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COMBINED METHOD FOR FORECASTING THE VALUABLE ASSETS PRICE BASED ON FINANCIAL DATA

Abstract: This paper presents a combined method for forecasting the value of securities based on financial statistical data. The proposed method allows to increase the accuracy of forecasts in conditions of high volatility of financial markets.

Keywords: information technology, price of valuable assets, forecasting method, aggregation, statistical data, numerical methods, data smoothing, data aggregation, adaptivity based approach.

1. Introduction

Securities such as bills, bonds, debentures and stocks have existed for hundreds of years, and this does not reduce their popularity and value today. The development of financial technologies in smartphones and online trading platforms has led to an increasing interest in investing and creating a financial portfolio. Among them, stocks are more profitable. Public joint-stock companies issue a block of shares in order to raise funds for development. They grant the right to manage the company through co-ownership and receive a percentage of the company's profits in the form of dividends. Some investors choose stocks to diversify their assets, while others choose to protect their wealth from inflation or beat it. However, with increasing profits, risk increases. A financial portfolio is defined as a set of assets, such as stocks and bonds, owned by an individual, investor, investment company or other institution [1-2].

Stocks are usually called assets for the reasons mentioned above. First of all, investors who invest for the long term are interested in the growth of the value of the company's securities. Such a company should be economically attractive and profitable. The average growth of the value of the company, and therefore its securities, relative to the general growth of the financial market and inflation in the country helps investors improve their financial condition. The stock market is a collection of publicly listed companies. Their shares are listed on stock exchanges around the world, which act as trading platforms [3]. Most stock exchanges operate only on weekdays during working hours of about seven to eight hours a day and are closed on public holidays.

Investing increases the demand for analysis tools for making informed investment decisions and at the same time has a positive effect on the general improvement of the population's well-being and the possibility of accumulation. The development of investment and trading exchanges is extremely important for the country's economy. As the study has shown, the development of stock exchanges has a positive effect on the economic growth of European countries [4]. Which, as the authors of the study note, increases investor confidence and encourages them to further invest in various economic sectors. In turn, the popularization of investing in financial literacy through software tools and information systems could improve the economic situation of the population. Italian researchers have shown that the lack of economic literacy of the population leads to a lack of diversification of financial portfolios [5]. The authors also showed a connection between a low level of education and a simpler approach to managing finances and called for the creation of long-term training programs to improve investor literacy. In contrast, a study conducted in Vietnam found no significant relationship between financial literacy levels and portfolio selection or diversification. However, the authors did show that basic economic knowledge has a positive impact on portfolio stock selection [6]. This study highlights the importance of developing investors' understanding of financial products.

Technical analysis becomes more popular every year and is used on a par with fundamental and sentimental analysis. It is easier to create knowledge systems and recommendation methods based on technical analysis. Therefore, new algorithms and indicators are being developed to try to create a somewhat autonomous system for trading and portfolio management. The next section discusses existing methods and algorithms for predicting the behavior of time series of asset values.

All the above indicates **the relevance** of research into methods for predicting the value of valuable assets. There is a large amount of scientific research in this area.

2. Literature overview

The study [7] is focused on the combination of technical analysis and machine learning methods for an indicator model. The authors used 10-day and 20-day moving averages and machine learning methods to obtain signals about selling or buying a given asset based on its price time series. In a comparative analysis of the use of moving average methods to predict the behavior of asset prices, the exponential moving average proved to be more accurate than the simple moving average in smoothing time series [8].

The study [9] focused on comparing sentiment analysis and technical analysis, as well as hybrid models based on them. It showed that the combination of sentiment indicators with machine learning and deep learning did not outperform traditional autoregressive models in predicting gold or euro prices. However, sentiment analysis showed better results in predicting prices of general consumer goods.

The work [10] focuses on comparing a method based on sentiment analysis and autoregressive integrated moving average (ARIMA). This study was conducted on volatile cryptocurrency markets, and Bitcoin was used as the basis for comparison. The authors proposed a method of using social media posts of famous people to calculate the ratio of their influence on the Bitcoin exchange rate, ATAPSN, which showed a more accurate forecasting result than ARIMA. However, this method depends on the quality of the input data and has limitations regarding its

In the paper [11], a comparison of linear and polynomial regressions and ARIMA was made. The authors showed that linear regression reproduces only the general trend without considering seasonality or local extremes of the time series. While polynomial regression reproduces the specified market factors better. Despite the advantage of using ARIMA, the authors suggest combining different models to consider other data besides price.

In [12], a method for constructing a sequence of polynomial forecasts to generate an average forecast of the value of a cryptocurrency was proposed. The authors proposed an automatic approach to selecting the number of points for polynomial models.

The author [13] considers the possibilities of using splines for extrapolation of a grid of geophysical data nodes. The proposal to use spline mathematics is argued by the complexity or impossibility of building a physical model.

Various statistical [14], neural network models such as LSTM [15], and machine learning models are used to forecast time series. However, the use of numerical methods is quite limited. Numerical methods are used for interpolation and extrapolation of data in various tasks due to their ease of use and speed of calculation. Embedded systems, microcontrollers, and real-time systems have limited resources. Unlike neural networks, polynomial-based methods require significantly less memory and processor time. Despite the development of machine learning methods, classical numerical methods remain the foundation for tasks where the amount of data is limited, and the interpretability of the model is a priority.

Thus, despite the large number of forecasting models based on numerical methods, the continuation of research on polynomial extrapolation is justified by the need to increase the accuracy of its forecasting.

In this work, the following sections present a combined method for forecasting the value of valuable assets, for the implementation of which combined method was developed.

3. Research goal and objectives

Therefore, **the purpose** of the research presented in this paper is to develop and substantiate a combined method for forecasting the value of valuable assets, which combines polynomial extrapolation and exponential smoothing in order to increase the accuracy, stability and reliability of forecasts in a changing financial environment.

To achieve the goal of the research, the following **task** was formulated:

To develop an algorithm for forecasting the value of valuable assets, which combines polynomial extrapolation and exponential smoothing.

The following section will present the materials and methods of this research.

4. Materials and methods

4.1. Experiment description

The experiment consists in studying the influence of the parameters of the Lagrange polynomial forecasting method on the forecasting accuracy and the influence of smoothing methods on the forecasting accuracy.

The experiments used financial data of the NIFTY 50 index of the National Stock Exchange of India (NSE) from January 1, 2000, to April 30, 2021 [18]. The assets of this index cover 13 sectors of the Indian economy. During the experiment, new polynomials are created with different numbers of data points in the interval from 2 to 6 inclusive. Different aggregation methods are used: weekly and monthly; and smoothing methods: simple and exponential. Data from 01.01.2020 to 01.03.2021 were used for the experiment. The price at the time of closing of trading is used as the value of the asset. Based on the specified data and the described scheme, experimental studies of the proposed method were conducted.

Object of research: the process of processing financial data and forecasting the value of financial assets based on time series.

Subject of research: data smoothing methods and numerical analysis methods.

The following paragraph presents a meaningful statement of the problem formulated in section 3.

4.2. Substantive formulation of the problem of forecasting the price of valuable assets

The task of forecasting the price of valuable assets is as follows: based on time series, historical data with a given frequency, and stock prices at the time of opening and closing of daily trading for an asset on a particular exchange, to predict the behavior of price changes for a certain period of time in the future.

This problem boils down to extrapolation, the process of estimating values beyond known data points based on trends observed in the available data. That is, a selected value $p \notin [h_0; h_n]$ within a given interval, h_0, h_n are the first and last values in the time-sorted data set, respectively. The problem involves extending a model or function beyond the observed data to predict unknown values in areas where there are no direct measurements.

Input: a set H of sorted historical asset prices data over time. An example of such data for the NVDA stock is given in Tab.1.

Output: set P of predicted data on the asset's future value. The format of the output data is as in Table 1. Forecasting is performed using interpolation polynomials.

The following section provides a justification for the chosen method of forecasting the price of valuable assets.

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Table 1.

Historical price data of NVDA stock

Date	Price in USD
21.10.2025	181.16
22.10.2025	180.28
23.10.2025	182.16
24.10.2025	186.26

4.3. Justification of the chosen method for forecasting the price of valuable assets

The task of adaptive algorithms is to adjust the parameter vector, with the purpose previously defined by the user: system control, identification, tuning. This vector $\vec{\theta}$ is the only interface of the controlled system and its definition requires an initial modeling phase. In order to adjust the parameter $\vec{\theta}$, the user must be able to supervise the system. Supervision is carried out through the state vector X_n, where n corresponds to the time of observation of the system. Then this state vector can be a set consisting of a regression vector and an error signal [16].

Adaptive control encompasses a set of methods that provide a systematic approach to automatically tuning controllers in real time to achieve or maintain a desired level of control system performance when the parameters of the dynamic model of the object are unknown and/or change over time [17].

Thus, the adaptive approach is used to configure or fine-tune the system during its use without the user directly influencing it. It is usually used in systems with variable object parameters. The described sources define the adaptive approach as parameter setting. However, one of the parameters of the meta-algorithm, which is defined inside the system, may be the parameter for determining the algorithm used to perform a specific task. This parameter, like many others, will be determined based on input data by the method itself.

The proposed combined method is based on the principles of adaptive approach and management in information technologies. Its detailed description will be given in section 4.4.

4.4. Description of the method for forecasting the price of valuable assets

For historical data on the change in the price of an asset H, an extrapolated function or asset price prediction function (formula (1)) should be found that will reflect the set of forecasted data P:

$$g(T) = H + \varepsilon_T, \tag{1}$$

where ε_T is the difference between the actual value of the time series and the predicted value, or the absolute prediction error; T – is the moment of time.

The second condition of the problem is the minimization of the absolute error, which is calculated by formula (2):

$$\min(\varepsilon_T), \mathrm{T} \in \mathrm{H}. \tag{2}$$

The method is divided into two stages. The scheme of the stages of the method is shown in Fig. 1.

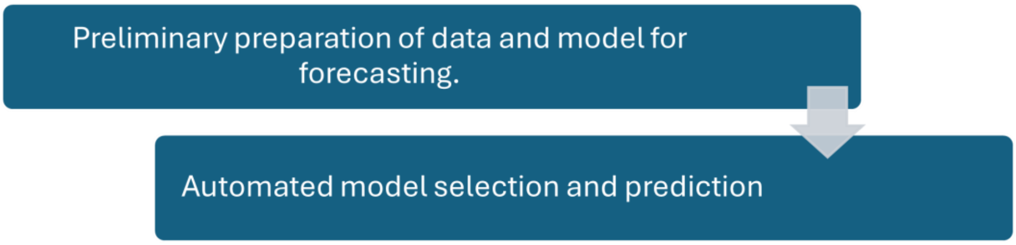

Figure 1. Step-by-step method diagram

Stage 1. Preliminary preparation of data and model for forecasting.

Input: set H of sorted historical asset price data in the time scale.

Output: set of sorted time interval indices for forecasting; forecasting function.

Stage 1 is divided into 4 steps. Fig. 2 shows a diagram of the steps of the stage.

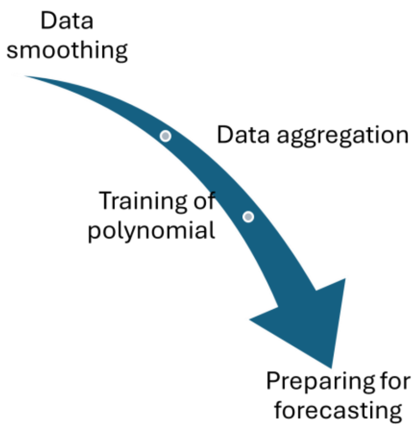

Figure 2. Step-by-step diagram of the first stage

Step 1: Smoothing is applied to the time series of stock trading data.

Input: set H of sorted daily historical asset price data over a time period.

Output: set of sorted daily smoothed data.

Rationale: daily data and data with a more frequent update period are high-frequency and hinder the identification of an overall trend.

To calculate smoothed data, it is proposed to use a simple moving average and an exponential moving average. A simple moving average (SMA) is the arithmetic mean of a certain number of data points. The price of the stock at the time of the stock market closing is used as a data point, it is called the closing price. The SMA is determined by the formula (3):

$$SMA_n = \frac{1}{n}\sum_{i=1}^{n} h_i, \tag{3}$$

where: h_i is the asset price for period i; n is the number of periods for calculating the moving average.

The exponential moving average (EMA) is a more complex method of calculating moving averages than the SMA. The key difference between the two is that the EMA gives more weight to recent data, making it more sensitive to recent price changes. The EMA is calculated recursively using the formula (4):

$$EMA_n = (h_n - EMA_{n-1}) * \frac{s}{n+1} + EMA_{n-1}, \quad (4)$$

where: h_n is the value for period i at the close of trading; n is the number of periods for calculating the average value; EMA_{n-1} is the value of the EMA for the previous period; s is the smoothing coefficient, which is equal to 2.

To calculate the initial value of the EMA, the SMA may be used. The difference between EMA and simple exponential smoothing is the use of a smoothing factor, which in exponential smoothing remains constant and lies in the interval $s \in [0; 1]$. Simple exponential smoothing is also used in signal processing to combat high-frequency noise.

Step 2: Calculate the average value for stock trading data over a specified aggregation period. It is suggested to take a work month or work week as the aggregation period.

Input: a set H of sorted smoothed daily historical asset value data over a time scale.

Output: a set of sorted aggregated smoothed data.

Rationale: Daily data and data with a more frequent update period are high-frequency and hinder the identification of an overall trend.

For aggregation over defined time periods, the workweek and the work month were the selected time periods. The workweek is defined as 5 workdays and the work month is defined as 20 workdays. These values are labeled as D.

Step 3: Limit the size of the training data set to a certain numberN_L. Train the polynomial model. Each date is converted to an integer index індекс $l \in [0; N_L]$.

Input: a set of sorted aggregated smoothed data.

Output: a forecasting function according to formula (1).

Rationale: training the model requires a limited number of points to avoid overfitting. The date conversion is done to match the intervals of the aggregated training data and the actual time intervals for forecasting.

The numerical method used for training is the Lagrange polynomial. It is a method of constructing an interpolation polynomial from a given data set when the approximate function is unknown or nonlinear. In the context of extrapolating future stock prices based on historical data, a Lagrange polynomial of degree n, constructed from a set of n+1 distinct data points, can be described by the sum of products according to the formula (5):

$$F_n(x) = \sum_{i=0}^{n} f_i L_i(x), \quad (5)$$

where $L_i(x)$ is the basis polynomial of the form according to formula (6):

$$L_i(x) = \prod_{j=0, j\neq i}^{n} \frac{(x - x_j)}{(x_i - x_j)}, \quad (6)$$

where $L_i(x_i)$=1, $L_i(x_j)$=1; x for time series is the time value of points at a certain moment; f_i is the value of the value of a certain asset at a certain point in time.

Step 4: Preparation of the forecast interval

Input: a set of sorted time intervals that correspond to the set of sorted data P.

Output: a set of sorted time interval indices for forecasting.

The values for calculating the forecast date index must start from the day consecutive to one that was used to train the model. The starting day index is zero, the date interval consists of integers 0 to N_P, where N_P is the number of days to forecast, to skip a certain number of days, d_p is introduced into the formula – the number of days ignored. The time interval index is converted by the formula (7):

$$c_i = \frac{d_p + d_i}{D} + N_L - 1, for\ i = 0, \dots, N_P, \quad (7)$$

where d_i is the date index.

Stage 2. Automated model selection and forecasting

Input: a set of forecasting functions, a set of test data, a set of sorted time interval indices for forecasting.

Output: a set of forecasted prices of an asset.

Fig. 3 shows a diagram of the steps of the stage.

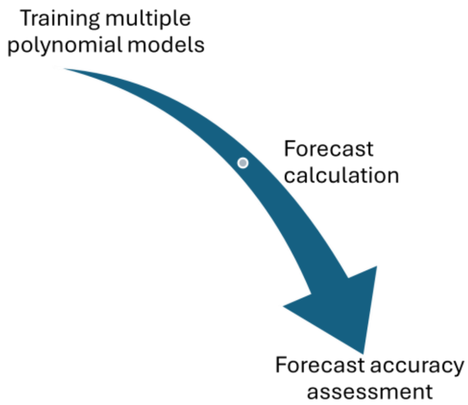

Figure 3. Step-by-step diagram of the second stage

Step 1: Train several polynomial forecasting models according to the given parameters for each processed data set: smoothing $= \{SMA, EMA\}$; smoothing window $= \{4; 7; 11; 21; 52\}$; aggregation $= \{weekly, monthly\}$; number of polynomial points $= \{2, 3, 4, 5, 6\}$.

Step 2: Calculate the forecast based on the given time interval indices using the trained model. Evaluate the accuracy based on the test set of sorted data.

Step 3: Evaluate the accuracy based on the test set of sorted data. To verify the effectiveness and accuracy of the proposed price forecasting methods, the symmetric mean absolute percentage error ($SMAPE$), which is defined by the formula (8), is used.

$$SMAPE = \frac{1}{n} * \sum_{t=1}^{n} \frac{|F_t - A_t|}{(|F_t| + |A_t|)/2} * 100\%, \quad (8)$$

where F_t is the predicted value at time t; A_t is the actual value at time t; n is the number of periods over which the prediction was done.

The method selects the most accurate model based on the $SMAPE$ score when comparing the predicted series and the test data set and performs stage 1 on the set of sorted financial data for which the set of forecasting time intervals is a direct continuation without gaps. The forecasted values are calculated using the selected model.

The next section is devoted to the description of the results obtained using the presented method.

5. The results obtained

For a better interpretation of the data obtained, the results for each type of smoothing are compared: SMA, EMA and without smoothing, which are denoted in the table as NoMA. If the same results are obtained by the $SMAPE$ metric, they are denoted together in the table as follows: SMA/EMA/NoMA, if the results are identical for each method, then the number of days of the smoothing window will be denoted as follows: 1/1, which will mean 1 day for SMA, and 1 day for EMA.

After conducting the study, the $SMAPE$ value was obtained for various combinations of smoothing and aggregation methods and parameters for model construction and testing. Tab. 2 shows the results of the unmodified model. Tab. 3 shows the main results of the conducted studies; Fig. 4 shows a graph of the dependence of $SMAPE$ on the number of data points and the forecast period.

Table 2.

Results obtained for unmodified polynomials

Number of polynomial data points	3-day testing period	4-day testing period	5-day testing period
3	6,741	9,572	12,873
4	18,636	28,407	39,403
5	38,610	55,717	71,414
6	63,247	84,220	101,315

Table 3.

Best results obtained

Number of polynomial data points	Testing period, days	Smoothing method	Smoothing window size, days	Lowest SMAPE received	Aggregation method
2	10	SMA/EMA/ NoMA	1/1	3,162	weekly
3	10	EMA	4	3,370	weekly
4	10	SMA	10	3,931	weekly
5	10	SMA	22	4,812	weekly
6	10	SMA	22	5,976	weekly
2	15	SMA/EMA	1/1	3,886	weekly

Закінчення табл. 3

Number of polynomial data points	Testing period, days	Smoothing method	Smoothing window size, days	Lowest SMAPE received	Aggregation method
3	15	EMA	7	4,517	weekly
4	15	SMA	21	5,292	weekly
5	15	SMA	22	6,923	weekly
6	15	SMA	51	10,917	weekly
2	20	EMA	3	5,182	weekly
3	20	EMA	11	5,792	weekly
4	20	SMA	20	6,425	weekly
5	20	EMA	22	9,876	monthly
6	20	SMA	52	12,022	monthly

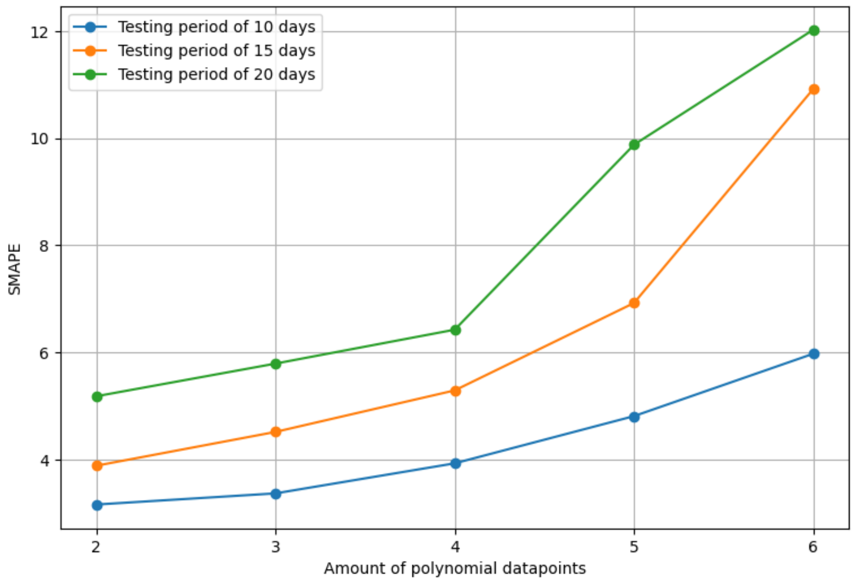

Figure 4. Dependence of $SMAPE$ on the number of data points for different testing periods

The next section discusses the results obtained.

6. Discussion of the results obtained

6.1. The interpretation of the results obtained

The results presented in Tab. 2 showed that smoothing methods positively affect the forecast accuracy for polynomials built on 4, 5 and 6 data points over longer forecast periods. For example, for a 20-day period, a polynomial built on 6 points using the SMA method with a 52-day smoothing window obtained an accuracy of 12,022% according to the SMAPE metric, compared to the same polynomial with a monthly aggregation type without using SMA with 26,903% $SMAPE$, which is a 54% reduction in the accuracy window in comparison. That is, when using SMA, an increase in accuracy of more than 2 times was obtained compared to the method without smoothing for this set of parameters.

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Among the results of smoothing with weekly aggregation, almost all values from the experiment showed a better result when using one of the smoothing methods. Most often, the simple moving average method showed better results. As for the previous aggregation method, smoothing showed a better result for longer forecast periods and for more complex polynomials. However, for weekly aggregation, smoothing was more effective. For example, for a 20-day forecast period, for polynomials built on 5 and 6 points, the difference was about 83% and about 80%, respectively, which is an increase in accuracy by the $SMAPE$ metric by more than 5 times.

From Tab. 3 it is seen that for most results it is better to use one of the smoothing methods for accuracy. Though, no dependence between the parameters and the chosen method was found. However, most of the aggregation methods are weekly. Thus, the smoothing methods were much more effective for the weekly aggregation method than for the monthly one, since they were able to show a better result, while without smoothing the accuracy for some parameters of the monthly aggregation is several times better. In addition, simpler polynomials show slightly higher accuracy, regardless of the tested period.

Table 4.

Interpretation of the results obtained [19]

$SMAPE$	**Forecasting quality**
$< 10\%$	High
$10\%\sim20\%$	Good
$20\%\sim50\%$	Reasonable
$> 50\%$	Inaccurate

Based on the values in Tab. 4, the use of the described method yielded highly accurate or good forecasting results, as shown in Tab. 3, depending on the chosen polynomial. Moreover, there is a significant increase in accuracy compared to the results in Table 2, which are examples of weak and inaccurate forecasting.

The adaptability of the described method lies in working with a data set without direct external user intervention. This approach eliminates the need for an external expert to select a suitable algorithm for specific data, since the experiment stage is automated. The method will change the logic of process execution and data processing depending on the input conditions. The method will keep a countdown, a ranking table, where the number of times each algorithm was selected will be recorded. Algorithms that lag significantly behind in the table are to be eliminated. The selection of the algorithm is determined by the accuracy, which is estimated by the $SMAPE$ metric, based on a comparison of predictions for the previous period and their historical data. As a result, a more accurate model is selected.

The next section suggests a practical application of the developed model and reviews its advantages and disadvantages.

6.2. Practical application of the proposed model

The proposed method could be useful for beginners and experienced investors as an additional analysis tool for decision-making. However, its use in a broader context is suggested. The method of estimating and predicting asset prices based on time series is an intermediate link in the information technology of asset analysis and creating an investment financial portfolio of the user. For further analysis and for diversification algorithms, the results of the prediction method described will be used in the future to improve the result.

In addition, regardless of the chosen field of study, the algorithm for predicting historical values primarily works with time series. Therefore, it can be used for the purpose of other economic market indicators, for example:

- economic indicators: commodity prices, currency rates, cryptocurrency rates;
- macroeconomic identifiers: inflation rate, GDP, unemployment rate;
- marketing and business analytics: calculating sales volumes, predicting changes in product and analytical metrics, predicting the number of users;
- medicine and epidemiology: predicting the spread of infections;
- agriculture: predicting crop growth, the spread of pests;
- automated asset trading and trading, investment portfolio management systems;

The following section lists the advantages and disadvantages of the developed model.

6.3. Advantages and disadvantages

Advantages of the proposed method:

1. no need for human intervention for calculation. The method will only require financial data on trades;
2. the selection stage within the method is an automated experiment, which eliminates the need for an expert;
3. the method is simple and transparent to understand and easy to calculate due to the use of numerical methods as the forecasting core;
4. the method is universal and can work with various statistical data.

Disadvantages of the proposed method:

1. the method is one-dimensional and uses only historical prices at the time of the closing of daily trading. The use of other indicators, such as trading volumes, volatility, is ignored;
2. the method does not take into account external factors such as fundamental and financial indicators of the company, sentiment analysis or macroeconomic news;
3. loss of information about market changes due to aggregation and smoothing. Which makes the method insensitive to sudden changes in the trend.

The next section presents the scientific novelty of the results obtained.

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6.4. Scientific novelty

1. A combined method for forecasting the price of valuable assets is proposed, which combines polynomial extrapolation based on the Lagrange polynomial with smoothing methods (SMA and EMA) in a single adaptive scheme, with the selection of the number of reference points for constructing the polynomial. The method provides for automatic adjustment of extrapolation parameters depending on the characteristics of the input time series. The method automatically adjusts to changes in financial time series.

2. A combined method for forecasting the value of securities is developed, which includes the procedures:

- dynamic data smoothing;
- construction of a set of alternative forecast models;
- automatic selection of the most accurate model based on minimization of $SMAPE$.

3. The dependences between the parameters of polynomial extrapolation are investigated: the number of points, the aggregation period, and the accuracy of asset value forecasting, which allows to formulate recommendations on the choice of parameters for different types of time series.

4. It is shown that the combination of exponential smoothing with polynomial extrapolation increases the accuracy of forecasting on highly volatile financial data, which is confirmed by experiments on historical prices of NIFTY 50.

Considering all of the above, the following conclusions can be drawn.

Conclusions

As part of this work, a combined method for forecasting the value of financial assets was developed. The results of the experiment showed that the use of pre-processing methods, such as smoothing using a moving average and time aggregation, significantly affected the accuracy of stock price forecasting using Lagrange interpolation polynomials for periods up to 20 days. The best model configurations demonstrated high forecasting accuracy with error rates of less than 10%. The key advantage of the proposed combined method is the automated selection of the most accurate model without the need for expert intervention, which makes it accessible to a wide range of investors. Despite the fact that the method is based exclusively on historical data and does not take into account fundamental factors, it is an effective, computationally simple tool for technical analysis and can serve as an auxiliary link in the formation of investment portfolios.

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