Analysis of Complex Natural Processes Activation with Catastrophic Consequences Using Bayesian Belief Network

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Abstract. The article presents an analysis of factors on which the activation of complex natural processes with catastrophic consequences depends. The model for forecasting catastrophic consequences of natural processes using the Bayesian belief network is proposed. The tops of the Bayesian network have been singled out, the expert estimation of possible values of indicators and training of the Bayesian network based on expert estimations has been carried out. The factor "Investments" was proposed as a managing influence on the network. Modeling and forecasting of possible development scenarios of complex natural processes and their catastrophic consequences were carried out. It is proposed to use Bayesian networks in building a decision support system for forecasting and assessment of risks of catastrophic consequences from damage caused by hazardous natural processes.

Keywords: Bayesian belief networks · Complex natural processes · Modeling of natural processes · Catastrophic consequences · Forecasting and prediction of activation of natural processes · Scenario analysis · Risk assessment · Decision support system

1 Introduction

At the beginning of the XXI century there is a sharp jump in the number of natural and man-made disasters. Particularly affected by natural phenomena are the coastal areas, where an increased level of urbanization is observed. The density of buildings, roads, and communications represents increased risks and is subject to destruction in the first place. Human activities are related to water resources (reservoirs, rivers, and seas), so special attention should be focused on coastal areas and especially the mountainous areas around them. Thus, there is a problem of assessing the risks of damage from natural and anthropogenic hazards, which can have a significant impact on economic activity.

The scientific study of natural phenomena and processes, as stated by the author [1] consists of creating a model of relationships and interrelationships that occur within these processes, and if the model is "good", it can help us understand, predict, or even control the behavior of a complex system that demonstrates this phenomenon.

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Thus, the reliability of the test results and the ability to predict trends [2] of activation and course of complex natural processes, as well as catastrophic consequences depending on changes in the external environment, i.e., endogenous and exogenous factors, directly depend on the effectiveness of the applied modeling methods and the corresponding numerical methods of data processing.

The decision-makers connected with the prevention of an increase in costs and damages of buildings and constructions, and also to avoid fatal cases at that, need suitable methods of risk assessment of dangerous events and natural processes [3].

Complex natural systems not only consist of a large number of components but also depend on their interaction with each other and with the environment, i.e. they react to the transfer of information, transmit and receive it both inside the system and in exchange with external sources. The informational exchange during a dynamic interaction is usually non-linear, while self-relationships are possible. In other words, the reaction to the influence is time delayed, i.e. there is a lag za-dependence or autocorrelation. In this case, the previous value of the external environment may activate the process or, conversely, contain it, the connection may be positive (intensifying the activation) and negative (deterring it). In such a system, information is transmitted only with the "neighbor", while the general state of the system may not change when some components are changed or affected. It means that each part of the system is not aware of the behavior of the system as a whole.

Natural systems are open complex systems due to their interaction with the external environment, which means that their state is not in equilibrium, although they aspire to it. The excitatory effects of external factors activate these processes, and human technogenic activity is mostly aimed at containing destructive natural processes, but sometimes it happens and vice versa. Undue human activity destroys sustainable natural ecosystems, which leads to irreparable consequences and disasters.

Thus, as a result of the destructive perturbation of the external environment, the author [4] identifies two main tasks in the analysis of complex natural phenomena: first, to detect the fact of perturbation and, perhaps, changes in the natural process; second, to determine the optimal (stable) in a certain sense, the organization of behavior of the natural system and possible managing (stabilizing) impacts and the adoption of appropriate decisions.

The complexity of natural systems is also due to the high level of uncertainty. It is sometimes difficult to identify the most significant factors if they have an accumulative effect, i.e. they change insignificantly, but having reached a certain value, they cause a sharp change and activation of the natural phenomenon, while the factor itself still changes insignificantly. Also, to observe and monitor a complex natural phenomenon requires reference points, special devices that can be successfully installed on uninhabited terrain (in the field, in the forest, on a slope, in the sea, etc.), and in a city where everything is built up and cast in concrete, it is very problematic.

Nevertheless, there is a wide range of observations, many parameters characterizing natural processes with possibly catastrophic consequences are recorded, but there is a question of processing these data, finding connections between them. Sometimes, the expert with great experience trusts his intuition and visual perception more, but it is not enough to make convincing forecasts and plan measures to prevent the destruction as a result of the activation of natural processes.

Complex natural processes have a long history, their past is the reason for their present state and behavior, so any analysis must be done over a long period, on large observation data, and use modern methods of analysis and simulation of complex systems.

Thus, the task is to combine the experience of professionals and mathematical methods of modeling, information computer technology to develop forecasts and make decisions on planning and implementation of measures aimed at counteracting the destruction due to natural disasters.

The use of Bayesian belief networks provides powerful tools for modeling complex stochastic processes, analyzing the structure and dependencies between components, using algorithms of numerical methods to analyze retrospective, current period, and predict the probability of activation of new destructive natural processes based on new and historical data.

The purpose of this article is to analyze factors and relationships for building the Bayesian Belief Network to model and predict the activation of complex natural phenomena and to make decisions about measures to prevent catastrophic destruction.

2 Bayesian Belief Networks as a Tool for Modeling Stochastic Processes

Bayesian networks are an effective tool for modeling stochastic processes occurring in time in various industries and spheres of activity [5]. They can be used to solve a wide range of tasks, including detection of anomalies, justification, diagnostics, time series forecasting, automatic understanding, and decision-making under conditions of uncertainty [6]. The Bayes Belief networks combine the processing of statistical data, time series, as well as interval estimates and expert evaluation for further analysis of the peculiarities of functioning and identification of causal relationships between the variables, forecasting of behavior and further development of the system, recognition of images and situations [7].

A model based on the Bayesian belief network allows combining both statistical data and expert judgment on the nature of behavior and relationships between elements [8]. In particular, the experts' knowledge and their assessments are used at various stages of model construction, as well as in selecting methods of model construction or its full description, including the model structure and parameters.

Bayesian belief networks can make a significant contribution to the study and modeling of complex systems of different natures through high transparency, the ability to combine empirical data with expert knowledge, and their apparent relevance to uncertainty [9].

At the present stage, Bayesian belief networks are used in information systems of analysis and represent a convenient probabilistic toolkit for a description of dynamics and statics of processes of different nature to analyze their functioning [7]. Formally, Bayesian networks are a pair: (G; P), where $G = \langle X, E\rangle$ - an acyclic directional graph on the finite set of X (vertexes), bound together by a set of oriented edges E, and P - a set of conditional probability distributions. Thus, Bayesian belief networks are a fairly accurate tool for describing very complex processes and events with uncertainties [10–13]. The Bayesian network theory is based on the Bayesian formula and the rule of constructing and calculating the network, which is a generalization of the rule of probability multiplication by calculating the joint probability distribution of random dependent events. Each vertex is a priori associated with numerical characteristics corresponding to the law of distribution of random variables [14].

The procedure for analysis of natural hazards carrying possible catastrophic destruction using Bayesian networks is as follows:

– identification of factors that have a direct impact on the activation of the natural process;
– identification of targets of the natural process, which have a destructive effect;
– assessment of the level of destruction, specification of qualitative and quantitative characteristics;
– identification of management impacts that can stabilize the natural phenomenon or reduce (minimize) the consequences of destruction;
– building the structure of the Bayes network, by distributing the identified factors and indicators by network levels and establishing dependencies between them;
– defining probability distributions for nodes (marginal distributions) and arcs (conditional distributions);
– calculation of a priori distribution of a target variable (e.g., damage from a natural hazard or possible timing of this phenomenon);
– compute a posteriori distributions for specific situations or scenarios by replacing a priori distributions of some variables with specific values observed in the situation.

The explicit consideration of uncertainties in Bayesian belief networks allows for the preparation of informed risk assessments for decision-makers [3].

3 Definition of the Bayesian Network Structure for the Assessment of Damage Risks from Natural Phenomena

To design a system for modeling the response of complex natural ecological systems to various changes and impacts we will build the Bayes network [15–19]. To determine the structure of the network, we identify the factors that primarily affect the activation of a natural process or phenomenon that can produce destructive actions.

First, we should take into account solar activity. It has long been established that the 11-year cycle of solar activity directly affects quantitative indicators in all spheres, namely, the number of natural disasters, social unrest, and the intensification of hostilities, fertility, and mortality, etc.

Secondly, it is necessary to analyze the process of the phenomenon itself, its speed and direction, to take into account whether there was an increase or decrease inactivation during the previous observed period.

Third, we will consider the factor that directly affects the activation of a complex natural phenomenon. For example, precipitation, seismic activity, sharp temperature changes, geological or geomorphological structure, etc. Professional experts determine these factors depending on the process or phenomenon for which the Bayesian network model will be built.

The next step is to consider the resulting indicators, such as the activation of a natural phenomenon, the level of destruction and disasters, the time left before the activation of the process. The latter indicator plays an important role as it allows us to take into account how much time is available for decision making and implementation of activities aimed at preventing or minimizing catastrophic consequences.

The study of natural and man-made disasters reveals the prospect of their formal description using three main variables: time, place, and power of a disaster or a stymie-disaster [20].

In addition to the above-mentioned indicators of activation of complex natural phenomena or processes, we propose to take into account a generalized indicator - the amount of money spent on preventive measures and rehabilitation after destruction.

All we have to offer is a controlling factor, which helps to counteract the activation of natural processes or minimize the level of destruction. The factor Investment in measures for the prevention of negative consequences to some extent satisfies the property of management of natural processes.

Each of the considered values takes "Yes" or "No", and the "Destruction Level" value will take "Low", "Medium" and "Catastrophic" values.

The graph of the Bayes belief network is constructed as a "tree" (see Fig. 1). The variables discussed above take on the values: *Yes* or *No*, and the variable *"Damage_Level"* takes on the values: *Min, Overage*, and *Catastrophic (Max)*. We place the input factors "*Solar_Activity", "Past_Period_Activation", "Significant_factor"* and the controlling "*Investments"* on the upper level, the three resulting indicators "*Activation_Risk",* and under *"Damage_Level", "Time_Risk"* on the next level, and the generalizing indicator *"Total_Costs"* on the lower level.

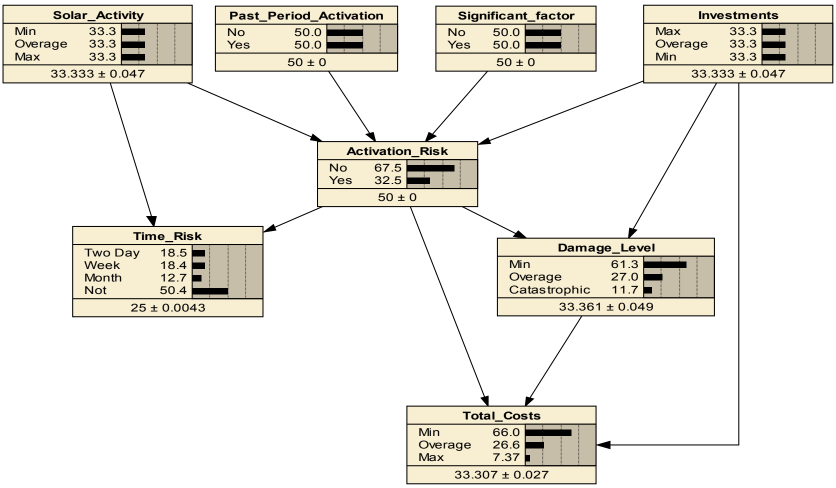

Fig. 1. The structure of the Bayesian network for modeling natural hazards and processes

The Bayesian network training is carried out by filling in tables of conditional probabilities for variables of the middle and lower levels and unconditional probabilities for input factors lying at the upper level (based on observation results). The tables are filled in with the help of expert assessments given by experts [12]. Modeling, construction, and training of a Bayesian network are carried out in the shareware program Netica. The training of the Bayesian belief network is shown in Fig. 2.

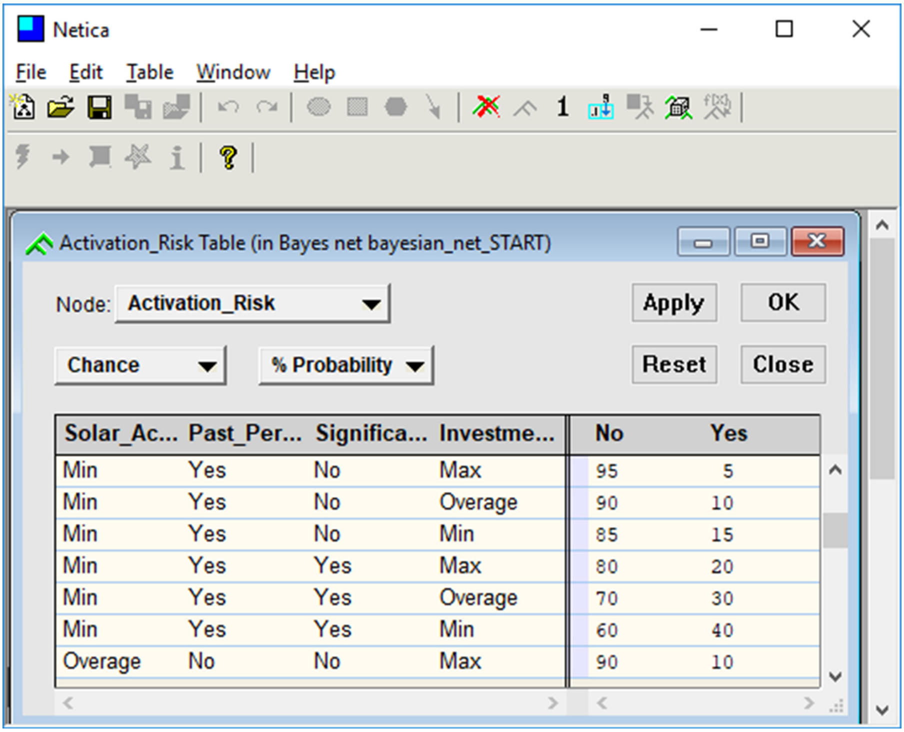

Fig. 2. Bayesian network training

After training the network can simulate different situations on it, get probabilistic values for different scenarios of natural processes and phenomena.

4 Modeling Dangerous Natural Processes Using the Bayesian Belief Network

Logical-probabilistic output operations in networks allow us to obtain the probability of formula truth (a priori output), to change estimates in the network based on the received certificate (a posteriori output) [21]. Let us set the initial values of input factors as shown in Fig. 3.

We see an encouraging picture with unfavorable values of factors. The activation of natural processes will occur with a probability of 75%, but the level of destruction will reach a catastrophic value with a probability of 7.75% (and the minimum - 60%). While the Total Costs will reach the maximum value with a probability of 6%, and the minimum value - 66% (at the expense of funds previously invested in preventive measures).

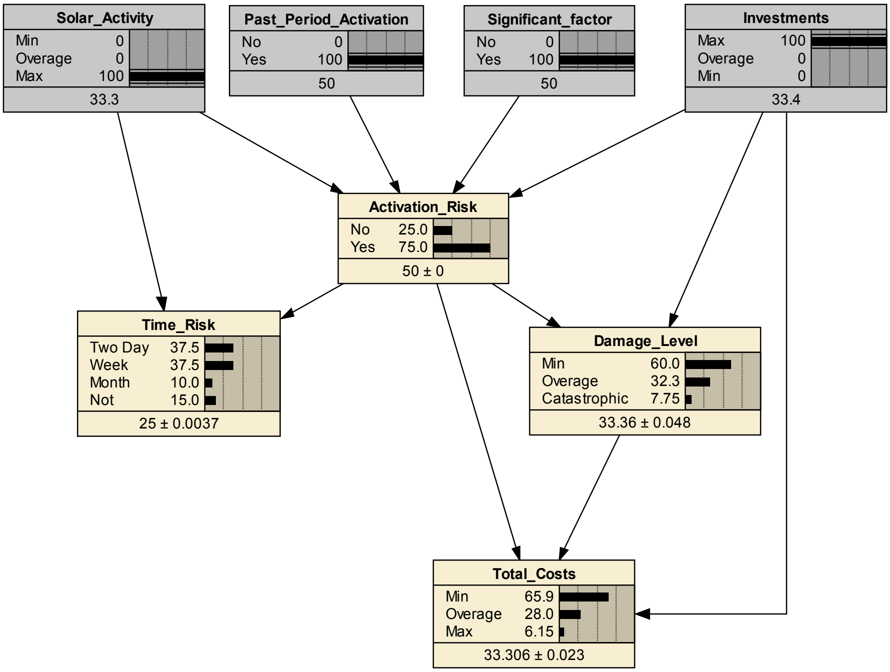

Fig. 3. Modeling of natural processes using the Bayesian network

Bayesian networks also allow modeling the situation from bottom to top, when you set the values of the resulting indicators and determine what the input factors should be to get the desired value for the result. For example, let's calculate what probabilities should be followed so that the Total Cost takes the minimum value (Fig. 4).

The result of the simulation shows that the distribution of the Investments is as follows: Max - 44%, Average - 34%, and Minimum - 22%, we get that the minimum level of costs is achieved, with the activation of natural processes about 76%, but no damage or they are minimal with a probability of 55% and will occur either within a week or the next two days - 38% each.

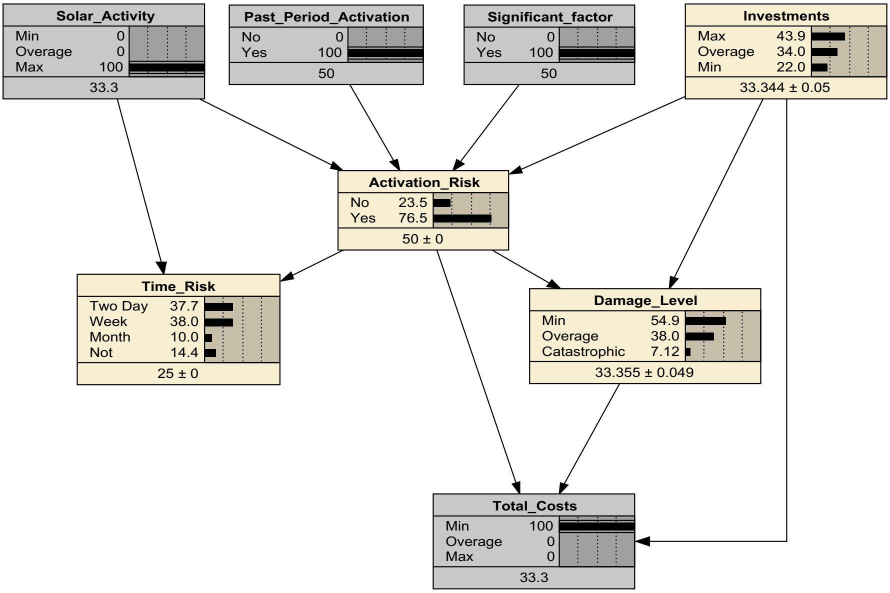

Fig. 4. Simulation of natural processes with the Bayesian network

5 Conclusion

Thus, the modeling of hazardous natural processes and phenomena with the use of the Bayesian belief network is a modern and promising trend in the field of data mining and decision making in the conditions of uncertainty. The Bayesian network is a powerful and effective mathematical tool for research and reproduction of the real picture of processes in the information system, which should be used to solve the problems of probabilistic forecasting and risk assessment [8].

The effectiveness of applied modeling methods and corresponding numerical methods of data processing directly depends on the reliability of test results and the ability to predict trends in the activation of hazardous natural processes and phenomena by changes in the environment. Bayesian networks provide rather powerful functional capabilities for modeling the structure of stochastic processes and algorithms of numerical methods of analysis of retrospective, current period, and forecasting of probabilities [2] of scenarios of natural processes, subsequent destructions, and the level of costs for the reconstruction of objects and territories.

Stochastic graphical models have long been used for the analysis of complex systems in various areas of research, for example, a typical structure of an auto-compensation system [22]; the synchronization process is analyzed, which consists of detecting a time interval with an optical pulse [23]; an analytical expression for the correct detection probability calculation of the photon impulse receipt in the algorithm proposed for the sync initialization of the QKDS [24].

The proposed Bayesian belief network model is interesting for modeling and forecasting the activation of complex natural systems with catastrophic consequences and the level of costs for the reconstruction of objects and territories.

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