ISSN 2226-3780

18. *Seti Petri. Struktura i pravila vypolneniya setey Petri.* Available at: https://itmodeling.fandom.com/ru/wiki/%D0%A1%D0%B5%D1%82%D0%B8_%D0%9F%D0%B5%D1%82%D1%80%D0%B8._%D0%A1%D1%82%D1%80%D1%83%D0%BA%D1%82%D1%83%D1%80%D0%B0_%D0%B8_%D0%BF%D1%80%D0%B0%D0%B2%D0%B8%D0%BB%D0%B0_%D0%B2%D1%8B%D0%BF%D0%BE%D0%BB%D0%BD%D0%B5%D0%BD%D0%B8%D1%8F_%D1%81%D0%B5%D1%82%D0%B5%D0%B9_%D0%9F%D0%B5%D1%82%D1%80%D0%B8. Last accessed: 07.09.2016.
19. *Merezhi Petri.* Available at: https://stud.com.ua/98834/informatika/merezhi_petri. Last accessed: 10.09.2016.

Popova Olena, *Department of Software Engineering, The Bohdan Khmelnytsky National University of Cherkasy, Ukraine, e-mail: olena.popova2016@gmail.com, ORCID: https://orcid.org/0000-0002-8838-8219*

UDC 336.74, 338.1, 004.02
DOI: 10.15587/2312-8372.2019.180552

Kruhlov A., Pyroh M.

ANALYSIS OF PROBLEMS OF FORECASTING OF FINANCIAL INSTRUMENTS IN STOCK MARKETS

Об'єктом дослідження є процеси прогнозування фінансових інструментів на фондових ринках в умовах невизначеності. Високий ступінь невизначеності на фондових ринках значно ускладнює процес прогнозування динаміки фінансових інструментів. Дана проблема має значення, як для держав, так і для інвестиційних компаній. А також для інших учасників ринку, яким необхідно приймати довгострокові інвестиційні рішення, засновані на превентивних заходах щодо зниження впливу ризиків фінансових криз на їх діяльність. У даній роботі автори аналізують ряд прогностичних моделей, які застосовуються в сфері розрахунків числових рядів. В контексті прогнозування цін на фондових ринках виявлені сильні і слабкі сторони популярних на практиці моделей. Наведено їх математичні функції, пояснені алгоритми розрахунку та дані авторські висновки про ступінь ефективності застосування окремих моделей в сфері фінансових інструментів.

В ході дослідження автори вивчили ряд різних наукових праць з даної проблеми і провели аналіз отриманих відомостей. Отриманий результат аналізу показав, що процеси прийняття рішень при прогнозуванні змін фінансових інструментів будуть ускладнені наявністю зовнішніх чинників, але також ці зовнішні чинники є результатом діяльності окремих учасників ринку. Це пов'язано з тим, що при прогнозуванні фінансових інструментів на фондових ринках можна нівелювати псевдо-випадкові події зовнішнього середовища. Багато існуючих рішень прогнозування допускають низьку точність при моделюванні прогнозу, тому раціональніше використовувати мультиагентні технології. Завдяки ним забезпечується більша точність показників, в порівнянні з аналогічними методами, такими як економетричні моделі (найбільш відомі з них : ARCH, GARCH, VAR).

Отримані у роботі результати досліджень можна використовувати для прогнозування фінансових криз, а також для розробки методів протидії ним.

Ключові слова: *моделі прогнозування, фондовий ринок, ланцюг Маркова, довгострокові інвестиційні рішення, мультиагентні технології.*

Received date: 22.05.2019
Accepted date: 28.06.2019
Published date: 30.08.2019

1. Introduction

Thanks to the rapid development of information technologies, it became possible in a matter of seconds to analyze a large amount of information, build complex mathematical models, and solve multicriteria optimization problems. Scientists involved in the cyclical development of the economy began to develop theories, believing that tracking trends in a number of economic variables would clarify and predict periods of ups and downs. One of the objects for study is the stock market. Multiple attempts have been made to build such a mathematical model that would successfully solve the problem of forecasting the price of financial instruments [1]. In particular, «technical analysis» has become widespread. The relevance of this study lies in the fact that at the moment, with the pace of development of the world economy, stock and foreign exchange markets, many forecasting methods have appeared. In this work, the author identifies the most accurate of them on the basis of a number of studied works and constructed analytical models.

2. The object of research and its technological audit

The object of research is the forecasting processes of financial instruments in stock markets in the face of uncertainty. A high degree of uncertainty in the stock markets significantly complicates the process of forecasting the dynamics of financial instruments. This problem is important both for states and investment companies, as well as other market participants who need to make long-term investment decisions based on preventive measures to reduce the impact of financial crisis risks on their activities.

One of the most problematic places in forecasting is the poor predictive ability of models. Seasonality, trending and non-stationary forecasting process, which leads to incorrect results.

3. The aim and objectives of research

The aim of research is identification of the existing problems of forecasting financial instruments in stock markets.

To achieve this aim it is necessary to perform the following objectives:

1. To analyze the existing forecasting methods and identify what problems are present in them.
2. To suggest solutions to these problems.

4. Research of existing solutions of the problem

Different authors offer numerous, different from each other, models for forecasting number series. However, many of the proposed instruments are unsuitable for predicting the dynamics of financial instruments due to the non-stationary nature of this process according to the Dickey-Fuller test. In this vein, it is worth highlighting regression forecasting models [1], autoregressive and other derivatives from them [2]. The key problem of these methods is as follows: the mentioned models are based on the assumption that the prediction elements do not correlate and are normally distributed. If this assumption is actually incorrect, then the risk of forecast error is significantly increased.

Some methods (models on Markov chains [3] and models of exponential smoothing [1]) are able to give an adequate forecast only at small time intervals, which makes them ineffective in long-term forecasting. They are also unsuitable for forecasting for long periods of time, since they do not take into account such important indicators as trends and seasonality.

Such a method as a model on a sample of maximum similarity [3], as well as some others similar to it, is in principle not suitable for forecasting financial instruments.

The main problem of neural network forecasting, according to [4, 5], is that assumptions change very quickly over a short time period, and this turns potentially good prognostic models into useless ones. The fundamental reasons for this transformation are: retraining of neural networks, variable impact indicators, and, in particular, ignoring neural networks of non-stationary characteristics in data on a financial instrument.

To solve this problem, economics suggests using stochastic atomic [1] and quantum [6] systems, which are able to predict the combined effect of individual bidders on pricing, considering them as particles. Modeling and predicting the behavior of market participants as individual agents can minimize the bias in assessing the dynamics of a financial instrument and improve existing prognostic models and methodologies. So, in the study [7], multiagent technologies are used to predict the dynamics of stock prices. However, the authors of these studies do not use neural network technology, so it seems impossible to increase the complexity of agent trading strategies. They, as in [4, 8], use this technology as a signaling system to help stock market participants.

In [4, 5], genetic algorithms are used to formulate strategies of individual agents. However, their approach consists mainly in selecting the most fit individuals, based on the profitability of strategies, replacing the original population with a population of more fit agents. Further, let's assume the necessity of modeling unprofitable strategies as well, since all bidders cannot simultaneously earn money and it is necessary to take into account negative selection.

The developments referred to by the authors of many scientific papers are either not published, or published without source code, or have significant structural limitations, which does not allow their further development [9, 10].

Thus, the results of literary analysis allow to conclude that this problem is not fully understood, and therefore the authors of the work decided to study this problem in more detail, based on existing works.

5. Methods of research

The following scientific methods are used:

– analysis method in the study of a number of scientific papers and articles on the problems of forecasting financial instruments in stock markets;

– classification method in the study of forecasting methods.

6. Research results

Regression-type prediction methods are required to investigate the correlation between more than two variables. Famous regressive models include the following.

Simple linear regression. The model is based on the hypothesis that there is a certain discrete external factor (t), under the dominant influence of which is the entire analyzed process (t), with a linear type of connection. The following equation describes this relationship [10]:

$$Z(t)=\alpha 0+\alpha 1X(t)+\varepsilon t,$$

where $\alpha 0$ and $\alpha 1$ are the regression coefficients; εt is the model error.

To get the forecast values (t) for the time interval t, it is necessary to have the value $X(t)$ for the same time interval t, but in reality this is not common.

Multiple regression. In fact, the numerous discrete external factors $X1(t)$, ..., $Xs(t)$ significantly affect the process $Z(t)$. Then the equation of the model will be like this:

$$Z(t)=\alpha 0+\alpha 1X1(t)+\alpha 2X2(t)+...+\alpha sXs(t)+\varepsilon t.$$

However, this method also has a significant weakness. Namely, the future value of the process (t) can be calculated only after determining the future values of all factors $X1(t)$, ..., $Xs(t)$, which is rarely possible to do in reality.

Nonlinear regression. The foundation of this model is the hypothesis that there is a function that confirms the existence of a correlation between the initial process (t) and some external factor $X(t)$.

The function of this model is:

$Z(t)=F(X(t), A)$.

To build this type of model, first of all, it is necessary to calculate the parameters of the function *A*. Then let's make the assumption that:

$Z(t)=\alpha 1\cos(X(t))+\alpha 0$.

Based on this, let's set the parameters $A=[\alpha 1, \alpha 0]$. Real processes can be called very rare, according to which the type of connection that combines the process (t) and the external factor $X(t)$ has already been determined in advance. It is precisely because of this fact that the use of nonlinear regression models is extremely limited, and such methods are used relatively infrequently in stock market practice.

The most widely used are fairly Dickey-Fuller tests [1]. The time series estimation method for integrability is represented by the formula:

$Yt=a1\cdot Yt-1+\varepsilon t$.

The main idea of this method is as follows: it is necessary to verify the fact that the process is stationary, that is, confirm or refute the corresponding hypothesis, and also check its difference in order, with a rising trend, in turn.

Tests such as the DF test contain a significant drawback, namely: they do not provide for probable residual autocorrelation. However, if autocorrelation is still traced in the residuals, the results of the least squares method may become unreliable [11]. It is seen in [12] that the right half of the equation is equipped with new variables, namely, lag values, transferring them from the left half. Then the equation will look like:

$$\Delta Yt = a1\cdot Yt - 1\cdot \sum_{i=1}^{k} ai + 1\cdot \Delta Yt - t + \varepsilon t.$$

This test is called the augmented Dickey-Fuller test (ADF test). It is important to emphasize that this is the most productive and most common of simple integrability tests [13].

Autoregressive forecasting models. In work [1] it is proved that the form of autoregression is considered extremely useful in order to determine the time series existing in reality. Modification assigns the key role of the process to the finite linear set of previous values of the process and momentum, which is called «white noise». The equation of such a function is represented as:

$Z(t)=C+\varphi 1Z(t-1)+\varphi 2Z(t-2)+\ldots\varphi pZ(t-1)+\varepsilon t$,

where the autoregression process of order *p*, denoted by $AR(p)$, while *C* is a real constant, $\varphi 1, \ldots, \varphi p$ are coefficients, εt is a model error. To determine φi and *C*, it is advisable to apply the maximum likelihood method or the standard least squares method. The general model is often referred to as ARMA.

The ARIMA (p,d,q) model has several modifications, one of which is ARIMAX (p,d,q), the equation of which is presented as [1]:

$Z(t)=AR(p)+a1X1(t)+\ldots asXs(t)$,

where $a1, \ldots, as$ are the coefficients of external factors $X1(t), \ldots, Xs(t)$. Often, $Z(t)$ is defined as the result of a calculation using the $MA(q)$ model. After that, the further predicted value of (t) is determined by the autoregressive model. It also contains regressors of external factors $X1(t), \ldots, Xs(t)$, as a clarifying addition.

The autoregressive model with conditional heteroskedasticity of T. P. Borreslev is essentially a residual model for the $AR(p)$ method [12]. First, let's determine the $AR(p)$ model for the required series. Then let's refer to the assumption that the model error εt has the components:

$\varepsilon t=\sigma t\cdot \vartheta t$,

where σt is the standard deviation, depending on the time indicator; ϑt is a random variable with a normal distribution, the average value is 0 (zero), and the standard deviation is 1 (one).

The value of the standard deviation is calculated by the formula:

$\sigma t2=\beta 0+\beta 1\varepsilon t-12+\ldots+\beta q\varepsilon t-q2+\gamma 1\sigma t-1+\ldots+\gamma p\sigma t-p$,

where $\beta 0, \ldots, \beta q$ and $\gamma 0, \ldots, \gamma p$ are coefficients.

The *GARCH* (*p, q*) model includes 2 indicators: *p* is the order of autoregression of the squares of residues; *q* is the number of previous residual estimates. The use of this method is especially common in the field of finance, since it is successfully used in case of the need to simulate volatility. There are many modifications of the GARCH method – these are both the NGARCH model, and EGARCH, etc. All of them include the assumption that the normal distribution of residues is uncorrelated. If at least one of these assumptions is incorrect, then there is a risk that the forecast intervals will be erroneous.

Exponential Smoothing (ES) Models Prajakta S. K. This is to a certain extent the filter model through which the members of the original series pass, and as a result, the current values of the exponential average are obtained, which is given by the equation:

$Z(t)=S(t)+\varepsilon t\cdot S(t)=\alpha\cdot Z(t-1)+(1-\alpha)\cdot S(t-1)$,

where $S(t)$ is the value of the exponential average at time t; εt is the white noise; α is the smoothing parameter in which $0<\alpha<1$.

The model shows adequate results on a small forecasting horizon, since it overlooks the trend and seasonal changes. On the other hand, these factors can be taken into account using:

– Holt model, which is based on a linear trend;
– Holt-Winters model, which takes into account both seasonality and the multiplicative exponential trend;
– Theil-Wage model using these additive linear trend and seasonality.

The advantages of these models are the relative simplicity of design and analysis, as well as uniformity, which allows to streamline the calculation process and make comparisons. The key disadvantage of this class of models is inflexibility [14]. And yet, it is this class of forecasting models that is most prevalent in the case when it becomes necessary to calculate for the long term [15].

Maximum Similarity Sampling Model (MMSP). This model can really be effective, but only in a limited range of applications. It is important to clarify that it is impractical to apply to a number of exchanges, including FOREX, because, in this case, according to studies, it works inefficiently [16].

A neural network model (ANN) implies that 2 functions are needed to describe a neuron model:

$$U(t)=\Sigma\omega i\cdot Z(t-i)+bmi=1,$$

$$Z(t)=\varphi(U(t)),$$

where $\omega 1$, ..., ωm are the synaptic weights of the neuron; $Z(t-i)$, ..., $Z(t-m)$ are the input signals; $(U(t))$ is the activation function; b is the threshold.

Neurons use different types of connections, therefore, in the scientific literature it is customary to distinguish three types of networks: recurrent networks, single-layer networks and multilayer networks [17].

The main advantage of such models is the lack of linearity, since they can connect current and future indicators with a nonlinear dependence. The advantages of neural networks traditionally include high adaptability, scalability (because the ANN structure, built on the principle of parallelism, allows to speed up the calculations) and uniformity [18].

Nevertheless, ANN models are filled with numerous weaknesses: the ambiguity of the algorithm for choosing the appropriate architecture; the opacity of the modeling process. Separately, it is necessary to emphasize the difficulty of meeting the requirements of the training sample, which implies consistency, hence the difficulty in determining the appropriateness of using one or another algorithm, as well as the high cost and resource intensity of the learning process [17].

Markov chains model is an effective way to predict the value of stocks, but to get better results, it is necessary to create sufficiently large intervals, a short period of time.

In essence, Markov theory is only a simplified model of a complex decision-making process. The structure of the Markov chain and the probability of state transitions are fundamental factors in determining the type of relationship between the current and future values of the analyzed process.

The strengths of these models are the relative simplicity of analysis and modeling. The weak side of the model on Markov chains is that they cannot be used in modeling processes with long memory characteristics [17].

Classification Regression Tree Model (CART). This method develops a model of processes influenced by continuous external and categorical factors. Given the continuity of external factors, it is advisable to use regression trees. Conversely, for categorical factors it is better to use the classification type of branching. There are also mixed CART models, which, if necessary, can take into account all the factors mentioned.

The obvious strengths of these models are:

– high speed and transparency of the learning process of the tree, which, for example, compares them favorably with the ANN models [18];
– scalability, due to which fast processing of large data arrays occurs and the opportunity to use categorical external factors opens up.

Weaknesses of CART models:

– opacity of the process of forming the structure of the tree;
– lack of uniformity;
– impossibility of a single choice of time and stage of termination of further branching (growth) of the tree [18].

The support vector method (SVM) is actively used in the electric power industry to model the future dynamics of the cost of electricity [19]. The model is based on classification in such a way that the initial time series go into a high-dimensional space. As a result, at the training phase, it becomes possible to uniquely determine external factors, the future values of which will need to be referenced when distributing forecasts (t) by subclass.

The transfer function model (TF) is used in predicting the process (t), taking into account the external factor $X(t)$ [19]. The dependence of the future value is defined as:

$$Z(t)=v(B)X(t)+\eta(t),$$

where B is the shift operator $BZ(t)=Z(t-1)$, ..., $BkZ(t)=(t-k)$.

The time interval (t) characterizes the perturbation from the outside. Then the function (B) has the form:

$$Z(t)=\alpha 0+\alpha 1X(t)+\varepsilon t.$$

The coefficients of the function vi define the relations between the processes (t) and $X(t)$ as dynamic.

All sorts of combinations (fuzzy logic + ANN, SARIMA + + ANN, regression + ANN, etc.) are also analyzed in a review of methods for predicting the amount of energy consumption [20].

ANN models with various combinations are effectively used for clustering purposes. In scientific work [20], the author mentions that combined models should be considered the most promising. Models are able to perform primary clustering and further forecasting in the context of a particular cluster.

The authors of [21] emphasize: clustering, as a method, must be used to increase prognostic accuracy and reduce the likelihood of error. Clustering is carried out according to the methods of K-means and fuzzy C-means. The goal of both methods is in increasing the accuracy of the forecast, which can be achieved by extracting the necessary information from the time series.

Models based on multi-agent systems. The agent approach is applicable when it is necessary to analyze multicomponent self-organizing processes that are characteristic of a number of applied areas and are characterized as complex. However, the development process of such a system seems nontrivial and even difficult, since the agent has the properties of independence and autonomy from the general system. An agent is inclined to perform targeted actions, to contact with other agents, to make decisions, to adapt to the environment, to make movements, etc.

Models based on economical physics. Models based on economical physics and their approaches differ from traditional econometric methods in the extensive use of graphic drawings. But in practice it turns out that in some situations this can lead to errors, since such an approach does not make it possible to detect features of the data under study.

For some reason, a number of scientists have noted the Laks-Marchezi model as the most effective [21].

ISSN 2226-3780

It presents three categories of stock market participants:

– representatives of the fundamental analysis who acquire shares when their price falls below the level that determines long-term factors;

– representatives of technical analysis (or «pessimists») who sell shares with an increase in quotes to fix income;

– representatives of technical analysis (or «optimists») who buy stocks exclusively when they rise.

This model is based on the concept of statistical physics about the interaction of elements under the influence of internal conditions of the system.

The model makes the probabilities of moving representatives of one category of market participants to other groups, while the income from the implementation of strategies forms the transition functions. The dynamics of quotations depends on the ratio of demand of all three categories of market participants. This model implies that a strong market position can come already after significant fluctuations, when the number of followers of technical analysis decreases and, in turn, the ranks of supporters of fundamental analysis are replenished. At the same time, the Laks-Marchezi model proceeds from the stability of the number of shares available on the market.

Since the late 1980s, many scientists have sought to find a solution to the problem of forecasting the dynamics of financial instruments in stock markets [16]. Despite this, and despite the large number of works on this topic, an extremely small number of real projects are found when modeling the market using a multi-agent approach.

In fact, the presence of the only clearly established approach is not observed in any of the types of analyzed models and methods. But to develop and create multi-agent models for each specific task is inefficient. The reason for this is that the presented model can be controlled by a certain number of heuristics that cannot be formally justified or allowed to the stage of simulation run. During the modeling process, the withdrawal methods, actions, and the system of mutual exchange of information between agents can be updated on a regular basis.

The solution to this problem may be the development of simulation modeling. However, this goal is not unreasonably considered even more complex and costly, in particular, in the framework of agent modeling.

According to some authors, nevertheless, optimization methods, graph theory, and systems based on neural networks can be considered quite effective. But the same neural network aspect cannot be considered fully optimal and takes into account all the necessary factors [22].

As a result, existing solutions indicate that this problem is either partially solved or there is no practical implementation. There is an obvious need to use neural network technology to model complex strategies of individual agents, eliminate pseudo-random, manipulative events and, as a result, increase predictive ability.

To date, according to research [23], the main difficulties in predicting number series are:

– lack of process stationarity;

– ignoring the trend and seasonality;

– small prediction interval;

– ignoring the strategies of individual market participants.

A review is made of the most practically used instruments for forecasting financial instruments. The strengths and weaknesses of each of the considered models are considered. It is noted that at the current stage of development of dynamics assessment and forecasting of stock instruments, the most widely used methods are neural network models, as well as autoregressive models (ARIMA).

7. SWOT analysis of research results

Strengths. The solutions to the problems of forecasting financial instruments in the stock markets are identified, which will increase the prognostic ability of existing solutions. And also to predict financial crises and prepare preventive measures to eliminate or mitigate them.

Weaknesses. The solutions identified in the work do not yet have a practical basis.

Opportunities. Forecasting can become more accurate due to the fact that heterogeneous strategies of all bidders are taken into account. This will positively affect the economic development of stock markets.

Threats. Technological methods may fail, which will entail further incorrect decisions, and technological methods may also be subject to external attacks.

8. Conclusions

1. The main problems of forecasting the dynamics of financial instruments are identified, such as: inaccuracy of modeling and the problem of non-stationary process. It is shown that the additional complexity of forecasting for large time intervals is the trending and seasonality of the process.

2. To increase prognostic ability, it is proposed to model the dynamics of financial instruments using multi-agent systems. This will take into account the strategies of all bidders in the aggregate and thereby increase predictive ability.

References

1. Astakhova, N. N., Demidova, L. A. (2015). The method of time series forecasting groups using algorithms of cluster analysis. *Prikaspiyskiy zhurnal: upravlenie i vysokie tehnologii, 2,* 59–79.
2. Keskin, M., Deviren, B., Kocakaplan, Y. (2011). Topology of the correlation networks among major currencies using hierarchical structure methods. *Physica A: Statistical Mechanics and Its Applications, 390 (4),* 719–730. doi: https://doi.org/10.1016/j.physa.2010.10.041
3. Nobi, A., Lee, S., Kim, D. H., Lee, J. W. (2014). Correlation and network topologies in global and local stock indices. *Physics Letters A, 378 (34),* 2482–2489. doi: https://doi.org/10.1016/j.physleta.2014.07.009
4. Roy, R. B., Sarkar, U. K. (2011). Identifying influential stock indices from global stock markets: A social network analysis approach. *Procedia Computer Science, 5,* 442–449. doi: https://doi.org/10.1016/j.procs.2011.07.057
5. Lü, L., Zhou, T. (2011). Link prediction in complex networks: A survey. *Physica A: Statistical Mechanics and Its Applications, 390 (6),* 1150–1170. doi: https://doi.org/10.1016/j.physa.2010.11.027
6. Armstrong, J. S., Brodie, R. J. (1999). Forecasting for Marketing. *Quantitative Methods in Marketing, 92*–120.
7. Andreas, J., Rohrbach, M., Darrell, T., Klein, D. (2016). Neural Module Networks. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR).* doi: https://doi.org/10.1109/cvpr.2016.12
8. Tihonov, E. E. (2006). *Metody prognozirovaniya v usloviyah rynka.* Nevinnomyssk, 221.
9. Tumminello, M., Lillo, F., Mantegna, R. N. (2010). Correlation, hierarchies, and networks in financial markets. *Journal of Economic Behavior & Organization, 75 (1),* 40–58. doi: https://doi.org/10.1016/j.jebo.2010.01.004

10. Bessec, M., Fouquau, J., Meritet, S. (2015). Forecasting electricity spot prices using time-series models with a double temporal segmentation. *Applied Economics, 48 (5),* 361–378. doi: https://doi.org/10.1080/00036846.2015.1080801
11. Aue, A., Horváth, L., F. Pellatt, D. (2016). Functional Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Time Series Analysis, 38 (1),* 3–21. doi: https://doi.org/10.1111/jtsa.12192
12. *Slovar' sovremennoy ekonomicheskoy teorii Makmillana*. (2003). Moscow: Infra-M, 21.
13. Ben Taieb, S., Huser, R., Hyndman, R. J., Genton, M. G. (2016). Forecasting Uncertainty in Electricity Smart Meter Data by Boosting Additive Quantile Regression. *IEEE Transactions on Smart Grid, 7 (5),* 2448–2455. doi: https://doi.org/10.1109/tsg.2016.2527820
14. Beran, J., Feng, Y., Ghosh, S., Kulik, R. (2013). *Long-Memory Processes*. Springer, 884. doi: https://doi.org/10.1007/978-3-642-35512-7
15. Nowotarski, J., Weron, R. (2014). Computing electricity spot price prediction intervals using quantile regression and forecast averaging. *Computational Statistics, 30 (3),* 791–803. doi: https://doi.org/10.1007/s00180-014-0523-0
16. Gontis, V., Havlin, S., Kononovicius, A., Podobnik, B., Stanley, H. E. (2016). Stochastic model of financial markets reproducing scaling and memory in volatility return intervals. *Physica A: Statistical Mechanics and Its Applications, 462,* 1091–1102. doi: https://doi.org/10.1016/j.physa.2016.06.143
17. Hu, R., Wen, S., Zeng, Z., Huang, T. (2017). A short-term power load forecasting model based on the generalized regression neural network with decreasing step fruit fly optimization algorithm. *Neurocomputing, 221,* 24–31. doi: https://doi.org/10.1016/j.neucom.2016.09.027
18. Vandewalle, N., Brisbois, F., Tordoir, X. (2018). Non-random topology of stock markets. *Quantitative finance, 1,* 372–374.
19. Mantegna, R. N. (1999). Hierarchical structure in financial markets. *The European Physical Journal B, 11 (1),* 193–197. doi: https://doi.org/10.1007/s100510050929
20. Rahman, M. H., Salma, U., Hossain, M. M., Khan, M. T. F. (2016). Revenue forecasting using holt–winters exponential smoothing. *Research & Reviews: Journal of Statistics, 5,* 19–25.
21. Levin, D., Peres, Y. (2017). Markov chains and mixing times. *American Mathematical Society.* doi: https://doi.org/10.1090/mbk/107
22. Wang, L., Zeng, Y., Chen, T. (2015). Back propagation neural network with adaptive differential evolution algorithm for time series forecasting. *Expert Systems with Applications, 42 (2),* 855–863. doi: https://doi.org/10.1016/j.eswa.2014.08.018
23. Zhang, Z., Brand, M. (2017). Convergent block coordinate descent for training tikhonov regularized deep neural networks. *31st Conference on Neural Information Processing Systems (NIPS 2017)*. Available at: https://papers.nips.cc/paper/6769-convergent-block-coordinate-descent-for-training-tikhonov-regularized-deep-neural-networks.pdf

Kruhlov Alexander, *Department of Intellectual Technologies, Taras Shevchenko National University of Kyiv, Ukraine, ORCID: https://orcid.org/0000-0003-4347-8584, e-mail: awahrhaft@gmail.com*

Pyroh Mykola, *Department of Applied Information Systems, Taras Shevchenko National University of Kyiv, Ukraine, ORCID: http://orcid.org/0000-0003-2588-6066, e-mail: mykola.pyroh@ukr.net*