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INFORMATION SYSTEM FOR FORECASTING NONLINEAR NON-STATIONARY PROCESSES IN FINANCE

Background. Financial processes are often characterised by nonlinearity and non-stationarity, which makes them difficult to accurately model and forecast. Traditional methods cannot effectively take into account the complex interrelationships and variability of such processes, which generates increased uncertainty and risks. This leads to the need to develop new information systems and methods to improve the accuracy and sustainability of forecasts.
Objective. The purpose of the paper is to provide a brief overview of the characteristics of nonlinear non-stationary processes, to develop a methodology for their modelling, as well as to build mathematical models based on actual statistical data and to obtain practically useful results of modelling and forecasting selected processes.
Methods. The methodology for modelling and forecasting nonlinear non-stationary processes is applied, models are built using data mining, such as regression models and a neural network, and the main metrics for assessing the adequacy of the model and quality of the forecast are used.
Results. The developed information system for modelling and forecasting nonlinear non-stationary processes is approbated on real statistical data. Based on data mining methods, models of the share price dynamics of a well-known company were built. The study's results demonstrate that using an integrated approach, which includes regression models and neural networks, significantly improves the quality of forecasting variance changing in time and the nonlinear non-stationary process.
Conclusions. The task of high-quality forecasting of processes due to rapid, sometimes hard-to-predict changes in the external environment, i.e. external shocks, which is typical for nonlinear non-stationary financial processes, is still relevant today. The literature provides a sufficient variety of methods for modelling these processes. However, in this research, the methods that have demonstrated their advantages in modelling financial transactions in the stock market were chosen, and therefore it makes sense to expand and improve the perspectives of this approach.
Keywords: information system; nonlinear non-stationary processes; methodology of modelling; forecasting; regression models; neural network; finance.

Introduction

Forecasting, as a research area in finance, economics and ecology is focused on optimising the management ideology, fully corresponds to the goals and objectives of sustainable functioning of these rather complex and important systems for humanity. The use of a modern, effective forecasting system can help in risk management, operational and strategic decision-making, and dynamic planning under conditions of uncertainty.

Effective forecasting systems include those built on the techniques of data mining and probabilistic-statistical methods, which are used for modelling and predicting the development of nonlinear non-stationary processes. Such information systems are complemented by appropriate sets of statistical criteria for analyzing data quality, model adequacy, assessing the quality of forecasts and relevant alternative solutions.

Providing accurate and credible forecasts using data mining can significantly improve risk management in businesses and various financial institutions. This will help reduce potential losses and increase stability to financial market turbulences.

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An information system for forecasting nonlinear non-stationary processes in finance is a key tool for modern financial analysis. It integrates large volumes of data, processes and analyses complex nonlinear relationships, and adapts forecasting models to changing market conditions. The use of such a system improves the accuracy and timeliness of forecasts, which is critical for timely management decision-making. Data mining in this system contributes to a deeper understanding of financial processes, more effective risk management and increased stability of financial institutions to external shocks.

Problem statement

The research is dedicated to solving the following tasks: 1) to analyse the types of statistical financial processes; 2) to structure the methodology of modelling nonlinear non-stationary processes; 3) to investigate some forecasting models; 4) to build mathematical models on actual statistical data, to obtain practically useful results of modelling and forecasting, and to analyse the obtained results.

Characteristics of statistical processes in finance

The nonlinear non-stationary processes in finance are characterised by the complexity of their structure, which makes them difficult to model and predict. They can be divided into several types, as shown in Fig. 1 [1].

Stationary linear processes have unchanged statistical properties as time changes, so they can be easily described by autoregressive models. Non-stationary linear processes are characterised by the presence of a first-order linear trend, which makes them difficult to model and forecast due to variable mean and variance.

Partially stationary nonlinear processes have a certain degree of stability but involve nonlinear dependencies between variables. They can demonstrate stationarity under certain conditions, but their nonlinear relationships make the analysis more difficult, as simple linear methods cannot adequately capture their behaviour [2].

Integrated processes are characterised by the presence of trends of the first order or higher. They become stationary after a certain level of differentiation, which adds to the difficulty of analyzing them, as it is necessary to determine the exact level of differentiation required to achieve stationarity. This makes it difficult to build models that correctly reflect the long-term tendencies of such processes.

Cointegrated processes involve several non-stationary time series that have stable linear relationships that may be stationary. These processes are particularly difficult to forecast, as they require the identification and analysis of stable relationships between different variables that can only be revealed by long-term observations [3].

Heteroscedastic processes have a variable dispersion that depends on time and can significantly vary under the influence of external factors, such as economic changes or market crises. The dispersion instability makes these processes particularly difficult to model, as it requires taking into account dynamic changes in volatility that can significantly affect the accuracy of forecasts [4].

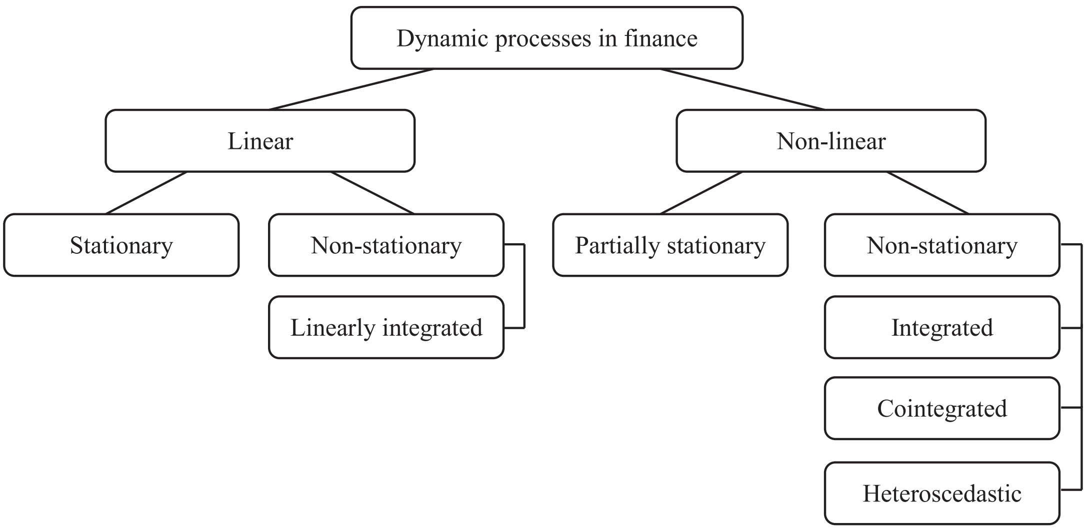

Fig. 1. Types of financial processes

These characteristics of nonlinear non-stationary processes in finance determine the difficulty of their analysis and modelling. Various nonlinear dependencies, variable trends and dispersion create challenges for analysts, requiring the use of complex approaches to improve the quality of forecasting and assessing the characteristics of these processes.

Methodology for modelling nonlinear non-stationary processes

With all the difficulties of determining the type of time series process under investigation and its interpretation, including all the features of external shocks and uncertainties, there is a need to develop a certain methodology for modelling nonlinear non-stationary processes in finance. It can be presented in the form of the following stages:

1. Data pre-processing.
2. Analyzing the statistical characteristics of the time series.
3. Selecting model types based on time series characteristics.
4. Building selected models and calculating model adequacy criteria.
5. Evaluating the forecast and calculating forecast quality assessments.

The process of modelling nonlinear non-stationary processes begins with data pre-processing, which may include normalisation, gap filling, smoothing and filtering [5].

The next step is to analyse the characteristics of the time series, which is a set of checks for nonlinearity, trend, stationarity, heteroscedasticity, and seasonality.

In financial processes, it is allowed to use the dispersion method, which helps to determine the presence of nonlinearity, using a function:

$$\psi_{zu}(t_1,t_2) = E_{u(t_2)}[E_{z(t_1)}[z(t_1) \mid u(t_2)] - E_{z(t_1)}[z(t_1)]]^2.$$

This function is solved using a complex integral equation [5], [6].

The problem of nonlinearity of process forecasting can also be solved with the help of Fisher's statistical general test (f-test):

$$\widehat{F} = \frac{\frac{1}{k-2}\sum_{i=1}^{k}\sum_{j=1}^{n_j} n_i(\overline{y_i} - \widehat{y_{ij}})^2}{\frac{1}{k-2}\sum_{i=1}^{k}\sum_{j=1}^{n_j} (y_{ij} - \overline{y_i})^2},$$

where k — number of data groups; n_i — number of dimensions in the group; $\overline{y_i}$ — average for the group; $\widehat{y_{ij}}$ — estimation of the process by direct regression; n — total number of dimensions [5], [7].

The assumption of linearity of the process is considered false if the statistic $\widehat{F}$ with degrees of freedom equal to $\nu_1 = k-2$, $\nu_2 = n-k$ equal to or greater than the significance level.

The problem of stationarity of the process is solved with the help of the extended Dickey-Fuller test. The feature of this test is that the value of the dependent variable with large lag values is entered into the regression expression, which is enough to avoid the use of autocorrelation residuals during testing. This expression has the following form: $\Delta y(k) = a_0 + a_1 k + by(k-1) + \sum_{i=1}^{p} c_i \Delta y(k-i) + \varepsilon(k)$, where a_0, a_1, b, c_i — unknown regression coefficients [5], [8].

An important step is to determine the heteroscedasticity, i.e. the dependence of the dispersion of the process on time. This is performed using heteroscedasticity tests, such as the Breusch-Pagan (Godfrey) test or the White test. Identifying heteroscedasticity allows you to take into account the variability of dispersion in the model [5], [9], [10].

The next step is to identify seasonality in the process. This involves analyzing seasonal components to identify regular fluctuations that recur at a certain frequency, enabling more accurate modelling and forecasting.

Determining how to extract or model a trend involves determining the order of integration of the process or whether the trend can be described by one of the functions: polynomial, exponential, logarithmic, or others. Extracting the trend allows you to focus on the residuals, which represent short-term fluctuations and random components. The analysis of residuals is carried out using the autocorrelation function (ACF) and partial autocorrelation function (PACF), which helps to identify the structure of dependencies in time series [11], [12].

After analyzing all the characteristics of the time series, the modelling method is determined, which will allow describing the process in the most accurate form. Based on the selected method, the model is built and the model adequacy criteria are defined.

The model adequacy criteria allow us to assess the statistical significance of the mathematical model coefficients separately, determine the integral error of the model concerning the original time series, establish the presence of correlation between the model error values since they should be uncorrelated, and determine the degree of adequacy of the model to the physical process as a whole. Here are some of them:

– Sum squared errors (residuals) of the model, calculated by the formula:

$$SSE = \sum_{k=1}^{N} e^2(k) = \sum_{k=1}^{N} [\hat{y}(k) - y(k)]^2 \to \min,$$

where

$$\hat{y}(k) = \widehat{a_0} + \widehat{a_1}\hat{y}(k-1) + \widehat{a_2}\hat{y}(k-2) + \widehat{b_1}x(k) + b_2 z(k);$$

$y(k)$ – data measurements; N – sample length (capacity).

– Determination coefficient $R^2 \to 1$, calculated by the formula:

$$R^2 = \frac{\mathrm{var}(\hat{y})}{\mathrm{var}(y)} = 1 - \frac{SSE}{SST},$$

where $\mathrm{var}(\hat{y})$ – dispersion of a part of the time series of the main variable of the equation; $\mathrm{var}(y)$ – is the sample dispersion of this variable; SSE – sum squared errors (residuals) of the model; $SST = \sum_{k=1}^{N} [y(k) - \overline{y}]^2$ – total sum of squares $\overline{y}$.

– Durbin-Watson statistic (DW), which is calculated by the formula:

$$DW = 2 - 2\rho,$$

where $\rho = \dfrac{E[e(k)e(k-1)]}{\sigma_e^2}$ – correlation coefficient between adjacent error values; σ_e^2 – dispersion of the error sequence $\{e(k)\}$. Thus, in the complete absence of correlation between the errors $DW = 2$ – is the ideal value. The threshold values for DW are 0 (where $\rho = 1$) and 4 (when $\rho = -1$) [5], [13].

Akaike information criterion (AIC), which is calculated by the formula:

$$AIC = N \ln\left(\sum_{k=1}^{N} e^2(k)\right) + 2n,$$

where $n = p + q + 1$ – number of model parameters estimated using statistical data (p – number of parameters of the auto-regression part of the model; q - number of moving average parameters; 1 appears when the bias (or cross-section) is estimated, that is a_0) [14].

– Theile coefficient, which is calculated by the formula:

$$U = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y_i})^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i)^2} + \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\widehat{y_i})^2}}.$$

The permissible values of the coefficient are $0 \le U \le 1$. The model cannot be used in forecasting when $U = 1$, else, when $U = 0$ it means that the forecast series coincides with the real series, i.e. in this case the model best describes the real process.

– Student's t-statistic.

– Fisher's F-statistic.

The next stage is to evaluate a forecast based on the developed model. The quality of the forecast is assessed by comparing forecast values with actual data using metrics. If necessary, in case of significant errors, the previous stages are returned to adjust the model and improve the accuracy of the forecasts.

These are some of the possible methods for assessing forecast quality:

– Root mean square error:

$$MSE = \frac{1}{S}(y(k+s) - \hat{y}(k+s,k))^2 \text{ or}$$

$$RMSE = \sqrt{\frac{1}{S}(y(k+s) - \hat{y}(k+s,k))^2}.$$

– Mean absolute error:

$$MAE = \frac{1}{S}\sum_{i=1}^{S}\frac{|y(k+s) - \hat{y}(k+s,k)|}{|y(k+s)|} \text{ [15].}$$

– Mean Absolute Percentage Error:

$$MAPE = \frac{1}{S}\sum_{i=1}^{S}\frac{|y(k+s) - \hat{y}(k+s,k)|}{|y(k+s)|} \times 100\%.$$

This comprehensive approach to modelling nonlinear non-stationary processes in finance ensures high accuracy and reliability of forecasts, taking into account all the essential characteristics of the processes.

To sum up all of the above, this methodology can be presented in the form of a flowchart in Fig. 2 [16].

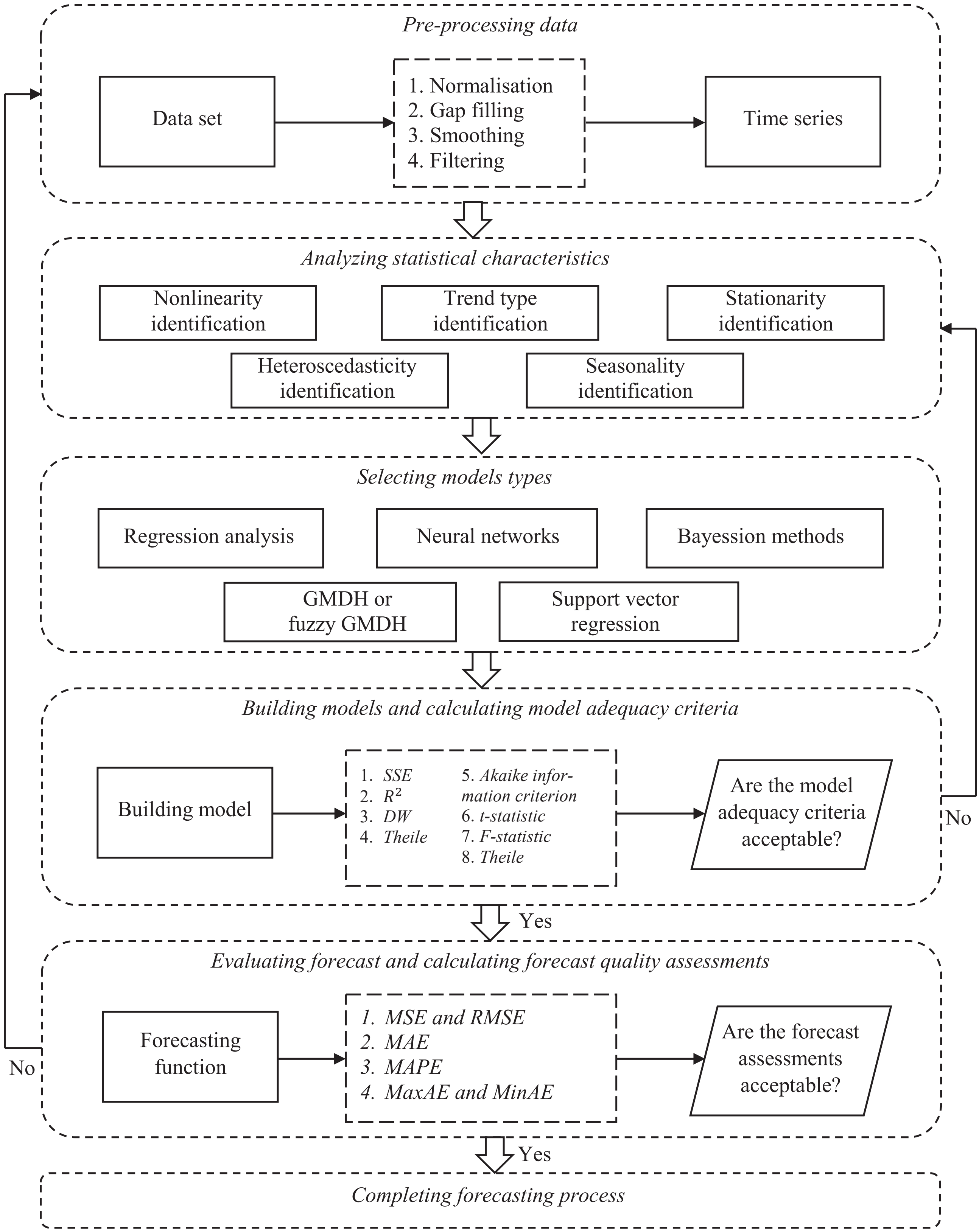

Fig. 2. Flowchart of the methodology for modelling nonlinear non-stationary processes

Characteristics of some forecasting models

Starting from the first application of AR autoregressive models to the development of ARMA models, these time series models have become the basis for both theoretical research and practical applications. For a long time, the popularity of these models remained unchanged. Although the original ARMA framework has been extended to incorporate long-term dependence with the partially integrated ARIMA, the multi-dimensional VARMA and VARMAX models, and the non-stationarity of random fluctuations due to cointegration. The models remain important due to their ease of implementation and flexibility.

ARCH models are widely used to model volatility in financial and economic processes. The main purpose of implementing ARCH models is to assess and forecast risk in financial time series by modelling the variable (conditional) dispersion.

Autoregressive conditional heteroskedastic model (ARCH) with order $p(\geq 1)$ is defined as:

$$X_t = \sigma_t \varepsilon_t \text{ and } \sigma_t^2 = c_0 + b_1 X_{t-1}^2 + \ldots + b_p X_{t-p}^2,$$

where $c_0 \geq 0$, $b_j \geq 0$ – constants, $\{\varepsilon_t\} \sim IID(0,1)$ and ε_t is independent of $\{X_{t-k}, k \geq 1\}$ for all values of t. A stochastic process $\{X_t\}$ defined by the equations above is called the $ARCH(p)$ process. [17]

The basic concept of their construction is that the distribution X_t, which is predicted on the basis of previous values, is a scaling transformation of the distribution ε_t with a scaling constant σ_t, which depends on the past values of the process. This makes it easy to estimate the conditional clusters of X_t based on its previous values [17].

The advantages of the ARCH model include the ability to detect and model volatility clusters when large changes in volatility are concentrated in certain periods. This is an important characteristic of financial markets, especially during crises or periods of instability.

The disadvantages of this model include the following: positive and negative model shocks have the same effect on volatility, as it depends on the square of previous shocks, but the price of a financial asset has different responses to these shocks; higher-order models have certain limitations; ARCH models describe the dynamics of conditional dispersion well, but do not provide an understanding of the causes of such dynamics of the financial process; models may overestimate volatility, as they tend to react slowly to significant isolashortted shocks in a time series [18].

The ARCH model has been extended for economic and statistical reasons. In particular, a significant development is the inclusion of a moving average component, in particular the generalised model (GARCH).

The generalised autoregressive conditional heteroscedastic model (GARCH) with the order $p(\geq 1)$ and $q(\geq 0)$ is defined as:

$$X_t = \sigma_t \varepsilon_t \text{ and } \sigma_t^2 = c_0 + \sum_{i=1}^{p} b_i X_{t-i}^2 + \sum_{j=1}^{q} a_j \sigma_{t-j}^2,$$

where $c_0 \geq 0$, $b_i \geq 0$, $a_j \geq 0$ – constants, $\{\varepsilon_t\} \sim IID(0,1)$ and ε_t is independent of $\{X_{t-k}, k \geq 1\}$ for all values of t. A stochastic process $\{X_t\}$ defined by the equations above is called the $GARCH(p,q)$ process [17].

The main idea of creating the GARCH model is to extend the ARCH model to more flexible and accurate modelling of financial time series volatility.

In the GARCH model, the conditional dispersion depends not only on the previous residuals, but also on the previous values of the dispersion itself. This allows for taking into account more complex dependencies in volatility and providing more accurate forecasts, especially when volatility is high and changes over time, which is its advantage. Other advantages include the model's ability to take into account both short-term and long-term components of volatility.

The GARCH model has the same disadvantages as the ARCH model. For example, it reacts equally to both positive and negative shocks. Moreover, the results of empirical research on high-frequency financial time series indicate that GARCH models are limited in their ability to reproduce the extremes of the distribution, even when standardised corrections are applied.

LSTM (Long Short-Term Memory) models are a type of recurrent neural network (RNN) designed to process sequential data efficiently. A key feature of LSTMs is their ability to store long-term dependencies due to a special structure of memory blocks and three types of gates:

– Forget gate: $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$, where W_f – weighting coefficients; x_t – input signal; h_t – memory block output; b_f – shift vector.

– Input gate: $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$, $\widetilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$ where $\widetilde{C}_t$ – vector of new candidate values.

– Output gate: $o_t = \sigma(W_0 \cdot [h_{t-1}, x_t] + b_0)$, $h_t = o_t * \tanh(C_t)$, where $C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t$ – is the state of the memory block at time t [19].

The main idea of using LSTM models is the ability to handle complex, nonlinear and non-stationary dependencies in time series. Due to their memory block architecture, they are able to store long-term information and take into account complex patterns in the data, which allows for more accurate forecasting of future financial performance.

The advantage of LSTM models is the use of gates, which avoids the problem of gradient damping, which is common in traditional RNN [20].

Among the disadvantages are the following: tendency to overfitting, which requires the use of regularisation methods (dropout, early stopping); the need to correctly adjust hyperparameters; complexity of the architecture.

Practical results of the research

Let us consider the building of several proposed models for short-term forecasting of the nonlinear non-stationary financial process of price dynamics at the close of trading of the well-known AMD company during 2017–2022. The data sample contained 1510 elements, 1434 of which were used as a training sample (95 %), and 76 to check the forecasting results (5 %).

In order to objectively select the orders of the ARIMA model, ACF were built at 40 lags. Based on the results of the building of these functions, it was decided that models can be built with the parameter p, corresponding to the first, second or thirteenth order. Based on the data autocorrelation graph, it was decided to use a second order moving average model of $q = 2$. Also $d = 1$ was determined.

The GARCH model was built with the first order of symmetric innovation $p = 1$ and the first order of transformed conditional dispersion $q = 1$. The standardised Student's distribution was chosen as the probability distribution function.

The LSTM neural network was built on the basis of the Adam optimiser. The network configuration includes 100 epochs and a batch size of 64. Testing was performed with configurations of 50, 100, and 150 epochs. Since the difference between 50 and 100 epochs was significant, and the difference between 100 and 150 epochs was almost imperceptible, the optimal number of epochs was chosen to be 100. The loss function in the constructed network is the mean absolute error.

Comparative Table 1 below shows the results of modelling and forecasting of ARIMA(2,1,2), GARCH(1,1) and LSTM neural network based on a dataset of AMD's price dynamics.

***Table* 1.** Results of the built models

Type of model	Adequacy criteria		Forecast assessment		
	R^2	DW	MSE	RMSE	MAE
ARIMA(2,1,2)	0.8433	1.9820	6.0518	2.4600	1.7882
GARCH(1,1)	0.3458	2.1010	0.0019	0.0435	0.0341
LSTM	0.8427	1.9978	6.3296	2.5159	1.8653

Analyzing the results of modelling and forecasting from the comparative table, which shows the criteria for adequacy and forecast assessment of the built models, it is possible to conclude that all models have quite good results based on the calculated statistics.

It can be seen that in the considered models, R^2 moves towards one and DW moves towards two, which is an indicator of the efficiency of using the models. Similarly, the forecast assessment scores tend to their best value.

The visual analysis of the graphs of the forecasts of each model shows the following: the ARIMA model correctly identifies price trends and has minimal discrepancies with actual values in the forecast period; changes in stock prices using the GARCH model do not always correctly identify price trends and sometimes have relatively significant discrepancies with actual values; the LSTM neural network effectively reflects price trends and demonstrates minimal discrepancies with actual data in the forecast period. For example, Fig. 3 shows the results of forecasting the LSTM neural network, which can be used as one of the tools for making investment decisions.

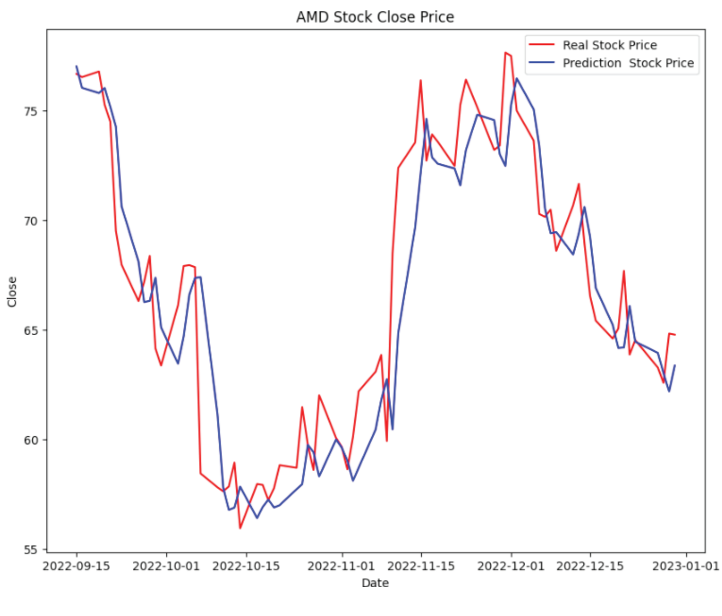

Fig. 3. Forecasting AMD price dynamics by LSTM neural network

Conclusions

This work has investigated the problem of forecasting nonlinear non-stationary financial processes, which are difficult to model accurately due to their variability and complex interrelationships. Traditional methods often do not take these features into account, which leads to increased uncertainty and risks. For this reason, an information system has been proposed to improve the accuracy and reliability of forecasts.

In the research, there was performed a brief review of the characteristics of nonlinear non-stationary processes and a methodology for their modelling was developed. Data mining methods, including regression models and neural networks, were used to build mathematical models. The main metrics for assessing the adequacy of models and forecasts ensured the accuracy of the results obtained.

The developed information system was tested on real statistical data, in particular, on the dynamics of share prices of one of the companies. The use of an integrated approach, including regression models and neural networks, has shown a significant improvement in the quality of forecasting the dispersion variable and the nonlinear non-stationary process itself. The results of the research confirmed that the use of data mining methods allows achieving more accurate and reliable forecasts, which is important for effective financial risk management.

Therefore, the results of this study confirm that the development of new information systems using data mining techniques is necessary to improve the accuracy and reliability of forecasting nonlinear non-stationary financial processes, which contributes to more effective financial risk management and stability of financial institutions.

Future research perspectives include expanding the range of models used to build forecasts, in particular by integrating more modern machine learning methods and other innovative approaches. It is also reasonable to expand the information system by adding automation elements to the data analysis process. This will allow faster and more accurate modelling of complex financial processes and adaptation of forecasts to changing market conditions.

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ІНФОРМАЦІЙНА СИСТЕМА ДЛЯ ПРОГНОЗУВАННЯ НЕЛІНІЙНИХ НЕСТАЦІОНАРНИХ ПРОЦЕСІВ У ФІНАНСАХ

Проблематика. Фінансові процеси часто характеризуються нелінійністю та нестаціонарністю, що ускладнює їх моделювання та прогнозування. Традиційні методи не можуть адекватно врахувати складні взаємозв’язки та мінливість таких процесів, що призводить до підвищеної невизначеності і появи ризиків. Це зумовлює необхідність розробки нових інформаційних систем і методів для підвищення точності та надійності прогнозів.

Мета дослідження. Виконати короткий огляд характеристик нелінійних нестаціонарних процесів, розробити методологію їх моделювання, а також виконати побудову математичних моделей на фактичних статистичних даних і отримати практично корисні результати моделювання і прогнозування вибраних процесів.

Методика реалізації. Застосовано методологію моделювання й прогнозування нелінійних нестаціонарних процесів, побудовано моделі за допомогою методів інтелектуального аналізу даних, а саме регресійні моделі та нейронну мережу, також використано основні метрики для оцінювання адекватності моделі та прогнозу.

Результати дослідження. Розроблену інформаційну систему для моделювання та прогнозування нелінійних нестаціонарних процесів апробовано на реальних статистичних даних. На основі методів інтелектуального аналізу даних було побудовано моделі динаміки цін акцій однієї з відомих компаній. Результати дослідження продемонстрували, що використання комплексного підходу, який включає регресійні моделі та нейронні мережі, значно покращує якість прогнозування змінної в часі дисперсії і самого нелінійного нестаціонарного процесу.

Висновки. Задача високоякісного прогнозування процесів внаслідок швидких, часом погано передбачуваних змін зовнішнього середовища, тобто збурюючих впливів, що характерне для нелінійних нестаціонарних фінансових процесів є актуальною і сьогодні. У літературі подано достатню варіативність методів моделювання цих процесів. Проте в цьому дослідженні обрані саме ті методи, які продемонстрували свої переваги в моделюванні фінансових операцій на фондовому ринку, а тому є сенс розширювати та вдосконалювати перспективи цього підходу.

Ключові слова: інформаційна система; нелінійні нестаціонарні процеси; методологія моделювання; прогнозування; регресійні моделі; нейронні мережі; фінанси.

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