Neural Networks Usability Analysis in Economic Security Indicators Dynamics Forecasting

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Abstract: The paper is devoted to neural network applicability analysis in economic security indicators forecasting models. Exchange indicators usage makes it possible to introduce tools for economic security operational monitoring, since they largely determine the economic environment dynamics development. Neural networks training and various models comparative analysis for economic time series values predictions were carried out using the dollar / ruble exchange rate example. The paper presents two initial data sets analysis with information content of different amounts. Predictive indicators calculation was carried out using three neural networks different models and gradient boosting method. The results obtained in the work make it possible to identify the best neural network model for target indicators prediction, as well as to analyse neural networks approaches effectiveness' in the problems under consideration, depending on the dimension of the initial data. Based on the simulation's results, there is a conclusion, that neural network methods in economic security indicators forecasting can be justified only on a significant sample size.

1 INTRODUCTION

Modern technological capabilities open up prospects for new tools usage regarding economic processes studies in systems of various hierarchy. It seems intuitive and scientifically substantiated that operational forecasting and strategic control require the automated information systems widespread implementation, including those based on artificial intelligence methods and machine learning algorithms (Tomashevskaya, 2020). Thus, in modern realities, machine learning methods are highly involved in solving various economic problems and are being implemented in almost all spheres of human life. The corresponding algorithms find their application both for economic processes in a broad sense analysis, and for solving specific practical business problems, becoming one of the management problems top-notch analysis tools (Shamin, 2019).

One of the key and widely discussed problem classes, which analysis mechanisms allow modern machine learning and artificial intelligence tools usage is economic indicators forecasting, since, as a rule, the analyzed values are quantitatively set by time series.

An important task in various hierarchies systems economic processes studies can undoubtedly be the ensuring economic security problem. Analysis, forecasting, monitoring and economic security management problems regarding national economy subjects are quite acute nowadays, due to endogenous and exogenous environment constantly changing situation. Appropriate scientific and methodological basis development will allow in a fairly accurate manner to predict relevant indicators values and, as a result, make scientifically grounded management decisions in order to minimize certain processes negative impact. New challenges and threats dictate new breakthrough technologies needs in management tasks at all national economy levels.

Corresponding economic security indicators operational control, analysis and dynamics forecasting in order to ensure an appropriate considering object safety level, along with traditional

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methods, require modern threats predicting algorithms usage and effective strategies choice, oriented on possible consequences prevention (Shmeleva, 2019). Considering social and economic processes, world's digital transformation, computing systems technological capabilities exponential growth alongside with databases and information storages significant development, machine learning could be effectively used as an approach towards the raised problem solution (Chio, 2020; Hastie, 2009; Flah, 2015).

Machine learning mathematical tools have been increasingly and effectively used in social and economic processes studies. In various fields of scientific knowledge, supervised and unsupervised learning, reinforcement learning methods are widely used (Bata, 2020). Machine learning methodology in economic problems is being explored in many authors' works. For example, works (Adadi, 2021; Athey, 2018) analyze machine learning impact on economy development as a whole, meanwhile article (Mullainathan, 2017) describes relationships between economics and "Big Data" technologies.

In economic systems security indicators analysis and prediction, artificial intelligence methodology and machine learning is presented mainly at the micro level, mainly regarding taxation, lending and banking fields (Andini, 2019; Andini, 2018; Chakraborty, 2017). In macro-level problems studies, named toolkit is presented mainly in exchange rates and indicators analysis, while regional and sectoral economy level has a lesser extent. The paper is devoted to neural network models set up and its following usage in economic time series values prediction comparative analysis based on dollar / ruble exchange rate historical indicators. Later, this toolkit can be used to predict other economic security indicators that have initial data sufficient amount.

2 MATERIALS AND METHODS

Quite often, in order to obtain a forecast, it is required to solve a regression problem, which consists of quantitative values predictions based on known data in the past (Drejper, 2007). Within the economic security framework studies the regression problem may appear when building predictive models for threats occurrence and economic security indicators values calculation in the foreseeable time interval. For example it is required to create a model predicting economic security indicators dynamics based on the initial data. Building such model can be attributed towards supervised machine learning task, since initially there is a retrospective data set (previous periods indicator values dynamics), thus model results should consist of indicators predicted values in a given forecasting horizon. The described problem structure unambiguously refers to regression methods solving.

One of the most common and relevant machine learning methods for forecasting time series are models based on neural networks mathematical apparatus. During its operation, algorithms based on neural networks usage are affected by learning, which is a key advantage, allowing to be used in processing and analyzing information. Technically, training is characterized by finding the model connections coefficients, identifying the dependencies between input and output data. The class of mathematical methods based on neural network modeling is quite extensive, since neural networks can have different characteristics, model types, hyperparameters variable values sets. Consequently, neural network one and only optimal type selection for predicting economic dynamics is a complex, relevant scientific task that goes beyond the scope of this study. In addition, optimal model choice largely depends on the amount and dynamics of the initial input data, imposing additional difficulties in the analysis. Nevertheless, in this work, three different neural networks comparative performance analysis, as well as the gradient boosting method, is carried out.

Solving economic forecasting problems using neural network methods is often an alternative to simulation and econometric analysis. At the same time, it is known that neural network models for economic processes are often characterized by redundant information of a significant amount. There are practically no systematic characteristics of the described phenomenon essence. The neural network approach states the fact that it is possible to transform a set of input parameters into an output variable with a sufficiently high accuracy. Meanwhile, the input variables number can be quite significant (several thousand), and training and tuning a neural network requires many model experiments. In this regard, the expediency question usage such tools in specific analysis practical problems and forecasting in various levels economic security systems remains open.

In our opinion, the neural networks apparatus usage is advisable in combination with traditional econometric analysis methods. Moreover, neural network mathematical apparatus implementation is justified only with a significant sample size initial data, which is far from standard regarding on the indicators adopted in official documents basis, since they usually have a measurement frequency of one month or more. Thus, it is advisable to use neural network forecasting methods as an auxiliary tool in stock indicators or exchange rates analysis likewise other indicators with a fairly extensive measurements base. Nevertheless, comparative analysis using results, obtained with traditional econometrics and machine learning models can significantly enrich research conclusions, as well as enchance results explanation and interpretation abilities with neural network modeling capabilities.

Speaking of time series forecasting, several approaches were used allowing to analyze initial data using different neural network models in order to achieve objective results comparison. The long short-term memory network known as the LSTM model was chosen at first. Model's formal definition, which includes the so-called forgetting gates, can be noted down as follows:

$$f_t = \sigma_g\left(W_f x_t + U_f h_{t-1} + b_f\right), \quad (1.1)$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i), \quad (1.2)$$

$$o_t = \sigma_g \sigma_g(W_o x_t + U_o h_{t-1} + b_o), \quad (1.3)$$

$$c_t = f_t \circ c_{t-1} + \\ + i_t \circ \sigma_c \sigma_g(W_c x_t + U_c h_{t-1} + b_c) \quad (1.4)$$

$$h_t = o_t \circ \sigma_h(c_t), \quad (1.5)$$

where: x_t, h_t stand for input and output vectors respectively, c_t represents system's states vector; W, U, b are parameters matrix and vectors, f_i, is a forgetting gate vector, i_t, o_t define input and output gate vectors, respectively.

It should be noted that model (1.1-1.5) is widely applicable to the time series problems analysis, which is explained by its relatively high accuracy in relation to the initial data under study. For comparative analysis needs, the second chosen approach refers to a recurrent network model, which is considered as a basis for short-term memory networks development (Bergmeir, 2021). Its formal record can be represented as follows (2.1, 2.2).

$$h_t = \sigma_g(W_i h_{t-1} + V_i x_i + b_i), \quad (2.1)$$

$$z_t = \tanh(W_o h_t + b_o), \quad (2.2)$$

where: h_t stands for hidden state, z_t refers to input and output parameters for the t moment of time. W_i и V_i define weight matrices, b_i – stands for bias vector.

The third model for comparative analysis was the RBF network, which uses radial basis functions as a tool for neurons activation (Truc, 2018). As a rule, RBF networks assume three layers, including an input, nonlinear activation layer and a linear output. The model can be represented as a real values vector, and the output vector is determined based on the following $\varphi\ R^n \to R^n$ mapping (3).

$$\varphi(x) = \sum_{i=1}^{N} a_i \rho\left(\left\|x - c_i\right\|\right), \quad (3)$$

N determines hidden layer neurons number, c_i is a neuron main hidden layer and a_i stands for i-th output neuron weight.

It is advisable to make the following assumptions (4.1-4.3) for time series analysis and forecasting:

$$\varphi(0) = x(1), \quad (4.1)$$

$$x(t) \approx \varphi(t-1), \quad (4.2)$$

$$x(t+1) \approx \varphi(t) = \varphi[\varphi(t-1)]. \quad (4.3)$$

In addition to these three models, the comparison also included gradient boosting method (XGBoost), which is also often used for time series forecasting, characterizing by a relatively higher prediction accuracy over short time intervals and data with seasonality pronounced presence. The gradient boosting method is associated with a corresponding optimization function aimed to improve model training processes efficiency (5.1, 5.2).

$$L^{(t)} = \\ = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i) + \Omega(f_t)\right), \quad (5.1)$$

$$\Omega(f_t) = \gamma T + \frac{1}{2}\lambda\left\|\omega\right\|^2, \quad (5.2)$$

where: l is the loss function, $y_i, \hat{y}_i^{(t)}$ are i-th sample element values used for training and t-first predictors sum, x_i represents i-th training sample elemt, f_t notes function trained at step t, $f_t(x_i)$ is a prediction on i-th training sample element, $\Omega(f_t)$ is function f regularization, T formalizes vertices number in the analyzing tree, ω represents leaves values, γ and λ are regularization parameters.

Summarizing, these tools make it possible to carry out predictive information qualitative characteristics comparative analysis obtained on the neural network basis. Obtained results were interpreted in the graphical form, ready for further analysis.

3 RESULTS AND DISCUSSION

Neural networks training and forecast data obtaining were carried out according to the dollar / ruble exchange rate historical values. This indicator belongs to the exchange-traded, as well as oil price or RTS index. Exchange indicators usage makes it possible to introduce tools for economic security operational monitoring, since they highly determine corresponding conjuncture progress dynamics.

The first dataset contains dollar value in rubles starting in January 1996 up to December 2020, with observations made every month, so the total observations number in the first dataset is 300. The second dataset included dollar value in rubles from March 21, 2000 to March 21, 2020, with daily observations, 4968 observations in total. Despite the higher observation frequency second set has many missing days, such as weekends and holidays, as well as occasional observations absences. Thus, second set represents significantly large data amount, but it is still incomplete and cannot be considered ideal. Both data sets were divided into training and test sets in accordance with the model requirements (Figure 1). Values up to November 2019 were assigned to the training set and observations starting from November 1, 2019 inclusive - to the test set.

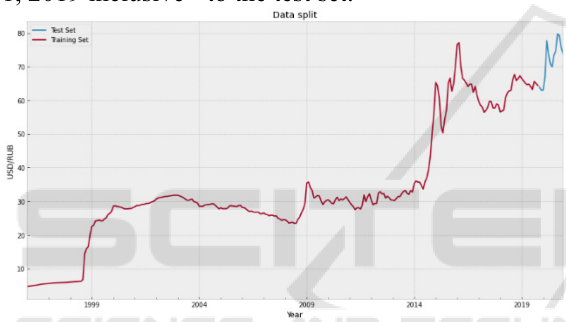

Figure 1: Training and test samples dataset distribution

When the models were trained using the first set consisting of 300 observations, as expected, the data turned out to be insufficient for acceptable accuracy predictions. The forecast using the XGBoost method returned closest to the real data result, although it did not repeat the trends. The radial basis function network presented the worst result. Forecast comparison results with real data on a segment of the test sample are shown in Figure 2.

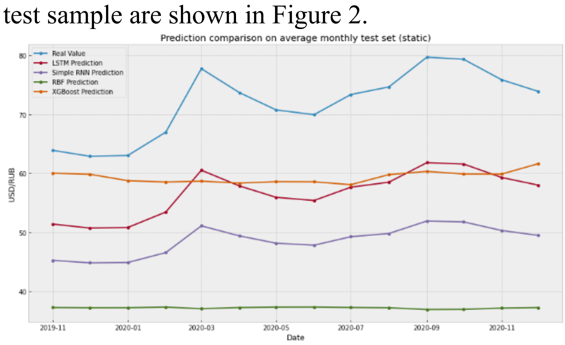

Figure 2: First dataset forecast results comparison

Based on presented forecasting models, it can be concluded that gradient boosting method is highly effective in studies based on priori information small amount. However, it is obvious that such forecasts have no practical sense with such a low accuracy. Figure 3 compares all methods root mean square and mean absolute errors.

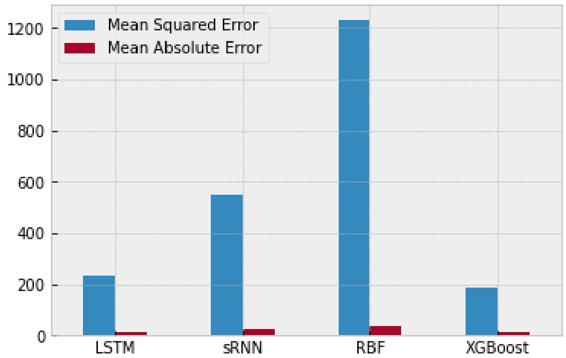

Figure 3: First dataset forecast errors comparison

Same models training on the second dataset with a much higher observations frequency (and, accordingly, a large number of them) provided a qualitatively different result. All three neural network models follow original data trends, in contrast to the gradient boosting method, which shows average value that is weakly correlated with real data over the entire interval. The most accurate prediction was recorded using the LSTM model with mean square and mean absolute errors of 0.254327 and 0.4625752, respectively. Apart from the XGBoost library, the least accurate forecast was obtained using a network of radial basis functions, however, it also came close to real data near peak values in the segment's end, as shown in Figure 4.

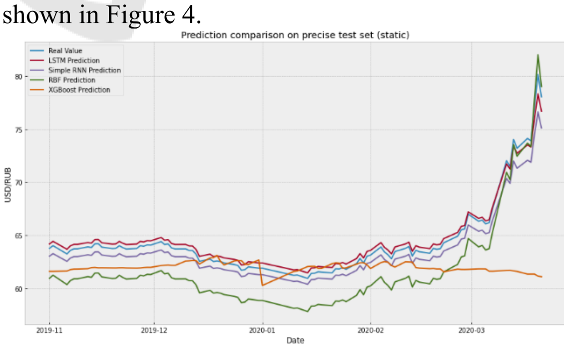

Figure 4: Second dataset forecast results comparison

Obviously, in this case, neural network predictions are much more accurate and more likely to have practical use. It is expected that with large training set representation, neural networks face overfitting problem. However, in accordance with this work's purposes, aiming to show fundamental differences in neural network models efficiency, the comparison was made exclusively between the basic models, without parameters precise manual adjustment. Predicted indicators errors comparison after second dataset training is shown in Figure 5.

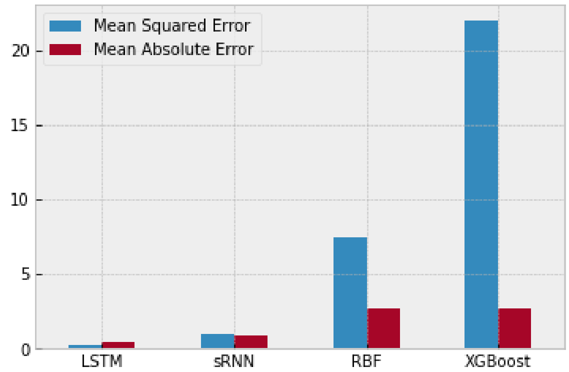

Figure 5: Second dataset forecast errors comparison

4 CONCLUSIONS

Based on the presented analysis, the following assumptions can be made: a dataset with a dimension of 300 observations is clearly not enough to train neural networks in order to predict such volatile time series. Neural networks with LSTM and sRNN models showed the best results in both cases, respectively. The radial basis function network, which performed the worst on the first set, gave a much more accurate result due to training on a larger sample. In both cases, gradient boosting method returned a fairly average result, weakly correlating with real data trends.

Thus, we can conclude that neural network methods usage in economic security indicators forecasting is justified only on a significant sample size. Therefore, machine learning methods in economic security analysis and forecasting problems have not yet become widespread, since typical research mainly involves indicators with a month or more discrete interval. At the same time, machine learning methodology in multi-level objects economic security analysis will be more and more in demand. This is mainly due to the information arrays exponential growth and initial data structuring needs. On one hand, machine learning algorithms provide fast and accurate results, on the other hand, additional resources are required.

Mathematical forecasting methods usage in economic security indicators studies based on the machine learning apparatus in combination with more traditional analysis methods allow to reach adequate comprehensive assessment results. This work results make it possible to identify the most relevant neural network model for economic systems indicators prediction, as well as to compare various forecasting methods effectiveness depending on the initial data dimension. Thus, we advise to keep caution aimed to secure management decisions effectiveness and validity based on machine learning methods evidence-based verification results. Compliance with this requirement will create new perspectives in analysis and forecasting, as well as reduce decision-making associated risks.

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