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Accident Damage Prevention Technology

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Abstract – The paper studies the methods of neural network modeling to prevent damage from accidents, compares different approaches to the analysis of time series, explores the mechanisms for estimating the accuracy of forecasting values, describes the models and uses them. The problem of choosing the optimal prevent damage from accidents model according to minimum forecast criterion error is stated and solved. To solve this problem, there was used the group of mathematical methods, including statistics and econometrics, such as: autoregression, moving average, exponential smoothing, and neural network modeling. The result of the study is an algorithm for estimation of possible accident damage. The model is based on minimizing the forecasting error and implements created algorithm.

Keywords – autoregression, ARIMA, exponential smoothing, forecast evaluation, moving average, neural networks, accident damage, time series.

I. INTRODUCTION

In recent decades, scientists have noted significant climate change on Earth. These changes are so noticeable that they attract the attention of not only the scientific communities, but also the public as a whole, because they began to have a significant impact on the living conditions of the population, the economic activity of enterprises, productivity, and the number of natural disasters.

As one of the ways to predict the internal and external activity conditions. Forecasting as a method is also used to reduce the risks caused by uncertainty. It allows to predict the most probable external environment conditions in the future (political, scientific, technical, financial, environmental, and social). Forecasting provides the assessment of short- and long-term consequences of possible decisions. Nowadays, the decision-making quality, especially in the sphere of accident damage forecasting, depends on a careful analysis of the environment. The economic environment mostly consists of different indicators that are expressed in the form of time series. At present there is a huge number of mathematical models and methods of time series analysis and forecasting.

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The complex usage of different models gives more precised forecasting values. The aim of the article is to review the existing time series analysis methods, to create an algorithm for estimation the possible accident damage by the criterion of minimal forecast error and its software implementation. Online ticket sales statistics is selected as the initial data.

1. Background paper

Russian and foreign authors (Troshin A.N., Horn J.K., Granberg A.G., Lapygin Yu.N., Krylov V. E., P., Armstrong J.S., Ferrer R.C. Kinnunen, Valuing J., Mabert, and others) (Burdina, 2006; Burdina & Moskvicheva, 2018; Kibzun & Kan, 2009; Moskvicheva & Melik-Aslanova, 2015; Kriesel, 2007) have reflected theoretical and methodological aspects of the problem in their works. Various studies analysis showed the development of methodical and methodological issues regarding the application of forecasting methods to solve prevent accident damage problems. However, these researches do not sufficiently address the issues of neural simulation, what gives the reason for research in this sphere.

II. TECHNIQUE

Observations of the Japan Meteorological Agency (JMA) also show that warming on our planet is uneven - the changes affected the highest northern latitudes to the greatest extent. (Fig. 1) [5] The time period starting in 1979 was chosen due to the most pronounced tendency of global warming on Earth since this year.

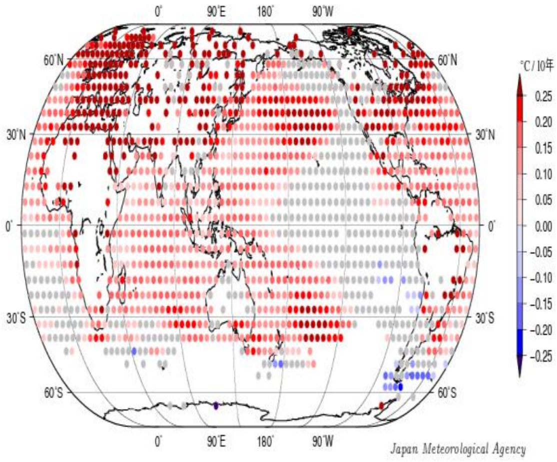

Figure 1. Annual long-term trend in average temperature from 1979 to 2018

The round marks on the map correspond to sectors of 5 to 5 degrees, for which the average long-term trend of temperature change (for every 10 years) from 1979 to 2018 is displayed. Gray circles indicate sectors where, according to JMA, with a 90% confidence, it can be said that the changes are minor.

The northern latitudes are characterized by the presence of permafrost rocks (IMF), which are also called cryolithozone. The term cryolithozone was first introduced by Shvetsov P.F. [6], in a general sense, is the upper layer of the earth's crust, characterized by the negative temperature of rocks and soils and the presence or possibility of the existence of underground ice.

The area of their distribution exceeds a quarter of all the land of the globe, including about 75% of the territory of Alaska and more than half of the territory of Canada and Russia. In Russia, the total area of permafrost areas is 10.7 million km2, which is about 63.5% of the entire country [7].

Russian scientists define thermo karst processes as a unique indicator of climate change in Western Siberia. Studies [7,6] show that, due to the fact that flat-bumpy bogs are very sensitive to climatic changes, as they contain frozen peat deposits, then, under conditions of global warming, the development of anomalous thermokarst is possible everywhere in Siberia.

The fuel and energy complex is a complex system that includes a set of industries, processes, material devices for the extraction of fuel and energy resources, their transformation, transportation, distribution and consumption of both primary and transformed types of energy carriers. [1] The oil and gas complex is part of the fuel and energy complex, it makes up more than 60% of the energy consumed in the world and more than 70% in Russia. [5]

Industrial facilities of the oil and gas complex are technogenic due to the specifics of industry products. Flammable and toxic oil, gas and oil products in case of explosion or leakage can lead to the death of people, animals and plants, cause significant harm to the environment, disrupt the ecological condition of soils, water bodies, forests, etc. Therefore, special attention is paid to reducing the risk of accidents at hazardous facilities.

In general, a large number of accidents in the oil and gas industry occur on linear sections of trunk pipelines. Trunk pipelines are capital engineering structures designed for a long service life and designed to transport gas, oil and oil products over significant distances from the places of their production or processing to the places of processing and consumption. [3] Their linear part is the main objects (the pipeline itself with crossings over obstacles, access roads, power lines, electrochemical protection system).

The peak of specific accident rate for cargo turnover on trunk pipelines occurred in 1993-1998. This is due to a significant decrease in the intensity of cargo turnover in this period. Since the beginning of the 2000s, the indicator has been decreasing, and in the beginning of the 2010s it reached the level of the 1990s (Fig. 2). In absolute terms, almost 70% of all accidents in trunk pipelines are recorded in gas pipelines, but they also account for approximately 70% of the length of all pipelines. [3] In Fig. 2, compiled on the basis of the analysis of annual reports on the activities of the Federal Service for Ecological, Technological and Nuclear Supervision [4], presents statistical data on emergencies at the facilities of the main pipeline transport, in particular, gas pipelines from 2005 to 2017.

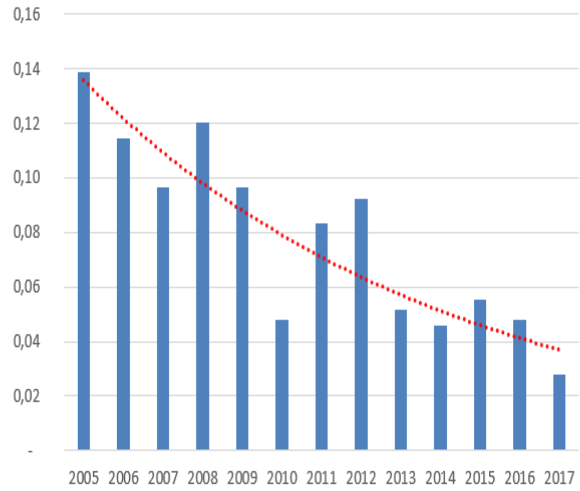

Figure 2 The specific frequency of the number of accidents recorded by Rostekhnadzor per 1 thousand km of the main gas pipeline from 2005 to 2017.

The analysis showed that despite the decrease in the frequency of accidents in the gas pipeline in recent years, the “price” of one accident increases. Therefore, an algorithm for predicting accidents based on factors changing the soil, climate, and vegetation in the vicinity of sections of the gas pipeline and oil pipeline is needed. Information is proposed to be obtained using satellite images, and terrain observation by unmanned aerial vehicles. It is proposed to form a neural network model to predict the possibility of disasters and damage.

The forecasting model that portrays test characteristics in a proper way is the basis for finding their future values. Methods are divided into two groups. The first one is domain models for instance mechanics, thermodynamics, and fundamental analysis. The second one is time series methods that analyze hidden dependencies within an exploring process. Domain models are forecasting models that use domain rules [8,11].

There is a problem of building the forecasting model with the minimum error criteria.

Let $\{Y_t\}$ be a stationary time series. Using a mathematical model $\xi \in M$, where M is the set of mathematical models, there can be obtained a forecasted time series $\{\hat{Y}_t\}$.

The accuracy of the model can be estimated depending on the way of error calculation, such as the mean absolute forecast error (MAE), the root-mean-square error (RMSE), mean absolute percentage error (MAPE). In this study, as a quality coefficient Theil non-corresponding coefficient was chosen, calculated using the formula [7,11]:

$$v = \sqrt{\frac{\sum_{t=1}^{n}\left(Y_t - \hat{Y}\right)^2}{\sum_{t=1}^{n} {Y_t}^2 + \sum_{t=1}^{n} \hat{Y}^2}}$$

This coefficient shows how approximate time series $\{Y_t\}$ and $\{\hat{Y}_t\}$ are. The more v is approximate to zero, the closer the comparing series are.

There is the following optimization problem:

$$\sqrt{\frac{\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t(\xi)\right)^2}{\sum_{t=1}^{n} Y_t^{\,2} + \sum_{t=1}^{n} \hat{Y}_t^{\,2}(\xi)}} \rightarrow \min_{\xi \in M}$$

In this instance, the minimization model can be expressed as:

$$\xi^* = \operatorname*{argmin}_{\xi \in M}\left(\sqrt{\frac{\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t(\xi)\right)^2}{\sum_{t=1}^{n} Y_t^{\,2} + \sum_{t=1}^{n} \hat{Y}_t^{\,2}(\xi)}}\right)$$

There was conducted a simulation of the autoregression model AR (p) and moving average model MA(q) in this study.

III. SIMPLE EXPONENTIAL SMOOTHING MODELS (ES)

Simple exponential smoothing (SES) is expressed by:

$$\hat{Y}_{t+1} = \begin{cases} Y_1\,, t = 1 \\ \hat{Y}_t + \alpha\left(Y_t - \hat{Y}_t\right), t > 1 \end{cases}$$

α ∈ (0;1) is the smoothing constant that characterizes the speed of weights' decrease.

The closer α is to zero, the more significant effect of previous values on the current one is. This coefficient is taken in advance.

Double exponential smoothing (DES) is a development of SES. This model has following idea: in the formula of simple exponential smoothing, an additional term is introduced, which weakens the previous value influence on the trend. The original time series is divided into two elements – level (intercept) and trend (slope). The level - forecast value - is calculated using previous models. Further, the ES is applied to the trend, taking into account that future value change depends on the weighted previous changes. This model can be used to obtain two forecasting values instead of one [10, 11].

Whereas, DES also has a development – triple exponential smoothing or the Holt-Winters method (HW).

The new third element – seasonality – is the main idea of this method. Therefore, the method can be applied only in case when the series has pattern of seasonality that is true in this study. The repeating fluctuations around the level and trend are explained be the seasonality of the model. Furthermore seasonal component will be characterized by the season length – the period after which the repetition of the oscillations begins [9,11]. For each observation in the season its own component is formed, for example, if the season length is 7 (for example, weekly seasonality), then we get 7 seasonal components, step by step daily.

Model's equations system is as follows (Kriesel, 2007):

$$\begin{cases} l_t = \alpha(Y_t - s_{t-L}) + (1-\alpha)(l_{t-1} + b_{t-1}) \\ b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \\ s_t = \gamma(Y_t - l_t) + (1-\gamma)s_{t-L} \\ Y_{t+m} = l_t + mb_t + s_{t-L+1+(m-1)modL} \end{cases}$$

The dependence of the level expresses in difference between current value of the series and the corresponding seasonal component. The trend remains without change, and the seasonality depends on not only the previous and current series value, but also the level. In addition, the components are smoothed through all available seasons [2, 11]. Now, having a seasonal component, we can predict not just one or two values, but *m* steps forward (Figure 3).

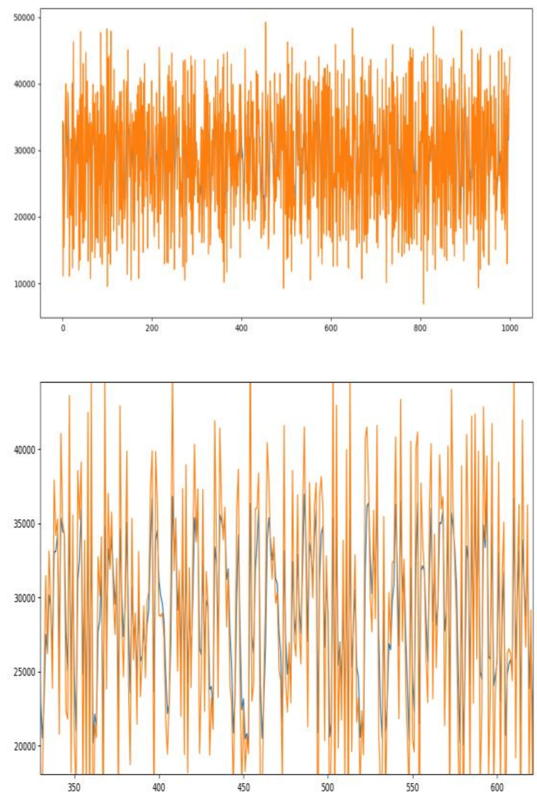

Figure 3. Holt-Winters method (at different scales)

Apart from this, to build confidence intervals the model can be expanded with Brutlag's method [11]:

$$\begin{cases} y_{\max\_t} = l_{t-1} + b_{t-1} + s_{t-T} + md_{t-T} \\ y_{\min\_t} = l_{t-1} + b_{t-1} + s_{t-T} - md_{t-T}, \\ d_t = \gamma \cdot |Y_t - Y_{t+1}| + (1-\gamma)d_{t-T} \end{cases}$$

where *T* is the season length, *d* is the forecasted error, and the rest of parameters are taken from HW-model (Figure 4).

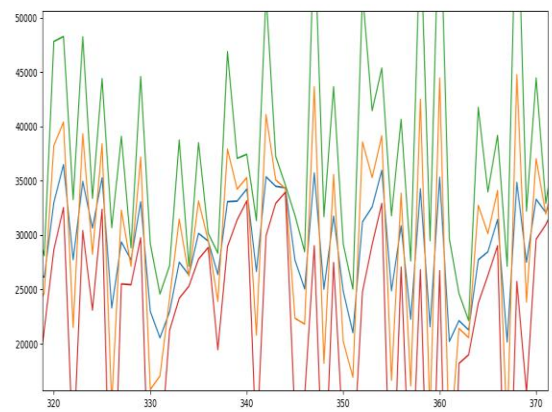

Figure 4. Holt-Winters method with confidential intervals

IV. RESULTS

At present there is no formal algorithm for projecting neural networks. That is why the issue of parameters and neuronet architecture adjustment requires creativity. When solving the problem of prevent damage from accidents optimization, a neural network was used.

Model's learning rate was selected as 0,1. The deep learning of neuronet model is conducted by the gradient descent method realized with the error back-propagation algorithm [9, 11]. One third of statistics data was used for learning the neural net. As a result of the program, the result is presented as shown in the Figure 5.

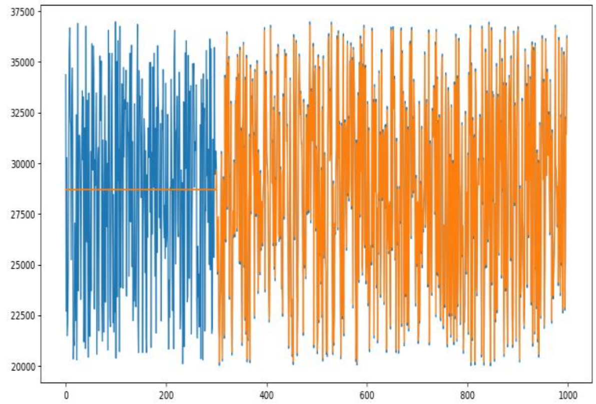

Figure 5. The program results

Theil coefficient calculation for the models described gives the following values (table 1).

Table 1. Theil coefficients

Model	Theil coefficient	Model	Theil coefficient
AR (1)	0.11812	ES (0.6)	0.0553
AR (5)	0.11827	ES (0.9)	0.0155
MA (1)	0.1214	DES (0.1,0.9)	0.1414
WMA (6)	0.0421	DES (0.9,0.1)	0.0306
ARIMA (2,0,1)	0.0918	HW	0.1162
ES (0.1)	0.1098	Nnet	0.0644

The best result for given time series was achieved using the ESM with $\alpha = 0.9$ (Table 1).

V. DISCUSSION

The forecasting models and methods were compared in this article and the necessity of the use of prevent accident damage method has got a justification in this study. In addition to this, this research also compares time series dynamics analysis methods, examines the technique for accuracy of predicting values estimation and provides a brief description of the models and examples of their use. The mathematical model building problem using the minimization forecast error criterion is stated and solved. Such mathematical methods of mathematical statistics and econometrics as autoregression, moving average, exponential smoothing, and neural network modeling were used to solve this problem.

VI. CONCLUSION

The study proved that despite the decrease in the frequency of accidents in the gas pipeline in recent years, the "price" of one accident increases. Therefore, an algorithm for predicting accidents based on factors changing the soil, climate, and vegetation in the vicinity of sections of the gas pipeline and oil pipeline is needed. Information is proposed to be obtained using satellite images, and terrain observation by unmanned aerial vehicles. It is proposed to form a neural network model to predict the possibility of disasters and damage.

Thus, the study stated and solved the problem of choosing the model to assess accidents damage. It observes the basic methods of analyzing and forecasting time series for solving the accidents problem. Based on the results, there was built algorithm, which can ground the choice of best time series approximation. In addition to solve the task, a software product that automates the specialist's work on forecasting was developed. The result is the algorithm for select the optimal model basing on minimal the forecasting error, as well as the software that realizes this algorithm. Due to the existence of complex dependencies in the time series, which linear methods can't deal with in a proper way, neural networks often can solve some such problems. Therefore, in further studies are going to improve the neural network model, as well as to research the use of non-stationary time series analysis methods.

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