Forecast of the Surface Tilt Based on the Monitoring Data of Settlement of a Group of Buildings

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Abstract. This paper presents the results of long-term monitoring of ground subsidence above flooded mining. To assess the change in the shape of ground surface, the data obtained by monitoring the settlement of the foundation of a large group of buildings were used. The control of the slope was carried out using automated hydrostatic level systems mounted on the foundations of 40 buildings located in this area. The accumulated data on the long-term evolution of the tilt were processed using the methods of statistical analysis of non-stationary time series. Choice of forecast model was made based on a comparison of forecast and real monitoring data. A forecast based on 5-year monitoring data predicts that the observed deformation processes in the rock massif will not change over the next 2 years.

1. Introduction

The geomechanical process occurring in undermined rock mass often leads to ground subsidence and can cause damage to the buildings and engineering structures located in this area. Such processes can be provoked by mining and get worse in an emergency condition such as flooding. Therefore, it is necessary to monitor this process to evaluate its impact on the structures. Assessment of stress-strain state inside the rock massif is difficult, but it can be estimated indirectly by observing the surface displacements. Various methods are used to monitor surface displacements: instrumental observations [1], GNSS [2], radar-satellite technologies [2,3] etc.

This work uses an approach, described in detail in [4]. It is assumed that the buildings located on the soil surface have the foundations arranged initially horizontally. The foundation normal coincides with the direction of gravity $G'$ (figure 1). As the soil surface subsides, the building tilts like a rigid body, and the foundation normal deviates by the angle $\varphi$ and takes the position $G$. The magnitude of the slope can be estimated from the length of the vector $G'$ (projection of vector $G$ onto the horizontal plane) and its direction – from the angle $\psi$ between $G'$ and the $x$ axis.

The change in the surface slope at the point of location of certain building is estimated by uneven settlements of this building. Based on the measured values of the settlement at several foundation points, we can build a real spatial configuration of the foundation (figure 2, blue surface). The approximation of this surface by the plane (figure 2, plate $S'$) shows the slope of the foundation as a rigid body. Uneven settlement is measured using automated hydrostatic level system [5] located on the building foundation.

Thus, an arbitrary building serves as a local sensor of a distributed monitoring system that records the subsidence of the ground surface at a sensor position, and the deflection of a group of buildings can be used to estimate the deformation of the ground surface in a large area where these buildings are located.

This approach has an important advantage. It allows you to obtain the data on the change in the slope of the soil surface in a large set of points. Measurements are carried out every day in automatic mode for a long time. Long-term measurement data with sufficient time resolution make it possible to analyze the processes observed in the object with the desired detail, and also make it possible to predict the
changes in the deformation state of the object both on the scale of the individual building and on the scale of the entire observation area.

**Figure 1.** The group of buildings above the mine.

**Figure 2.** Assessment of building tilt using settlement monitoring data.

### 2. Forecasting Methods

There are different approaches to predict the processes of surface subsidence: analytical methods and numerical simulation of geomechanical processes occurring in rocks [6, 7]. We propose to use the statistic processing and analysis of accumulated monitoring data to predict the evolution of the shape of the earth's surface in this area.

Monitoring data on the changes in building settlements and slopes are the time series. Time series forecasting is a modern science discipline based on the methods of statistical analysis [8]. Currently, the following predictive models are known: the differential models [9], exponential smoothing models [10], autoregressive models [11], moving-average models and neural networks models [12]. These models may be used to predict deformation parameters, such as displacement and structural strain [13], settlement and subsidence [14, 15]. This article discusses the use of some of these models to predict the ground surface slopes.

#### 2.1. Exponential Smoothing Models

**2.1.1. Theory.** Exponential smoothing models have been developed from the works of Brown [10], Holt, Winters [16] and others. In the simplest case (Brown model), the next term of the smoothed series is written in terms of the previous one as

\[ \hat{y}_t = \alpha y_t + (1 - \alpha) \hat{y}_{t-1} \]  

where \( 0 < \alpha < 1 \) is the smoothing coefficient, \( y_t \) is the initial series. The predicted values of a variable are determined to a greater extent by its later values. Earlier terms of the series have less influence on the forecast. Therefore, in more complex models, the initial time series is decomposed into three components: level, trend and seasonality, and similar relations are written for each of them. Components can be combined as sums, products or other combinations, the time series decomposition can be categorized as additive, multiplicative and mixed additive-multiplicative. The most famous is the Holt-Winters additive model. This forecast is obtained as the sum of level, trend \( bh \) and seasonality \( s_c \):

\[ \hat{y}_{t+h} = l_t + bh + s_{t+h-m(k+1)} \]  

\[ l_t = \alpha (y_t - s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1}) \]  

\[ b_t = \beta (l_t - l_{t-1}) + (1 - \beta)b_{t-1} \]  

\[ s_t = \gamma (y_t - l_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m} \]

where \( k \) is the integer part of \((h - 1)/m\); \( m \) is the season frequency. The selection of model parameters \( (\alpha, \beta, \gamma, m) \) is carried out by minimizing the parameter (for example, the mean-square deviation, mean
absolute error, etc.), which characterizes the difference between the forecast and the initial time series in the training interval. The combination of optimal model parameters is specified by the selected criterion and interval. The procedure for constructing Holt-Winters models are implemented using the statistical software R (ver. 3.6) [17].

2.1.2. Model testing. The Holt-Winters model was tested based on the data on the change in the slope of one building, accumulated over monitoring period. One part of this data is used to make a forecast, and the another part – to compare the predicted values with real ones. Based on 5-year data, a 1-year forecast was made, and on 1-year interval, the forecast and measurement data were compared. Colored lines in figures 3 and 4 represent the forecast for the tilt magnitude and direction, obtained in accordance with Holt-Winters model. Real monitoring data are shown in black line.

Numerical experiments with Holt-Winters model show the following. A forecast based on rather monotonous data on the evolution of the tilt magnitude reflects the main trend of changes in real data quite accurately. But the forecast based on periodically changing data on tilt direction turned out to be unsatisfactory. In addition, the predicted values revealed a dependence on the future starting point. In the figures, colored lines show forecasts with starting points that differ by 10, 20 and 30 days. The predicted values of tilt magnitude and direction by the end of the 1-year forecast period differ significantly among themselves and with the actually observed values.

![Figure 3. Evolution of tilt value according to Holt-Winters forecast.](image)

![Figure 4. Evolution of tilt direction according to Holt-Winters forecast.](image)

2.2. Autoregressive Moving Average Models

2.2.1. Theory. The autoregressive moving average model [11] is used to analyze the stationary time series and consists of the following components:

\[ y_t = c + \epsilon_t + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{q} \beta_i \epsilon_{t-i} \]  

where \( c \) is a constant, \( \epsilon \) is white noise, \( \alpha \) are autoregressive coefficients (AR) and \( \beta \) are moving average coefficients (MA), \( p \) and \( q \) are the orders of the AR and MA models. Traditionally, the order of the model is denoted as ARMA \((p, q)\).

The analysis of real observation data, which often represent non-stationary series, is based on the integrated model (autoregressive integrated moving average – ARIMA). In this approach, the original non-stationary series are reduced to a stationary one by successive differentiation of the original series. So, \( d \)-times differentiation of the data described by the ARIMA \((p, d, q)\) model leads them to a stationary time series, which can be described by the ARMA \((p, q)\) model. Seasonal changes in data are taken into account using the coefficients \((P, D, Q)\). Here \( P \) is the order of the seasonal component of autoregression (AR), \( Q \) is the order of the seasonal component of the moving average (MA), \( D \) is the order of integration of the seasonal component. In practice, firstly one should determine the value of \( d \) by means of different tests (for example, Dickey-Fuller) and then perform transformation to a stationary series and construct
an ARMA model for it. The selection of optimal orders of the model is ambiguous; there are special procedures for estimating the maximum value of \( p, d, q, P, D, Q \). The detailed description of these models can be found in [11]. An increase in orders allows taking into account the characteristic features of a series, but also requires significant computing resources.

2.2.2. Model testing. The ARIMA model was tested in accordance with the above procedure using tilt monitoring data from several buildings. Testing showed that the predicted values fairly well convey the features of the observational data. In addition, the forecast results do not depend on the position of the starting point of the forecast interval. Also, the necessary minimum orders \((p, d, q) \ (P, D, Q)\) of the ARIMA models are estimated. According to 4-year monitoring data of the slope of one building, a 2-year forecast was made, which was then compared with 2-year observation data. Figures 5 and 6 show the monitoring data (black line) and predictions by the ARIMA model with different parameter values (colored lines). It can be seen from the figures that the forecast according to the ARIMA model reflects well both the general trend of data evolution and its seasonal changes. A numerical experiment has shown that the values \( p = d = q = P = D = Q = 1 \) are suitable for a satisfactory prediction of the tilt data.

Comparing the predicted values obtained by exponential smoothing model (Holt-Winters) and ARIMA model, we can conclude that model ARIMA better matches the observed data. Thus, the ARIMA model was chosen to analyze monitoring data and make forecast.

3. Results and Discussions

The developed approach was applied to analyze the data obtained during the monitoring of a group of buildings located in the city of Berezinki, on the territory above the flooded salt mines. Ground subsidence in this area caused by flooding has been observed from 2006 [18]. Five sinkholes were formed after this date.

To monitor the state of ground surface, an automated deformation monitoring system was used, installed on a large group of buildings located in this area. The hydrostatic leveling systems were installed on the foundations of about 40 residential buildings. Changes in the tilt of these buildings were recorded from 2014 to 2020. Figures 7 and 8 show a fragment of a city map with 14 buildings equipped with monitoring system (they are marked with arrows). Eight buildings have the most significant slopes, and some of them are visibly damaged. These buildings are numbered 1-8. In the figure 7, the length of the arrows is proportional to the tilt value at a certain time, and the direction of the arrows indicates the tilt direction.

3.1. The tilt forecast

On the basis of the monitoring data, a ARIMA forecast of changes in the tilt angles of these buildings for the period 2021-2022 was made. Figure 8 shows the state of the observed group of buildings expected by the end of 2022. Below, the forecast for the development of slopes is discussed in detail.
The monitoring results obtained for the buildings No 1-8 are shown in figures 9 and 10. The changes in tilt value obtained over 6 years of observation are shown in Figure 9 as solid line. The same changes in tilt direction are shown in Figure 10. Predicted evolutions of tilt value and direction for each of the buildings are shown as dotted line in Figures 9 and 10. The graphs show that the trends in the slope evolution observed over 6 years will continue for the forecast period. The tilt values will increase; the tilt directions will remain the same or change slightly. Significant change in the tilt speed is not expected. Thus, observing the evolution of the slope of the buildings located above the flooded mine, ARIMA models predicts that no significant changes in the condition of the rock massif are expected over the next 2 years.

3.2. Discussion
Data on the surface subsidence in the territory of interest to us were obtained independently with SAR Interferometry [3]. Also, subsidence and tilt at different points of ground surface in this area were predicted by three-dimensional mathematical modeling of the mining-induced change in the rock mass stress state and dissolution of load-bearing elements in underground mining [6]. The estimates of the subsidence rates and inclinations given in these works are in good agreement with our data. A more detailed comparison is planned in the future investigation.

4. Conclusion
Based on the data of long-term observations of uneven settlements of foundations of a large group of buildings located above the mine workings, an approach is proposed for assessing the change in the shape of the ground surface provoked by processes in the rock massif. In accordance with this approach, a set of houses located over a large area can be considered as a distributed deformation monitoring system that registers the slope of local points on the ground surface. The data from continuous long-term monitoring of the slope of these buildings makes it possible to judge the change in the shape of the ground surface in this area.
A number of mathematical models are considered to predict changes in the slope of buildings on the basis of accumulated monitoring data. These models are based on statistical analysis of a large amount of data and various forecasting technologies. The advantages of ARIMA model for obtaining a forecast for a 2-year period is demonstrated. A forecast of the slope change has been made for a number of buildings for the period up to September 2022.

Dependences have been established that make it possible to predict changes in the shape of the ground surface according to the data of long-term observations of the slope of a large group of buildings located on a given territory.

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