In the paper titled "Investigation of prospects for forecasting non-linear time series by example of drilling oil and gas wells," the authors A V Vlasenko et al. present their research. They address the challenge of forecasting non-linear time series, which is crucial in the oil and gas industry. The article is published in the Journal of Physics: Conference Series, volume 1015, issue 052036.

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Investigation of prospects for forecasting non-linear time series by example of drilling oil and gas wells

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Abstract. Discrete time series or mappings are proposed for describing the dynamics of a nonlinear system. The article considers the problems of forecasting the dynamics of the system from the time series generated by it. In particular, the commercial rate of drilling oil and gas wells can be considered as a series where each next value depends on the previous one. The main parameter here is the technical drilling speed. With the aim of eliminating the measurement error and presenting the commercial speed of the object to the current with a good accuracy, future or any of the elapsed time points, the use of the Kalman filter is suggested. For the transition from a deterministic model to a probabilistic one, the use of ensemble modeling is suggested. Ensemble systems can provide a wide range of visual output, which helps the user to evaluate the measure of confidence in the model. In particular, the availability of information on the estimated calendar duration of the construction of oil and gas wells will allow drilling companies to optimize production planning by rationalizing the approach to loading drilling rigs, which ultimately leads to maximization of profit and an increase of their competitiveness.

1. Introduction

New information technologies are increasingly determining the degree of economic development of the state. Economic competition, both at the interstate and at the domestic level, is increasingly moving to the scientific and technical sphere, becoming a competition of intellectual capital.

At present, information technologies, mathematical and computer modeling are widely implemented in the practice of oil and gas companies, which allows one to diagnose the whole complex of drilling equipment at a high level, to measure parameters and to calculate well’s characteristics directly in the drilling process.

Oil companies are increasing volumes of oil and gas production. At the same time, natural and economic conditions impose increasingly stringent requirements for the drilling time. Therefore, there is a need to continuously improve the technique and technology of well drilling and also methods for forecasting the process of borehole wiring, including the speed and timing of drilling.

2. Materials and methods

In accordance with the above mentioned information, the development and application of systematic analysis methods for complex research objects, processing information, forecasting of technological
processes, especially the commercial speed of achieving results, are most relevant.

At present, there are various developments in the field of forecasting time series. From the point of view of mathematics, time series is numerical sequences that naturally arise in experiments, both natural and numerical [1]. Let us distinguish deterministic (strictly defined) and stochastic (random) processes, as well as stationary and non-stationary time series.

The most widely used models of forecasting time series are in the economy [2, 3], but they are highly specialized, which excludes the possibility of their adaptation for forecasting the drilling speed of oil and gas wells. They include: regression models, autoregression models, exponential smoothing models, neural network models, models based on Markov chains. The relative error of their application for forecasting the drilling speed of oil and gas wells is from 15 % to 50 %, which is beyond the limits of acceptable values.

3. Features of forecasting commercial speed of drilling oil and gas wells

Let us consider nonlinear dynamical systems that can be described using a discrete time series or mapping.

Nonlinearity implies the property of a process or a system to have various stationary states corresponding to various admissible laws of behavior in its structure. Whenever the behavior of such objects can be expressed by a system of equations, these equations turn out to be nonlinear in the mathematical sense. Mathematical objects with this property correspond to the appearance of a spectrum of solutions instead of a single solution of the system of equations describing the behavior of the system. In this case, one must assume that in the nonlinear system there is a spectrum of potential opportunities of its development and a non-unique stationary state. Each solution from this spectrum characterizes a possible way of behavior of the system.

The time series can be considered as a process, first of all, the dynamic characteristic of the object or the system, as well as the type of motion, transformation or evolution over a certain time [4], the modification of quantitative or qualitative characteristics of the object (for example, oil and gas wells) are studied. The time series in this aspect can be defined as a sequential change in the state of the object (well).

Let us consider the dynamics of the change in the bottom of a single individual well. At each time interval, the well deepens, which consumes some of the resource. The resource is limited to initial conditions, such as the depth of the oil- or gas-bearing layer.

To build a mathematical model, it is necessary to describe the dependence of the commercial drilling speed on time. The description in the mappings is the same as in the differential equation, but written for discrete time [5, 6].

Let us describe the change in the bottomhole in the depth interval from n to n+1. It will be equal to the depth of the well, reached at cycle n, plus the penetration for the current time interval. The depth of the well on cycle n is denoted by \( x_n \), and in the next cycle - by \( x_{n+1} \).

The potential depth of the well (this is a capacity of the niche) will be denoted by \( L \), accordingly, the undeveloped depth in cycle n will be equal to \( L - x_n \).

Let us denote the intensity of drilling by \( A \). Then, the change in the depth of the well can be written in the form of a mapping:

\[
x_{(n+1)} = x_{n+1} = x_n + Ax_n(L - x_n).
\]

The first term determines the depth of the well at the previous step, the second – the penetration at this step. It is numerically equal to the commercial drilling speed, since the authors took the time of one step (cycle) as one:

\[
V_{(n+1)} = V_{n+1} = Ax_n(L - x_n), V_0 = 0.
\]

For the further analysis of the model, let us assume that the total depth of the well (the capacity of
the niche) is one \((L=1)\). Let us normalize the depth of the well at each step:

\[
 x_{n+1} = x_n \cdot L^{-1}.
\]  

(3)

Taking into account (3), equation (1) takes the form:

\[
 x_{n+1} = x_n + a x_n(1 - x_n),
\]

where \(a=A \cdot L\) – the drilling intensity, correlated with the total depth of the well (technical speed).

Equation (2) for commercial drilling speed is converted to the form:

\[
 V_{n+1} = a x_n (1 - x_n).
\]

(5)

The commercial speed of drilling oil and gas wells can be considered as a series where each next value depends on the previous one. The main parameter here is the technical drilling speed. First, when it increases, the commercial speed increases, but if a certain threshold is exceeded, the system increasingly turns into critical states, which are characterized by an increase in the number of incidents, complications, and various equipment failures. The commercial speed begins to fluctuate, then its behavior becomes even more complicated, and can even become chaotic [7].

In general, commercial drilling speed \(V_k\) is determined by the penetration for 1 month \(H_p\) of the drilling rig operation, taking into account all types of work including non-productive time. Commercial speed, including productive \(T_{pt}\) and non-productive time \(T_{npt}\), can be calculated as follows:

\[
 V_k = H_p \cdot 30 \cdot (T_{pt} + T_{npt})^{-1}.
\]  

(6)

The value of commercial speed is influenced by factors of technical, technological and organizational nature. Increasing \(V_k\) requires a reduction and elimination of unproductive time and shortening the duration of productive operations. This can be achieved by improving drilling equipment and technology, mechanizing labor-intensive operations, improving the organization of production.

Commercial drilling speed is a general indicator characterizing the efficiency of the entire drilling process. This indicator is widely used in the practice of planning, analyzing and financing works at drilling enterprises.

The technical drilling speed is determined by the penetration volume drilled by one drilling rig per month. It includes the time spent on battering, round-trip and support operations, cementing, all types of geophysical studies, preventive maintenance, etc. Technical speed is used for the comparative evaluation of the efficiency of new equipment, and various drilling methods. The factorial model of technical speed can be represented as follows:

\[
 a = F(k_1, k_2, ..., k_n) + \varepsilon,
\]

(7)

where \(k_1, k_2, ..., k_n\) are factors that characterize the depth of productive horizons, the type of well (prospecting, exploration, etc.), the rock hardness, the presence of zones of inconsistent drilling conditions and the overall level of organization of work. Climatic conditions, the degree of dispersion of production facilities, their remoteness from the supply bases also influence the drilling speed;

\(\varepsilon\) – a random error characterizing the error of measuring instruments, malfunctions in the operation of measuring equipment, as well as other factors that distort the reliability of the received signals.

The problem of determining the necessary and sufficient parameters for estimating the predicted values of the commercial speed of well construction influences the possibility of a reliable forecast of the drilling time. At the same time, the desire to take into account as many indicators and evaluation criteria as possible in the model can lead to the fact that the computer system will come close to the
«Turing limit». In order to eliminate the measurement error and to represent the commercial speed of the object with necessary accuracy at the current, future, or any of the previous moments of time, a Kalman filter must be applied to the developed discrete model [8-10].

The Kalman filter uses a well-known mathematical model of object dynamics that describes what changes in the state of the object are possible in order to eliminate the measurement errors and to present the position of the object with good accuracy at a given moment (filtration), at future moments (forecasting), or in some of the past moments (interpolation or smoothing).

The work of each step of the Kalman filter can be divided into two stages: forecast and correction. The forecast phase calculates the state vector of the system by its value in the previous step of the filter operation.

At the stage of correction, the algorithm receives data from current measurements (observations) that are used to refine the predicted value of the state vector, and calculate the actual estimate of the state vector of the dynamic system.

The algorithm sequentially processes newly arriving measurement vectors, taking into account the values calculated on the previous cycle.

At the final stage of the algorithm's work, preparation for the arrival of a new measurement vector takes place. Based on the given linear transformation, linking the subsequent state vector with the previous one, an estimation of the state of the system, referred to the time of the next measurement, is forecasted.

For a nonlinear system with dissipation, it is practically impossible to predict the concrete course of its evolution, since real initial conditions can never be defined with absolute accuracy, and the presence of bifurcation points leads to the fact that even small perturbations can strongly turn the direction of evolution. It was shown in [5, 6] that even with clearly defined initial conditions and uniquely determined parameters, the system can have several stable states, which it takes successively with a period depending on the parameters. In this case, even a slight change in the parameters of the system leads to a change in the dynamic mode. The transition to a new period occurs through a field of chaotic behavior. Thus, any uncertainty in the initial conditions or parameters of the system does not allow one to accurately predict its state at subsequent times. The last statement extends as well to well-defined parameters corresponding to stable cycles.

Information about the uncertainty of the forecast of system behavior is extremely important for making a managerial decision. Such information will not only simplify decision making, depending on the reliability of the model, but also help users of the model understand how substantiated their calculations are for obtaining an accurate forecast of the simulated system behaviour.

Determining the probability of a forecast is the usual way of assessing its uncertainty; now it becomes a common practice in many types of human activity. The formulation of a probabilistic model carries an a priori estimate of its quality.

The main purpose of providing information on the uncertainty of the model is to assist its recipient in making decisions. An estimate of the uncertainty can be, for example, information about the range of variation of the simulated quantity in the form of a confidence interval. It is even more important that users of the model understand that when making decisions based on models that are inherent in uncertainty, «false alarms» are possible. This is a characteristic feature of probabilistic forecasts and any probabilistic models [11].

One of the ways of transition from a deterministic model to a probabilistic one is ensemble modeling. When using ensemble modeling methods, an attempt is made to quantitatively evaluate the sensitivity of the situation to the initial conditions and, thus, to determine the degree of uncertainty of the model arising from this reason.

The simplest ensemble is a set of models starting with slightly different (perturbed) initial data (ensemble of initial data). The scatter of the ensemble characterizes the quality of the model, depending on the situation. The ensemble average gives the best (in comparison with the deterministic model) estimate of the true state of the system.
Sources of model uncertainty:
1) uncertainty in the initial data – ensemble (set) of phase trajectories;
2) uncertainty in the parameters of the model – an ensemble (set) of models with fixed initial data, but with different parameters;
3) the uncertainty in both the parameters and the initial data is a two-dimensional ensemble.

For each individual member of the ensemble (deterministic forecast), the uncertainty of the model leads to a deviation of the forecast value from the actual state of the system.

The task is to express the inherent uncertainty in a quantitative way. In this case, the utility of the model for decision-makers is significantly increased. The solution to this problem consists in using the group of forecasts (ensemble) for a number of different initial conditions for one model or group of models with different but equally possible approximations.

The ensemble of models covers a number of possible outcomes, providing a range of data where uncertainties can increase. As a result, the ensemble of models can automatically obtain information on the probabilities applicable to the requirements of consumers [12].

4. Conclusion

As a result of the analysis of classical methods of forecasting time series, their inefficiency has been established in case of forecasting the drilling speed of oil and gas wells. The relative error of their application for forecasting the drilling speed of oil and gas wells is from 15% to 50%, which is beyond the limits of acceptable values.

As a result of the analysis of the hole deepening process, the models of temporary bottom change and commercial drilling speed have been developed. It was shown that the commercial speed of drilling oil and gas wells can be considered as a series where each next value depends on the previous one. The main parameter here is the technical drilling speed. First, when it increases, the commercial speed increases, but if a certain threshold is exceeded, the system increasingly turns into critical states, which are characterized by an increase in the number of incidents, complications, and various equipment failures. The commercial speed begins to fluctuate, then its behavior becomes even more complicated and can become even chaotic.

In order to eliminate the measurement error and to represent the commercial speed with necessary accuracy at the current, future, or any of the previous moments of time, a Kalman filter is adapted to the oil and gas wells drilling.

In order to transit from a deterministic model to a probabilistic one, ensemble modeling is proposed. The main purpose of providing information on the uncertainty of the model is to assist its recipient in making decisions.

The availability of information on the forecasting calendar duration of the oil and gas wells construction will allow drilling companies to optimize production planning by rationalizing the approach to loading drilling rigs, which leads to maximization of profit and an increase of their competitiveness.

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