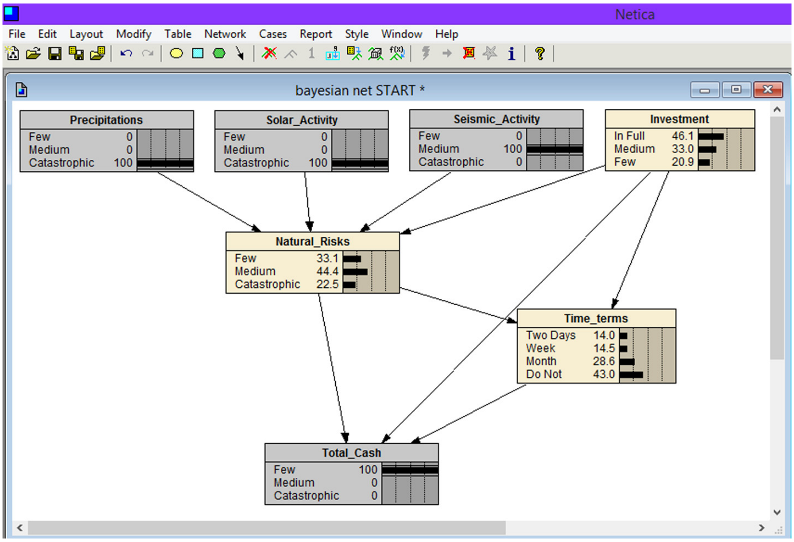


Fig. 5. The Bayesian Belief Network for assessment of the minimization of the total amount of money.

5 Conclusion

Thus, the factors were been identified, which have the greatest impact on the activation of natural processes with disastrous consequences. The Bayesian Belief Network was been built to model complex natural processes on the Northern Mountainous Black Sea Coast. A graph was been drawn up for the Bayesian Belief Network, and the network was trained by filling in tables of unconditional and conditional probabilities. The states of the vertices of the Bayesian Belief Network was been defined and the corresponding calculations were made for them. The controlling factor was been chosen as "Investments". The calculation of the management strategy was been carried out using the indicator: "Investments to strengthen hazardous zones" (pre-invested funds).

The Bayesian network makes it possible to update the decision-making strategies in accordance with the selected criteria after obtaining new observations for the hydrometeorological, seismic, solar and complex natural processes of the Northern Mountainous Black Sea Coast. The model obtained helps to optimize the costs of preventing the catastrophic consequences of complex natural processes or their elimination. The resulting Bayesian network can easily will been expanded with the help of new vertices taking into account new information on the state of the flow of the process under investigation [4].

Therefore, the Bayesian Belief Network can been used to model complex processes and systems under uncertainty. Thus, such a model is becoming increasingly popular. Bayesian networks would also be useful for modeling and forecasting processes of various origins, including complex natural processes, since the model allows us to take into account the structural and statistical uncertainties of the processes under study.

However, it is necessary to take into account some deviations, including the low flexibility of frequently used software packages, the difficulty of obtaining expert knowledge, and the impossibility of simulating feedback loops [16].

Bayesian Belief Network was been proposed for the first time for use in scientific developments in the field of natural disasters of the Northern Mountainous Black Sea Coast. This model is adequate and offers the decision maker the results of calculations for developing and making managerial decisions. It is been planned to continue research and development of methods for assessing the adequacy of the constructed models of the Bayesian Belief Network in the future [4].

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