

Modern Methods of Monitoring and Predicting the State of Slope Structures

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Abstract. The increasing complexity of mining and geological conditions in the development of mineral deposits, the operation of careers with a 600 and more meters depth, as well as the formation of unique artificial and alluvial massifs determines the need to obtain complete and reliable information about the state of slope structures for their proper assessment and to determine timely management decisions in order to prevent accidents and ensure industrial and environmental safety. The majority of modern geomechanical models are built on the basis of analytical mathematical methods that are not able to calculate all the factors affecting the conditions of the slope structures. With the advent of digital technologies and artificial intelligence systems, it became possible to develop new methods to collect, transfer and store information about engineering geological and hydrogeological factors, as well as to create software solutions aimed at improving the accuracy of slope structure behavior prediction affected by rapidly changing environmental and technological operating conditions.

1 Introduction

In the 21st century as a result of the economic activity and, first of all, the mining activities, unique artificial and alluvial massifs made of barren rocks and various wastes of ore, coal and other minerals were formed. These days more than 100 billion tons of rock masses are moved annually. These values can be easily compared with the amount of materials moved during several amount of geological processes. These transformations of the geological environment, as a result, lead to the changes in the atmosphere, hydrosphere and violate the ecological balance of the regions, as well as, worsen the living conditions of local population [1]. However, the most severe problems affecting industrial and environmental safety appear in cases of partial or complete uncontrolled destruction of slope structures resulting from landslides or other deformations.

During the extraction and processing of mineral raw materials, waste materials are generated in various aggregative states: solid rocks - overburden rocks transported by road or rail transport, as well as by a transport-free scheme; wet tailings, sludge and overburden rocks transported by hydraulic transport form massifs of liquid waste. It is evident that

these massifs have different mobility and different degrees of danger in case of uncontrolled movement in the environment.

2 Materials and Methods

Over the past 60 years, there have been over a hundred of accidents associated with the destruction of the tailing dams and the subsequent spill of wet washery rejects. With the increase of size and complexity of modern hydraulic structures, the frequency of accidents remained the same. However, it is observed that the violations of technological processes, as well as, rapid changes in environmental conditions lead to the increase of deformation or partial destruction of slope structures. For instance, on 25 January 2019, in the municipality of Brumadinho (Minas Gerais, Brazil) the tailing dam of the Corrego de Feijao mining enterprise was collapsed. As a result, over 12 million m³ of washery rejects flowed down the Kaza-Brance river valley, resulting in formation of 15 meters thick tailings at some sites. This accident led to the death of more than three hundred people. It should be noted that in the same state in 2015 a similar accident occurred at the mining and processing plant Samaraco, a joint venture of Vale and BHP enterprises. This was called the largest environmental disaster in Brazil at that time [2-5].

In recent years in the Russian Federation several major accidents of deformation and destruction of slope structures should be noted: a landslide on the “Zarechny” coal mining site, a landslide on the “Mikhailovsky” iron ore refinery plant, a partial destruction of the “Karamken” iron ore refinery plant’s dam and a number of other smaller accidents [6].

The prediction of the large artificial massifs behavior formed over the past half century is complicated by the lack of the experience and determines the need for constant monitoring the changes of the engineering geological, hydrogeological and geotechnical factors. This allows evaluating the influence of natural and man-made factors on the stability of slope structures [7-8].

Therefore, several tasks aimed to monitor the state of slope structures are formed: collection, storage and transfer of the information;

- data analysis;
- benchmarking calculations;
- modelling the elements of natural and artificial mining systems;
- assessment of the status of object.
- development and integration of measures to improve the stability of natural and artificial mining systems;
- and adjustment of monitoring parameters.

3 Results and Discussion

The analysis of accidents and modern methods of modeling and predicting the slope structures state shows that these days it is necessary to create new approaches in the organization, collection, transfer and storage of received information as well as in the modeling of artificial massifs [10]. While assessing the slope structure state, the main attention is usually paid to these factors: hydrogeological (the position of the aquifer level in the massif), technological (geometric parameters of the structure, vibration impact of transport systems and impact of blasting works) and engineering geological (lithological composition of the massif and its base, physical and mechanical properties of sediments) [10]. In fact, the slope structure state (the sides of quarry, the slope of blade or the dam of hydraulic structure) is affected mainly by a much larger set of factors that cannot be fully

considered by current models due to the underdeveloped instrumental measuring base, the lack of a reasonable mathematical approach and several other reasons.

The described mathematical model for the estimation of a potential landslide at a particular time can be presented in the following form:

$$\eta = \frac{\sum_i [(P_i \cos \alpha_i - \gamma_{w,i} H_{av,w,i} l_{w,i}) \operatorname{tg} \varphi_i + C_i l_i] + F_{other\ holding}}{\sum_i P_i \sin \alpha_i + F_{other\ shear}} \quad (1)$$

where $P_i = \gamma_i H_{av,i} l_i$;

γ_i – the density (volumetric weight) of deposits in the slip zone;

$H_{av,i}$ – the height of the calculated unit;

l_i – the length of the calculated unit base;

$\gamma_{w,i}$ – the density of water;

$H_{av,w,i}$ – the average aquifer level of the calculated unit;

$l_{w,i}$ – the length of the watered calculated unit base;

φ_i – the angle of internal friction;

C_i – the specific cohesion of deposits in the slip zone;

α_i – the angle of calculation unit base inclination to the horizontal;

$F_{other\ holding}$ – the other holding forces;

$F_{other\ shear}$ – the other shear forces.

Therefore, in the presented mathematical dependence, all parameters are considered independent of each other. These days, in most cases, the value of the stability factor is calculated depending on the changes of groundwater level positions; in this model this parameter is distinguished by the most significant variability in time. However, changes in physical and mechanical properties due to an addition moistening of the massif are not considered.

Thus, the monitoring of slope structure state is mainly reduced to observation of the changed in levels of aquifers and surface deformations. In most cases, critical values for individual parameters are determined on the basis of laboratory tests of massif and its sediments and by methods of inverse calculations. However, changes in the parameters in time are not predicted. This kind of monitoring is ineffective in case of rapid changes in environmental and operating conditions of artificial structures. Despite the fact that the changes in the geomechanical situation will not occur immediately, it still require more time to take measures and improve the stability of slope structure [11].

With the increase of aquifer level in the massif, the density of the deposits is changed, and the slip zone with increased filtration properties causes an increase in the weathering of the deposit and suffusion. These factors determine the reduction of mechanical properties of deposits, including the angle of internal friction and specific adhesion, which are fundamental in the model. Therefore, a more accurately corresponding mathematical description will take the form:

$$\eta(H_w) = \frac{\sum_i [(\gamma_i(H_{av,w,i}) H_{av,i} l_i \cos \alpha_i - \gamma_{w,i} H_{av,w,i} l_{w,i}) \operatorname{tg} \varphi_i(H_{av,w,i}) + C_i(H_{av,w,i}) l_i] + F_{other\ holding}}{\sum_i \gamma_i(H_{cp,e,i}) H_{cp,i} l_i \sin \alpha_i + F_{other\ shear}} \quad (2)$$

where H_w – the level of aquifer in a potential landslide body

Likewise, it is possible to add into the model the influence of other factors on the slope structure state or to adjust the value of the model parameters depending on changed in certain environmental or operating conditions. Therefore, an attempt to consider all the factors affecting the slope structure state leads to a significant complication of the mathematical approach on the one hand and the inability to measure several parameters on

the other. In this regard, several non-analytical methods that aimed at assessing the state of complex natural, artificial and socio-economic systems have been widely developed. This includes tools of neural networks, pattern recognition and other methods to create and educate artificial intelligence systems. The main difficulty remains the widespread introduction of this approach to the geological and mining industries due to the lack of a sufficient data to be used as a training set.

The accumulated results of many years of hydrogeomechanical monitoring at mining sites and natural slopes, combined with meteorological observations, allowed us to form a database that was used for training and verification of an artificial neural network that is designed to predict changes in the level of the aquifer (Fig. 1). The main reasons for changing the hydrogeological conditions in the rock massif are: abundant precipitation, snow melting, a change in the mode of operation for hydraulic structures. This determines the presence of a certain time period between the moment when the maximum amount of water enters the feeding zone and the moment when the maximum aquifer level is reached in the body of the ramp structure. At the same time, the filtration properties of rocks in the massif are quite heterogeneous, and it is extremely difficult to reliably determine their distribution in the body of the ramp structure, in addition, they can be influenced by environmental factors (for example, temperature), in some areas a barrage and other effects can occur [12].

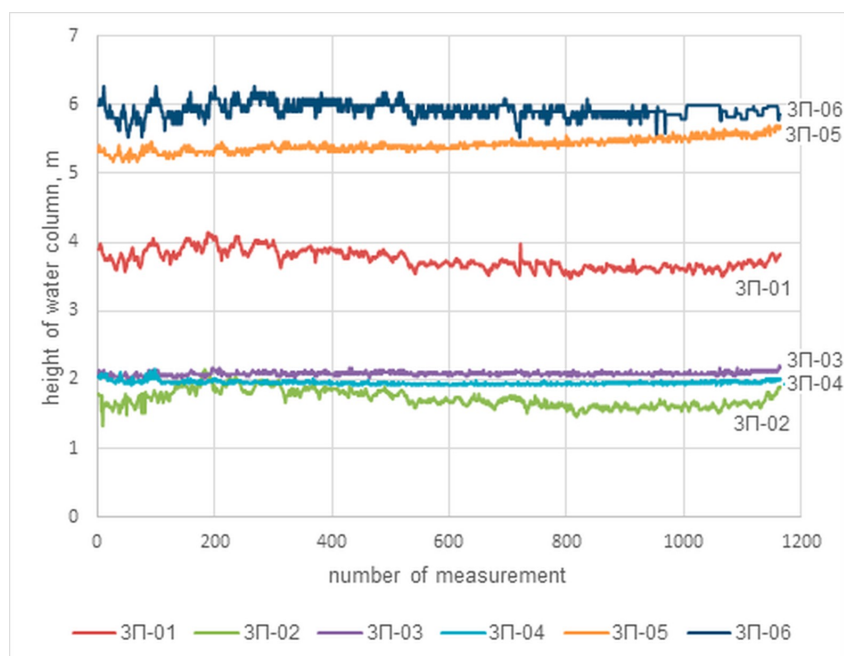


Fig.1. Dynamics of changes in the water level column in the wells of the control automated profile 3P of the head dam of the tailing dump from January 1 to October 17, 2018.

In connection with the above factors, the following parameters were used to predict the level of the aquifer in the body of the potentially landslide massif and, accordingly, to assess the state of the latter by input data for an artificial neural network:

- the amount and distribution of precipitation that fell out over a time interval that is equal to the maximum period of the influence of precipitation on the position of the level of the depression curve in the rock massif;
- other meteorological data (temperature, cloudiness, wind strength and direction, air humidity, etc.) for the period indicated above;

- current position of the depression curve;
- weather forecast for the considered forecast time interval.

In this system, artificial intelligence is constantly undergoing additional training, which is carried out on the basis of the existing database and the additional information obtained as a result of monitoring (Fig. 2). This approach has a number of distinctive features:

- the digital model of the object is constantly being improved, which improves the quality of modeling the behavior of an object when environmental conditions and operating parameters change;
- the system-user cannot track the clear dependencies between the component parts of artificial intelligence, the latter becomes to “black box”, which can be assessed only on the basis of the relationship between the input and output parameters;
- the neural network does not reflect the essence of the physical model of the object;
- and monitoring of parameters and objects state becomes a kind of regulator with negative feedback for the artificial intelligence system [12-13].

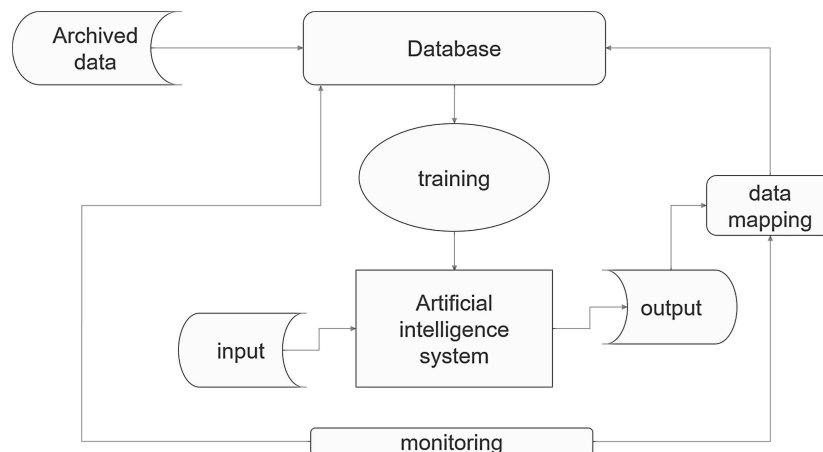


Fig.2. Big data accumulation scheme and their interaction with the artificial intelligence system.

Software was developed to implement the proposed methods. To write the software code was chosen the object-oriented language C #, which is one of the most convenient for creating Windows-compatible applications for the Microsoft platform. In addition, software developers recommend it to create applications aimed at processing big data arrays [14].

The developed software has been adapted to the conditions of the fencing of the tailings of one of the major Russian mining companies. At the moment, in the test mode, the program has worked for 6 months. During this time, about 900 measurements of the aquifer level were obtained from six test wells. At the same time, in the process of learning the neural network, about 8,000 outcomes were used. The convergence of the prediction of the position of the depression curve based on an artificial neural network and real data was 92.48% [15].

The tests have shown the prospects of using the developed methods for predicting the state of inclined structures using artificial intelligence systems. The considered example demonstrates that neural networks make it possible to give a sufficiently high-quality forecast based on factors that cannot be taken into account in the analytical models used today.

4 Conclusion

The transition from analytical mathematical models to the neural networks methods and pattern recognition makes possible to take into account a larger number of factors affecting the state of the inclined structures. At the same time, the subjectivity of the selected design parameters is minimized and accuracy of the forecast is increased. In many cases, to build systems of artificial intelligence, it is necessary to form a set of input parameters, which significantly, in many cases, fundamentally differs from the characteristics of the ramp structure, which are used in modern models.

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