DOI: https://doi.org/10.15276/hait.07.2024.7
UDC 004.9

Modeling and forecasting of stock market processes

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ABSTRACT

Stock market valuation uses a variety of indicators, such as indices and ratings, to reflect its state and movement. For example, a stock exchange index reflects activity on a stock exchange and is calculated using specific formulas. The calculation of indices is based on statistical data on securities and helps to assess the risks of investments. These indices reflect market conditions. The methodology for forming stock indices includes four stages: sampling, weighting of shares, calculation of the average, and conversion to the index form. Two types of sampling are used: deterministic and floating-power sampling. The weighting coefficients are determined by the price criterion and market capitalization. The studied approaches to stock market modeling allow identifying functional dependencies in the data and developing forecasts. In particular, the methods of approximation and modeling by the Wiener process are allocated. Stock market forecasting using the multi-layer architecture of Long Short-Term Memory in the Keras library is investigated. The overall results confirm that an intelligent information system for automated trading decisions is effective, providing traders with competitive advantages and reducing risks.

Keywords: Stock exchanges; stock market forecasting; stock selection; investment performance; trading decisions

For citation: **Uhryn D. I., Karachevtsev A. O., Shevchuk S. F., Uhryn A. D. "Modeling and forecasting of stock market processes".** ***Herald of Advanced Information Technology.*** **2024; Vol. 7 No. 1: 85–98. DOI: https://doi.org/10.15276/hait.07.2024.7**

INTRODUCTION

The modern world of stock trading is characterized by great instability and unpredictability. One of the main problems faced by stock market participants is the instability of macroeconomic factors, such as geopolitical conflicts, economic crises, and trade wars, which negatively affect asset price dynamics and disrupt market predictability. In addition, sharp changes in the stock market situation can also be caused by technical problems, failures in trading systems, as well as abuse and manipulation by large market participants. The growth in trading volumes and the availability of financial instruments also creates new challenges for traders and investors. The variety of assets and the fast growth of innovation in financial products can complicate decision-making and require market participants to constantly update their knowledge and adapt to new conditions. These factors require traders to react quickly to market changes and to analyze large amounts of data in a customized manner to make informed decisions, improve strategies and analytical tools to remain competitive.

In this context, intelligent automated trading systems are becoming not only key tools for achieving competitive advantage, but also a necessity for those seeking to remain profitable in such a dynamic environment. Therefore, the development and implementation of intelligent systems in the modern stock market is critical to achieving success in a constantly changing and volatile environment. They enable not only a rapid response to changes in financial conditions, but also provide traders and investors with reliable tools to make informed and successful investment decisions. Intelligent systems are based on analyzing large amounts of data, using machine learning algorithms and artificial neural networks to predict market trends, identify possible risks and search for potentially profitable investment opportunities. These systems automate the analysis process, make decision-making faster and more efficient, and reduce the likelihood of human error. This approach allows traders and investors to remain competitive in a constantly changing financial market, providing them with the opportunity to increase profitability and reduce the risks of their operations.

PROBLEM DEFINITION

Movements and trends in the stock market can be analyzed through the use of stock (exchange) indices calculated by experts from rating agencies, stock exchanges or business period analysts. The wide range of consulting and rating agencies specializing in the development and analysis of stock indices, as well as the variety of indices themselves, demonstrate the importance of stock indices in the stock market's performance system. Changes in the value of specific stocks can be compared to an index for the entire market or an index for a specific market segment to draw conclusions about the demand for stocks in the context of the market as a whole. This also allows investors to identify the most profitable market segments at a given time, etc.

ANALYSIS OF LITERARY DATA

Stock market indices are indicators that reflect the state of a particular market segment, including the levels and dynamics of prices for shares and other assets, transaction volumes, etc. The securities market indices are defined as indices of share prices in a given market and differ in their calculation methods and coverage of different types of securities [1].

The use of stock market indices is based on the assumption that fluctuations in share prices of leading companies affect changes in prices, supply and demand for securities in the stock market as a whole. The units of measurement of a stock index can be expressed as a percentage of the nominal value of shares or in currency per security, especially if shares do not have a nominal price.

The indices have the following characteristics:

1. Index list (sample). The criteria for selecting stocks to form the index are determined by the reliability of the corporations and representativeness. This means that the price fluctuations of the selected stocks should adequately reflect general price changes in the securities market or fluctuations in the prices of shares of issuers in a particular sector of the economy.
2. Averaging method. Various methods of averaging are used, such as arithmetic, geometric, moving average, and others.
3. Types of weights. Different weighting factors can be used for the shares included in the index: the exchange rate value of a corporation's share (price-weighted index) or the capitalization of the issuing corporation (market-weighted index). The use of the capitalization index determines the impact of changes in share prices of companies with the largest capitalization, while the use of the market value pays attention to shares with a high market value. In the absence of weights, changes in the share prices of different corporations have the same effect on the index, regardless of the absolute value of the share price.
4. Base value of the index. This is the value at the beginning of the period, which is chosen as the base for measuring changes.
5. The statistical base. To calculate the indices, the results of trading on the stock exchange and the over-the-counter securities market are used. A wide selection of stocks provides an objective picture of changes in the price situation on the capital market and creates the prerequisites for analyzing the behavior of investors and portfolio managers.

The index can be viewed as a key technical indicator of the market. Using technical analysis methods in relation to an index allows effectively analyzing the market situation and responding to possible changes in it in a timely manner. Simple methods of technical analysis can be applied to indices consisting of sufficiently liquid stocks. For example, the construction of an exponential moving average of an index provides signals for making buy or sell decisions, which can be used to confirm similar signals for individual securities. In the absence of new significant external factors, the approach of the index to the exponential moving average always leads to a slowdown in price movements, sometimes prompting them to start moving in the opposite direction.

THE PURPOSE AND OBJECTIVES OF THE RESEARCH

The objective of the study is development and implementation of an intelligent information system for automated trading decisions in the stock market. This system will provide traders with competitive advantages and reduce risks by using data analysis through various approaches, such as approximation methods, Wiener process modeling, and multi-layer Long Short-Term Memory architectures in the Keras library. The main stages of realizing this goal include data sampling, stock weighting, index calculation, and development of predictive models to effectively forecast stock market movements.

To achieve this goal, the following tasks need to be solved:

1. Analyze and describe the indices of the current state of the stock market, the comparative efficiency of investments in stocks and placement of funds on deposit according to various criteria: taking into account the adjustment factor, with market weighting and a combination of price and market capitalization weighting criteria.

2. Based on the defined functional dependence, make a forecast by formalizing the methods of modeling and forecasting the processes of stock market development.

3. Develop the information technology for stock market forecasting based on the Keras library, which will allow conducting research on stock market forecasting through experiments on creating a multilayer LSTM (Long Short-Term Memory) architecture.

MATERIALS AND RESEARCH METHODS

All indices based on the methodology of calculating the simple arithmetic mean, weighted arithmetic mean and geometric mean. The simple arithmetic mean determined by summing the prices of the component stocks and equating the resulting value to the underlying value of the index. This method results in assigning equal weight to the importance of each stock's price, without taking into account the unique characteristics (financial condition, image, etc.) of each company. Such an index is of limited value as a benchmark for building an investment portfolio.

The geometric mean calculated by taking the square root of the product of the prices of the shares included in the index and dividing the result by the number of prices in the calculation.

In the case of a weighted arithmetic average, the prices of each share are multiplied by the number of shares in each company's issue. This helps to better simulate an investment portfolio, as a change in the share price of a large company now has a greater impact on the change in the index than a change in the share price of a smaller company. A characteristic feature of the portfolio representing this index is the same percentage of shares in all companies. An additional feature is the determination of the base date from which the stock index starts; this date and the corresponding base value of the index become the basis for analyzing the successful development of the stock market during the period of the index's existence.

The calculation of the index with the price weight is as follows:

$$I = \frac{\sum_{i=1}^{N} Z_i}{D},$$

where Z_i determines the market price i -h stock; N defines the number of stocks in the index; D is a correction factor necessary to ensure that the index values are consistent over different periods of time with different index compositions, as well as when the nominal values of the stocks included in the index change.

The correction factor D is calculated as follows:

$$D = \frac{I_{ns}}{I_s}$$

where I_{ns} determines the value of the index in the current period, which differs from the value of the index in the base period due to changes in the composition of the index:

$$I_{ns} = Z_1 + \ldots + Z_{ins} + \ldots + Z_N,$$

where Z_{ins} determines the price of a share that is included in the index again; I_s determines the conditional value of the index in the current period, which is based on the previous composition of the index and is equalized with the value of the index in the base period:

$$I_s = Z_1 + \ldots + Z_{is} + \ldots + Z_N,$$

where Z_{is} indicates the price of a share that is excluded from the index.

In this way, the index calculated on the basis of the updated composition in the current period will be synchronized with the index in the base period:

$$\hat{I} = \frac{I_{ns}}{D}.$$

To start indexing from a certain level, the relative percentage change in the average price is used, and the resulting value is multiplied by the index value for the previous day to determine its change.

Under the capitalized weighting method, the prices of the shares included in the index are multiplied by the respective number of shares outstanding and added together to determine their aggregate market value as of a particular date. Then this value is divided by the total market value of the shares on the initial day of the index calculation, and the resulting value is multiplied by the selected initial index value.

The calculation formula for market-weighted indices is as follows:

$$I = \frac{\sum_i ZC_{i,t}}{\sum_i ZC_{i,t_0}} I_0,$$

where $ZC_{i,t}$ indicates the market price (capitalization) of the i corporation in the t period; ZC_{i,t_0} is market price (capitalization) of the corporation in the t_0 period; I_0 is the base index value.

Indices with the same weighting are calculated daily by multiplying the value of the index for the previous day by the arithmetic mean of the relative values of the index's share prices, which is determined daily (relative price value is the ratio of today's price to the price of the previous day).

The geometric index is also used, which is determined daily by multiplying the index value for the previous day by the geometric mean of the daily relative values of the prices of the shares included in the index.

The calculation formula for the geometric mean index is as follows:

$$I = I_0 \left(\frac{\prod_{i=1}^{N} Z_{i,t}}{\prod_{i=1}^{N} Z_{i,t_0}} \right)^{\frac{1}{N}},$$

where Z_{i,t_0} indicates the price of the i-th stock в in the base period; $Z_{i,t}$ is the price i-th stock in the current period; I_0 is the index value in the base period.

In order to take into account the impact of equities on the formation of the index and to create a mechanism for assessing the consolidated impact of equities on the index, it is advisable to combine the price criterion and the market capitalization weighting criterion. Alternative weighting methods may include setting requirements for the design sample, so that issuers that do not need to be assigned weights due to similar parameters can be assigned appropriate rankings using methods such as hierarchy analysis. This may involve ranking issuers across a large number of criteria, using spectral analysis to select the best issuer for each individual criterion.

To estimate the state and dynamics of the stock market, it may be useful to calculate indices focused on retrospective and operational analysis, such as the current stock market index:

$$I = \frac{\sum_{i=1}^{100} Z_{i,n}}{\sum_{i=1}^{100} Z_{i,n-1}}.$$

This index indicates changes in the current state of the level of selling prices or demand for a group of 100 issuers on one exchange. It can be calculated for different groups of exchanges, different types of issuers (banks, industrial joint stock companies, insurance companies, etc.), and different types of shares.

Stock market benchmark index:

$$I = \frac{\sum_{i=1}^{100} Z_{i,n}}{\sum_{i=1}^{100} Z_{i,o}},$$

where o is base level; $Z_{i,o}$ is nominal price of the i-th stock.

This index provides a measure of the change in selling prices or demand for 100 types of shares of the largest issuers in a country or region on the reporting stock exchange day compared to their nominal price. The analysis of the dynamics of the underlying index allows us to identify seasonal fluctuations in supply and demand in the stock market, take into account inflationary processes, and determine the impact of political factors on the activity of investment processes.

Index efficiency of equity investments in stocks:

$$I = \frac{P \pm \Delta ZR}{ZR_0},$$

where P is the amount of the annual dividend per share of the i-h type; ZR_0 is the average value of the selling price of a share of the type (issuer) for December of the previous year and January of the reporting year; ΔZR is change in the selling price of a share of a particular type compared to ZR_0.

Index of comparative efficiency of equity investments and deposit placement:

$$I = \frac{P \pm \Delta ZR - ZR_0 r}{ZR_0},$$

where r is the interest rate on a one-year deposit in a bank under the i number.

This index reflects the comparative performance of investments in a particular type of shares and placement of similar financial resources in a particular bank.

The index of comparative efficiency of investments in shares and placement of funds in foreign currency is determined by:

$$I = \frac{P \pm \Delta ZR - (\pm \Delta KV \times ZR_0)}{ZR_0},$$

where ΔKV indicates the change in the exchange rate of the currency type during the reporting year.

This index helps investors determine a medium-term investment strategy to maximize their profit, taking into account changes in exchange rates, dividends and share price.

The index of comparative efficiency of placement of funds in deposits and foreign currency is defined as $I = r - \Delta KV$, on condition that $r,\ \Delta KV > 0$.

When calculating the values of these indices, adjustments should be made on an ongoing basis to take into account new share issues by various companies, their acquisitions or mergers, changes in company ratings, and other factors. Today, almost every stock exchange has its own system of stock indices that reflect the level and dynamics of prices of shares traded on the market.

The study and forecasting of financial time series is an important component in planning activities in the context of the constant development of financial and economic systems. This is especially true for investors in the stock market, since the amount of their profits or losses depends on the accuracy of forecasts of stock market development processes. In particular, the use of regression analysis and extrapolation methods is a classic approach to modeling and forecasting stock market development processes [3, 4], [5]. To predict these processes, methods are used that allow identifying functional dependencies in these processes and making forecasts of their future development. To determine such functional dependencies, approximation methods are used. Their essence lies in the fact that, given information about a given function $y(t)$, it is possible to construct an approximation function $\bar{y}(t)$, it is possible to construct an approximation function that provides approximate values of the function $y(t)$, i.e., it is assumed that $y(t) \approx \bar{y}(t)$. Based on the defined functional dependency $\bar{y}(t)$ a forecast is made.

In this case, it is important to select the quality of the nodal points and approximation functions, as well as to determine the degree of approximation that will ensure the required accuracy in calculations using the relevant models. For example, indicators of such accuracy may be the maximum approximation error for the entire period: $\varepsilon = \max_t \varepsilon_t$, or the integral absolute deviation: $I = \sum_t \varepsilon_t$.

Popular approximation functions include polynomials (polynomials), Fourier series, and the Fourier integral. In cases involving the accumulation, decay, or growth of a security's price over time, an exponential function is often used for approximation. The approximation can be evaluated based on the sum of the squares of the deviations at the nodal points.

Lagrange and Newton extrapolation methods are used to forecast securities prices [3, 5]. When using the extrapolation method, a given function $y(t)$ is often approximated by a polynomial of the n-th power:

$$\bar{y}(t) = a_0 t^n + a_1 t^{n-1} + a_2 t^{n-2} + \ldots + a_{n-1} t + a_n.$$

In particular, from the conditions of equality $\bar{y}(t_k) = y(t_k),\ k = 1,\ldots,m,$ to find the coefficients of $a_0, a_1, \ldots, a_n$ use interpolation polynomials of a special kind, such as the Lagrange polynomial:

$$\bar{y}(t) = \sum_{k=1}^{m} y(t_k) \prod_{i=1}^{m} \frac{t - t_i}{t_k - t_i},$$

This function is a polynomial of power $m-1$, which passes through the m points $(t_k, y(t_k)),\ k = 1,\ldots,m.$ At points other than the interpolation nodes, the Lagrange polynomial generally does not coincide with the given function.

The Newton method allows you to obtain the approximating values of a function without explicitly constructing an approximating polynomial.

The expression for polynomial $\bar{y}(t)$, which approximates function $y(t)$ is as follows:

$$\bar{y}(t)=\Delta(t_1)+\Delta(t_1,t_2)(t-t_1)+...+\Delta(t_1,t_2,...,t_m)(t-t_1)(t-t_2)...(t-t_m)$$

and

$$\Delta(t_1,t_2,...,t_s)=\frac{\Delta(t_1,t_2,...,t_{s-1})-\Delta(t_1,t_2,...,t_s)}{t_1-t_s}$$

separated difference of the $s-1$-h order, $s=2,\ldots,m.$

Interpolation functions are highly sensitive to errors, especially at the boundaries of the interval under study. Therefore, their use, for example, for forecasting securities prices, requires a cautious approach, since even small changes in the values of the output function at certain points can lead to inadequate forecast results.

Spline approximation is also used to forecast stock market development processes. The use of spline functions allows to increase the number of points in the original series of statistical data, simulating intermediate values. This approach makes it possible to obtain adequate estimates of stock market development indicators at short time intervals, increasing the meaningfulness of the modeling results.

Simulation of intermediate values for dynamic series of statistical indicators, as well as approximation of first derivatives for variables represented by the corresponding series, can be effectively implemented using a rational spline. Rational splines, as piecewise polynomial functions, allow you to more fully take into account the features of the interpolation function, in particular, providing a good approximation of functions with large gradients. At the same time, they retain an important property - simplicity and efficiency of calculations, which allows them to be effectively used in various computer programs.

Let's assume that we have a function $y(t)$, for which on the segment $[t_0,t_n]$ the values are given at the points (nodes) $t_i, i=0,...,n$, where $t_0<t_1<...<t_n$. A rational spline is a function $S(t)$, that is expressed on each segment $[t_i,t_{i+1}]$ by the following expression:

$$S(t)=A_i x+B_i(1-x)+\frac{C_i x^3}{1+p_i(1-x)}+\frac{D_i(1-x)^3}{1+r_i x},$$

where $x=\frac{t-t_i}{h_i}$; $h_i=t_{i+1}-t_i$; p_i; r_i are the given numbers, with $-1<p_i$, $r_i<\infty$.

In addition, the rational spline $S(t)$ on segment $[t_0,t_n]$ has continuous derivatives up to and including the second order.

A rational spline is considered interpolable if it satisfies condition $S(t_i)=y_i$ for all values of $i=0,...,n$. To construct an interpolating rational spline, consider the boundary conditions: $S'(t_i)=y_i^{'}$ for values $i=0,...,n$.

The equation for the first derivative of a rational spline is given as follows:

$$S'(t_i)=\frac{y_{i+1}-y_i}{h_i}+\frac{C_i}{h_i}\left(\frac{3x^2(1-p_i)-2x^3p_i}{(1+p_i(1-t))^2}-1\right)+$$
$$+\frac{D_i}{h_i}\left(\frac{-3(1-t)^2(1+r_i)+2(1-t)^3r_i}{(1+r_it)^2}+1\right).$$

If $u_i=S'(t_i)$, $i=0,...,n$, then

$$C_i=\frac{-(3+r_i)(y_{i+1}-y_i)+h_iu_i+(2+r_i)h_iu_{i+1}}{(2+r_i)(2+p_i)-1}$$
$$D_i=\frac{(3+p_i)(y_{i+1}-y_i)-h_iu_i-(2+p_i)h_iu_i}{(2+r_i)(2+p_i)-1}.$$

The realization of the second derivative of the rational spline is given as follows:

$$S''(t)=C_i\frac{2p_i^2x^3-6p_i(1+p_i)x^2+6(1+p_i)^2x}{(1+p_i(1-x))^3h_i^2}+$$
$$D_i\frac{2r_i^2(1-x)^3-6r_i(1+r_i)(1-x)^2+6(1+r_i)^2(1-x)}{(1+r_ix)^3h_i^2}$$

Based on the continuity of $S''(t)$ at points t_i for $i=1,2,...,n-1$ follows

$$\omega_iE_{i-1}u_{i-1}+\left[\omega_iE_{i-1}(2+r_{i-1})+\nu_iF_i(2+p_i)\right]u_i+\nu_iF_iu_{i+1}=$$
$$=\omega_iE_{i-1}(3+r_{i-1})\frac{y_i-y_{i-1}}{h_{i-1}}+\nu_iF_i(3+p_i)\frac{y_{i+1}-y_i}{h_i},$$

ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)

where $\omega_i = \frac{h_i}{h_{i-1} + h_i}$, $\nu_i = 1 - \omega_i$,

$$E_{i-1} = \frac{3 + 3p_{i-1} + p_{i-1}^2}{(2 + r_{i-1})(2 + p_{i-1}) - 1},\ \mathrm{F}_i = \frac{3 + 3r_i + p_i^2}{(2 + r_i)(2 + p_i) - 1}.$$

Taking into account the boundary conditions with respect to unknown u_i, the system of equations is given in the following system of equations:

$$\begin{cases} u_0 = y_0', \\ \omega_i E_{i-1} u_{i-1} + \left(\omega_i E_{i-1}(2 + r_{i-1}) + \nu_i F_i (2 + p_i)\right) u_i + \nu_i F_i u_{i+1}, \\ \omega_i E_{i-1}(3 + r_{i-1}) \frac{y_i - y_{i-1}}{h_{i-1}} + \nu_i F_i (3 + p_i) \frac{y_{i+1} - y_i}{h_i}, \\ u_n = y_n',\ \text{i=1,2,...,n-1.} \end{cases}$$

In this system of equations, the roots are found in the following way:

$$u_i = P_i u_{i+1} + Q_i \quad \text{i=1,2,...,n-1}$$

where the parameters are determined by iterative relations P_i i Q_i

$$P_i = -\frac{\nu_i F_i}{\omega_i E_{i-1} P_{i-1} + \chi_i},\quad Q_i = \frac{\psi_i - \omega_i E_{i-1} Q_{i-1}}{\omega_i E_{i-1} P_{i-1} + \chi_i},$$

$$\psi_i = \omega_i E_{i-1}(3 + r_{i-1}) \frac{y_i - y_{i-1}}{h_{i-1}} + \nu_i F_i (3 + p_i) \frac{y_{i+1} - y_i}{h_i},$$

$$\chi_i = \omega_i E_{i-1}(2 + r_{i-1}) + \nu_i F_i (2 + p_i),\ \text{i=1,2,...,n-1},\ P_0 = 0,\ Q_0 = y_0'.$$

Limit values are set using difference equations:

$$y_0' = (1 + \nu_1) \frac{y_1 - y_0}{h_0} + \nu_1 \frac{y_2 - y_1}{h_1},\ \nu_1 = \frac{h_0}{h_1 + h_0},$$

$$y_n' = -\omega_{n-1} \frac{y_{n-1} - y_{n-2}}{h_{n-2}} + (1 + \omega_{n-1}) \frac{y_n - y_{n-1}}{h_{n-1}},$$

$$\omega_{n-1} = 1 - \nu_{n-1}.$$

Parameters p_i, r_i are used to adjust the spline curve in the vicinity of node t_i. In particular, when $p_i = r_i = 0$ spline $S(t)$ will be a cubic polynomial, and when $p_i = r_i \to \infty$ it will behave like a linear function. Cubic splines provide high accuracy for approximating smooth functions. However, if the original function is convex, it is important that the spline is also convex. As for the linear spline, it does not have the property of smoothness, and therefore, when using it, you may have difficulty approximating functions with large gradients.

With the appropriate choice of parameters p_i, r_i interpolation conditions can usually be satisfied, including functions with large gradients. This makes the use of rational splines appropriate for function approximation.

The behavior of the spline at the intermediate nodes t_i determines its suitability for approximation, since the values of the spline at the main nodes coincide with the values of the function: $S(t_i) = y_i$, where $i = 0, \ldots, n$.

The least-squares method is based on the statement that the best approximation of $\overline{y}(t)$ gives a number for which the sum of squared deviations is minimum [4]:

$$\sum_{k=1}^{m} \left(\overline{y}(t_k) - y(t_k)\right)^2 \to \min.$$

According to this method, the available observations can be approximated by a polynomial that minimizes the function:

$$F = \sum_{k=1}^{m} y(t_k) - a_0 t_k^s + a_1 t_k^{s-1} + a_2 t_k^{s-2} + \ldots + a_{s-1} t_k + a_s \to \min.$$

To determine the minimum, we will differentiate for each of the unknowns and get the system:

$$\frac{\partial F}{\partial a_j} = 2 \sum_{k=1}^{m} t_k^j \left(a_0 t_k^s + a_1 t_k^{s-1} + a_2 t_k^{s-2} + \ldots + a_{s-1} t_k + a_s - y(t_k)\right),\ \text{j=1,...,s.}$$

The determinant of this system is not zero, and the problem has a unique solution. In cases where particularly careful statistical processing of the experiment is required, orthogonal polynomials with a set weight on a given system of points are used.

The least squares method for forecasting can be used to estimate the approximate value of securities in long-term forecasting or as a linear trend.

Forecasting using the moving average method is performed by averaging values over a specified time interval - a sample [3, 4], [5]. The averaging interval h can be moved along the time axis, leaving its width unchanged. When moving from moment t_0 to $t_0 + 1$ the values of the mathematical expectation and variance of the time series of the financial indicator are updated.

The calculation of the moving average of the time series at a moment $t_0 + 1$ is determined as follows:

$$\overline{y}(t_0+1)=\frac{1}{h}\sum_{t=t_0-h+1}^{t_0+1} y(t).$$

The use of averages implies their stability or stationarity, which is usually not the case over the entire sample interval. The input data included in the averaging interval are treated with the same weight, while the weight of other observations is equal to zero, which can be considered a disadvantage of this approach.

Improving the moving average method is the assignment of weights to each element of the statistical series of a financial indicator. However, determining the weights requires building additional models to reduce subjectivity in solving the problem.

The use of exponential smoothing implies a decrease in the importance of financial series indicators over time, since the latest values of indicators are usually more significant for obtaining their forecast values compared to more distant ones. Thus, the weights of the elements of the time series are determined in descending order, starting with the most recent indicator, whose weighting factor is taken to be one.

For exponential smoothing, all values of financial time series $y(t)$ з from the selected sample consisting of the last h indicators are recalculated as follows [3, 4], [5]:

$$y_\sigma(t)=y(t)\sigma^{t_0-t},\ \mathrm{t{=}t}_0-h+1,...,t_0,$$

where σ is the exponential smoothing coefficient, h is the sample depth of the time series.

When using exponential smoothing, the exponential average of the financial time series at a moment t_0+1 is calculated as follows:

$$\overline{y}_\sigma(t_0+1)=\zeta\sum_{t=t_0-h+1}^{t_0+1} y(t),\ \zeta=1-\sigma.$$

The exponential average can be calculated iteratively using the expression [2]:

$$\overline{y}_\sigma(t+1)=\sigma\overline{y}_\sigma(t+1)+\zeta y(t+1).$$

One of the classical methods for studying stock market development includes modeling stock indices using a Wiener random process [2-4]. According to the Wiener model, the trend of a stock index is exponential, and the index itself fluctuates freely (using the Brownian motion method) around this trend. This model also implies that the current return of the index has a lognormal distribution with constant parameters [4, 5].

A random process $y(t)$ is considered to be a moving average autoregressive process of order p and q, if the following condition is fulfilled [3, 4]:

$$y(t)=\sum_{i=1}^{p}\alpha_i y(t-i)+\sum_{j=1}^{q}\beta_j\varepsilon_{t-j}+\varepsilon_t$$

The solution of the task includes the search for coefficients, such as α_i, β_j. At the same time, the forecast will receive some averaged values of the elements of the time series, which may make it difficult to use it to forecast real financial indicators.

Another approach is based on the Ito’s equation [3, 5], where the efficiency of an investment is considered as a random function of a variable investment duration t. This is especially important for the theory of derivatives and general arbitrage theory.

The model can be expressed as an equation:

$$dy(t)=fdt+MdW(t),$$

where f is expected differential efficiency; M is fixed matrix of a given form; $W(t)$ is standard Wiener process with independent increments.

As the duration of the deposit increases, the expected value of efficiency increases in proportion to the differential dt.

RESEARCH RESULTS

Researching and analyzing the main approaches to modeling and forecasting stock market development allows us to identify and understand the functional relationships in these processes, as well as to make forecasts of their future development. Methods of approximating and modeling stock indices using a Wiener random process serve as the basis for intelligent data analysis using machine learning. The main goal of this analysis is to predict the price of the test data depending on real quotes over time, taking into account the errors of real prediction [6, 7], [8, 9], [10,11], [12,13], [14,15], [16,17], [18,19], [20].

The development of stock market forecasting technology and, accordingly, the creation of an intelligent information system depends heavily on the accuracy and efficiency of market data analysis, as well as the effectiveness of the algorithms used to make trading decisions. In particular, the introduction of advanced machine learning and artificial intelligence technologies can significantly improve the performance and accuracy of the system. For this reason, the use of advanced machine learning and artificial intelligence technologies becomes extremely important. With this in mind, the Python library Keras stands out as a powerful tool for building neural networks, in particular multilayer architectures such as LSTM (Long Short-Term Memory) [9, 11], [21, 22], [23, 24], [25]. LSTMs are one of the most efficient types of recurrent neural networks that are specifically designed for analyzing sequential data, such as time series, which is typical for market data [19, 20], [21, 22], [23, 24], [25, 26], [27, 28], [29, 30].

Therefore, for more efficient analysis, it is necessary to have an LSTM neural network architecture consisting of at least several layers, especially if the amount of information is large. Complexity in decision-making may provide an effective result only for a specific trained case, but this result may be inadequate on new data. A general overview of the multilayer architecture of the LSTM algorithm presented at Fig. 1.

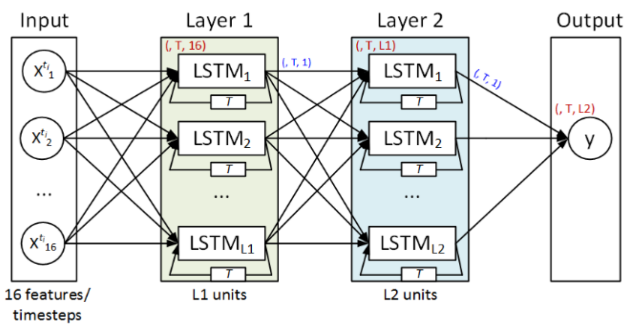


Fig. 1. **LSTM architecture using multiple layers**
Source: **compiled by the authors**

Fig. 2 presents the process of creating a test LSTM model.

```
# Build and compile the LSTM model
model = Sequential()
model.add(LSTM(50, input_shape=(x_train.shape[1], 1)))
model.add(Dense(25))
model.add(Dense(1))
# model.add(Activation('linear'))
model.compile(optimizer='adam', loss='mean_squared_error', metrics=['mae'])
```

Fig. 2. **LSTM model for the experiment**
Source: **compiled by the authors**

Let's consider each line separately:

1) model = Sequential() – create a Sequential neural network model object. The Sequential model allows us to linearly add layers to our neural network.

2) model.add(LSTM(50, input_shape=(x_train.shape[1],1))) – add the first layer to our model, which is the LSTM (Long Short-Term Memory) layer. In this case, we create an LSTM layer with 50 neurons. The input_shape parameter indicates the shape of the input data that the model expects. In the case of an LSTM layer, this parameter specifies the shape of a single data sample. The shape is defined by a tuple, where the first element indicates the number of time steps (i.e., how many time points of data we feed into the network), and the second element indicates the number of features in each time step. In our case, input_shape=(x_train.shape [1], 1) means that the model expects input data that has the shape (number of time steps, 1 feature). x_train.shape[1] indicates the number of time steps, and 1 indicates the number of features in each time step.

1) model.add(Dense(25)) – add a fully connected layer (Dense) with 25 neurons to our model.

2) model.add(Dense(1)) – add another fully connected layer with one neuron, which will be responsible for the output of the model.

3) model.compile(optimizer='adam', loss='mean_squared_error',metrics=['mae']) – compile the model. The compile method takes several parameters: optimizer, which is responsible for the optimizer, loss, which defines the loss function used to estimate the model's error, and metrics, which specifies the metrics that will be displayed during model training. In this case, we use the optimizer 'adam', the loss function 'mean_squared_error' (root mean square error), and the metric 'mae' (mean absolute error).

Using this algorithm, we obtained the average absolute error of the forecast presents at Fig. 3.

```
Training Data MAE: 746.6161003365849
Test Data MAE: 262.05302977376556
```

Fig. 3. **The result of training and testing the LSTM model**
Source: **compiled by the authors**

As a result, a visualization of the price forecast on the test data (in red) depending on the real quoted price (in blue) over time with the error of the real forecast is performed as shown

DISCUSSION OF THE RESULTS

This means that there is a deviation from the actual data, where you need to make corrections according to the lows and highs. Since the chart follows the quotes movement, it should be adjusted vertically in Fig.4.

Fig. 4. **Illustration of the deviation of the actual forecast**
***Source*: compiled by the authors**

After testing various model configurations with different hyperparameters, the results are shown in Table 1. It turned out that training takes considerable time, and given the variety of currency pairs on the market, the process of selecting hyperparameters is complicated.

The result graph of the mean absolute error (MAE) (Fig. 5).

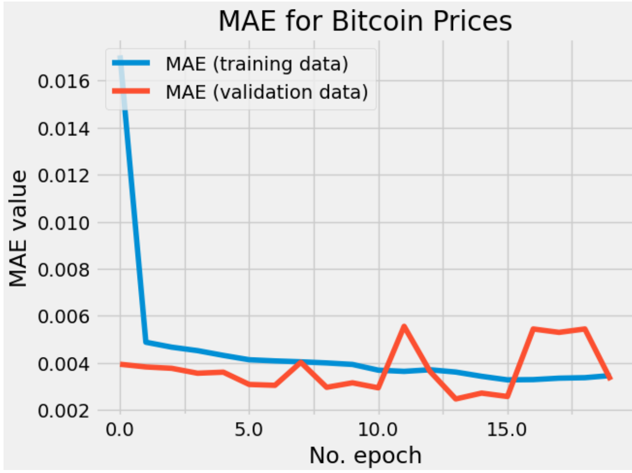


Fig. 5. **Graph of absolute error indicators**
***Source:* compiled by the authors**

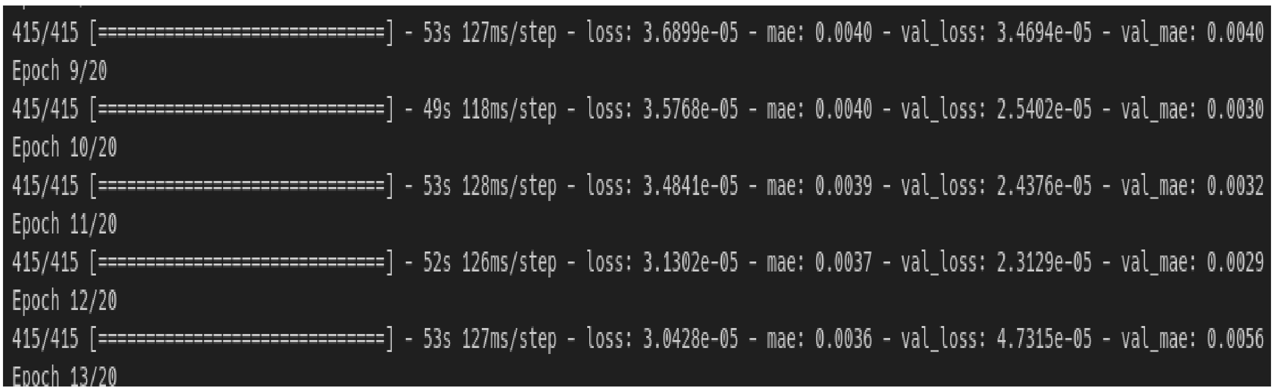
A specific correlation study can be conducted between the batch size, the number of epochs, and the accuracy of the absolute error.

At the same time, there is a problem of overtraining at a certain stage, which manifests itself in a sharp increase in error, as illustrated in Fig. 6.

Table 1. **Conclusions from training and testing of LSTM models**

First layer	Second layer	Output layer	batch_size	epochs	Train MAE	Test MAE	Time (minutes)
16	8	1	200	5	122.18	128.35	5
32	16	1	200	5	175.57	173.71	5
32	16	1	150	15	130.55	112.72	9
32	16	1	50	15	108.80	102.78	14
32	16	1	20	20	90.30	102.38	24

***Source:* compiled by the authors**



```
415/415 [============================] - 53s 127ms/step - loss: 3.6899e-05 - mae: 0.0040 - val_loss: 3.4694e-05 - val_mae: 0.0040
Epoch 9/20
415/415 [============================] - 49s 118ms/step - loss: 3.5768e-05 - mae: 0.0040 - val_loss: 2.5402e-05 - val_mae: 0.0030
Epoch 10/20
415/415 [============================] - 53s 128ms/step - loss: 3.4841e-05 - mae: 0.0039 - val_loss: 2.4376e-05 - val_mae: 0.0032
Epoch 11/20
415/415 [============================] - 52s 126ms/step - loss: 3.1302e-05 - mae: 0.0037 - val_loss: 2.3129e-05 - val_mae: 0.0029
Epoch 12/20
415/415 [============================] - 53s 127ms/step - loss: 3.0428e-05 - mae: 0.0036 - val_loss: 4.7315e-05 - val_mae: 0.0056
Epoch 13/20
```

Fig. 6. **Sharp increase in error at the 12th epoch**
***Source:* compiled by the authors**

ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)

CONCLUSIONS

A crucial role in the functioning of the stock market is played by the assessment of its condition using various indicators, such as stock market indices and ratings. The state and movement of the stock market is determined by indices, which reflect the ratio of a comparative indicator to a certain standard. For example, a stock market a stock market index is an indicator of stock market activity that tracks stock prices and is calculated using specific formulas.

The calculation of indices that determine the state and movement of the stock market is based on statistical information about securities and allows for the assessment of investment risks. These business activity indices accurately reflect the current situation on the stock market.

The methodology for forming stock indices includes four key stages in their creation: creating a sample, weighting the selected stocks, calculating the average, and converting the average into an index. Two types of sampling are used: deterministic and floating power sampling. The price and market capitalization weighting criteria are used to determine the stock weights.

Analyze the main approaches to modeling and forecasting the development of the stock market, which allow identifying functional dependencies in these processes and developing forecasts of their future development. In particular, the methods of approximation, modeling of stock indices using a Wiener random process are allocated.

On the basis of the Keras library, a study of stock market forecasting was carried out by experimenting with the creation of a multilayer LSTM architecture. The overall results of the research and development show that an intelligent information system for automated trading decisions is an effective tool. It can provide traders with a competitive advantage in financial markets by helping to reduce risks and increase the potential for profit.

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Conflicts of Interest: the authors declare no conflict of interest

Received 12.01.2024
Received after revision 14.03.2024
Accepted 21.03.2024

DOI: https://doi.org/10.15276/hait.07.2024.7
УДК 004.9

Моделювання та прогнозування процесів фондової біржі

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АНОТАЦІЯ

Оцінка фондового ринку використовує різноманітні індикатори, такі як індекси та рейтинги, які відображають його стан та рух. Наприклад, біржовий індекс відображає активність на біржі та обчислюється за конкретними формулами. Розрахунок індексів базується на статистичних даних про цінні папери і допомагає оцінити ризики інвестицій. Ці індекси відображають кон'юнктуру ситуацію на ринку. Методологія формування фондових індексів включає чотири етапи: вибірку, зважування акцій, розрахунок середнього та конвертацію у форму індексу. Використовуються два типи вибірки – детермінована та вибірка з плаваючою потужністю. Вагові коефіцієнти визначаються за ціновим критерієм та ринковою капіталізацією. Вивчені підходи до моделювання фондового ринку дозволяють виявляти функціональні залежності в даних та розробляти прогнози. Зокрема, виділено методи апроксимації, моделювання вінерівським процесом. Досліджено прогнозування фондового ринку за допомогою багатошарової архітектури Long Short-Term Memory у бібліотеці Keras. Загальні результати підтверджують, що інтелектуальна інформаційна система для автоматизованих торговельних рішень ефективна, забезпечуючи трейдерам конкурентні переваги та зменшуючи ризики.

Ключові слова: Фондові біржі; прогнозування фондового ринку; відбір акцій; ефективність інвестицій; прийняття торгових рішень

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ISSN 2663-0176 (Print)
ISSN 2663-7731 (Online)