Technoeconomics. 2025, Vol. 4, No. 1 (12). Pp. 4–12.
Техноэкономика. 2025, Том 4, № 1 (12). С. 4–12.

Scientific article
UDC 330.47
DOI: https://doi.org/10.57809/2025.4.1.12.1

THE POSSIBILITY OF CONSTRUCTING UNIVERSAL NONLINEAR AUTOREGRESSIONS

Kirill Luparev, Sergey Svetunkov ✉

Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russia

✉ sergey@svetunkov.ru

Abstract. Autoregression models are widely used in economic practice both in modelling stochastic processes and in forecasting them. However, all these models generating nonlinear dependencies are essentially linear models. The accuracy of these models can be increased by giving them a nonlinear form. However, at present, there are no universal methods and techniques for forming such models, and the problem of constructing nonlinear autoregressions does not have a satisfactory solution. Researchers add non-linear components to autoregressions, most often using intuition. In our study, we examine the possibility of using the model of the elementary image of the Kolmogorov-Gabor polynomial as a formalized and universal tool for solving such problems. Several examples show that imparting nonlinearity to autoregression models can lead not only to an increase in the accuracy of approximation but also to an increase in the accuracy of short-term forecasting.

Keywords: autoregressions, elementary image of Kolmogorov-Gabor polynomial, modeling of stochastic processes, short-term forecasting, nonlinearity

Citation: Luparev K., Svetunkov S. The possibility of constructing universal nonlinear autoregressions. Technoeconomics. 2025. 4. 1 (12). 4–12. DOI: https://doi.org/10.57809/2025.4.1.12.1

Научная статья
УДК 330.47
DOI: https://doi.org/10.57809/2025.4.1.12.1

ВОЗМОЖНОСТЬ ПОСТРОЕНИЯ УНИВЕРСАЛЬНОЙ НЕЛИНЕЙНОЙ АВТОРЕГРЕССИИ

Кирилл Лупарев, Сергей Светуньков ✉

Санкт-Петербургский политехнический университет Петра Великого,
Санкт-Петербург, Россия

✉ sergey@svetunkov.ru

Аннотация. Модели авторегрессий широко используются в экономической практике как в моделировании стохастических процессов, так и в их прогнозировании. Однако, все эти модели, генерирующие нелинейные зависимости, по своей сути являются линейными моделями. Повышения точности этих моделей можно добиться, придав этим моделям нелинейную форму. Но в настоящее время отсутствуют универсальные методы и методики формирования подобных моделей, и задача построения нелинейных авторегрессий не имеет удовлетворительного решения. Исследователи добавляют нелинейные составляющие в авторегрессии, чаще всего, используя интуицию. В данном исследовании изучается возможность использования в качестве формализованного и универсального инструмента решения таких задач модели элементарного образа полинома Колмогорова-Габора. Показано на нескольких примерах, что придание нелинейности авторегрессионным моделям может привести не только к повышению точности аппроксимации, но и к повышению точности краткосрочного прогнозирования.

Ключевые слова: авторегрессии, элементарный образ полинома Колмогорова-Габора, моделирование стохастических процессов, краткосрочное прогнозирование, нелинейность

Для цитирования: Лупарев К., Светуньков С. Возможность построения универсальной нелинейной авторегрессии // Техноэкономика. 2025. Т. 4, № 1 (12). С. 4–12. DOI: https://doi.org/10.57809/2025.4.1.12.1

Introduction

One of the most in-demand tools for short-term economic forecasting and modelling stochastic processes is the modelling of autoregressive dependencies using the corresponding models.

The essence of autoregressive models stems from the stochastic process they model, where the current values of the variable being modelled are not determined by external forces but by the previous values of the variable itself. Such stochastic processes are quite common in economics, as the economy has a cyclical nature of development.

There are cases where the modelled process has an obvious cyclical component; for example, the volume of goods consumed in retail is determined by the day of the week, and for such series, an autoregression with a lag of 7 observations would be suitable.

Much more frequently in economics, we encounter cases where the modelled process contains several cycles of varying lengths, which ultimately generate complex time series with nonlinear dynamics.

The task of modelling such series is tackled with varying degrees of success using different types of autoregressions, the main ones being simple autoregressions with a lag p AR(p); autoregressions with moving averages of residuals ARIMA(p, d, q), where residuals are included with a lag of q; autoregressions with a seasonal component SARIMA(p, d, q); autoregression and distributed lag model ADL(p, q), where external factors with a lag q are used instead of residuals; and vector autoregressions, where instead of one indicator, a vector of k indicators VARk (p) is used along with their modifications.

In this group, there are theoretically known, but rarely applied in practice, nonlinear autoregressions.

This feature can be explained by the fact that linear autoregressions generate nonlinear processes.

In these nonlinearities, it is impossible to distinguish between factors that affect the process linearly and those that affect it nonlinearly.

Therefore, non-linear autoregressions are not used as often as they could be, and their practical application has been fragmented, as identifying nonlinearity remains a subjective task.

Let's consider the possibility of formally constructing nonlinear autoregressions.

Materials and Methods

All the main types of autoregressions are linear with respect to the variables and parameters of the model. However, these models describe various types of nonlinear dynamics. The first and simplest first-order autoregression model, studied by A.A. Markov, has the following form (Markov, 1900):

$$y_t = ay_{t-1} + \varepsilon_t \tag{1}$$

Here, y_t is the current modeled value of the indicator, y_{t-1} is its previous value, a is the proportionality coefficient, and ε_t is the random component, which is normally distributed with a zero mean.

Depending on the values taken by the constant a, the process can be either divergent or convergent. However, in all cases, nonlinear dynamics are being modeled. Even when this coefficient equals one, due to the influence of the random component, the model represents a nonlinear stochastic process known as "random walk" (Bhattacharya, 2021).

It is evident that the more complex the autoregression model used, the more intricate nonlinear stochastic processes it can describe. This very factor has determined the widespread popularity of autoregression models in solving applied problems across various scientific fields, including the modeling and forecasting of stochastic processes in economics.

Clearly, model (1) can be further refined and represented, for example, in the following nonlinear form:

$$y_t = a(y_{t-1})^b + \varepsilon_t \tag{2}$$

It is clear that model (1) will be a special case of model (2). By assigning different values to the coefficients a and b, different types of dynamics can be generated. Even more complex trajectories are generated by such nonlinear autoregressions of order p:

$$y_t = a_1(y_{t-1})^{b_1} + a_2(y_{t-2})^{b_2} + \ldots + a_p(y_{t-p})^{b_p} + \varepsilon_t \tag{3}$$

However, solving the inverse problem, namely, determining the order of the autoregression (3) from the available data, turns out to be impossible. This problem does not yet have a satisfactory solution even for autoregressions in linear form, and it is even more unsolvable when applied to autoregressions of type (3).

Moreover, nonlinear autoregressions, which can perfectly describe complex nonlinear types of dynamics, do not reduce to power functions like (3). They can involve logarithmic, exponential, or trigonometric functions, as well as their combinations. It is impossible to identify the best ones from the available statistical data.

Therefore, autoregressions of any type are presented in a linear form, and the emergence of nonlinear models in practice is very rare.

This problem can be solved by using the elementary Kolmogorov-Gabor polynomial model. The basic model, which we call the Kolmogorov-Gabor polynomial, was independently developed by V. Volterra (Volterra, 1930) with N. Wiener (Wiener, 1958) and Kolmogorov (Kolmogorov, 1956) with Gabor (Gabor, 1961). It has the following form:

$$y = a_0 + \sum_{i=1}^{m} a_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} a_{ij} x_i x_j + \ldots + \sum_{i=1}^{m}\sum_{j=1}^{m}\ldots\sum_{z=1}^{m} a_{ij\ldots z} x_i x_j \ldots x_z \tag{4}$$

Here, y is the modeled nonlinear discrete process, x_i are the discrete variables influencing the process, a_i are the polynomial coefficients, and *m* is the number of discrete variables considered in the polynomial.

The Kolmogorov-Gabor polynomial (or the Volterra-Wiener series) can theoretically describe very complex nonlinear dependencies accurately. However, this polynomial sharply increases the number of its terms and, consequently, the number of unknown coefficients. Therefore, this model has not found practical application.

At the end of the last century, the Ukrainian scientist A.G. Ivakhnenko proposed a method for stepwise construction of polynomial (4) (Ivakhnenko, 1963; 1971; 1975). However, his method turned out to be cumbersome, resulting in a polynomial with a number of terms exceeding that of polynomial (4) (Svetunkov, 2024). It is evident that the properties of this new polynomial by A.G. Ivakhnenko differ from those of the original polynomial (4), and thus it will not always demonstrate the expected accuracy. Consequently, there are very few examples of successful applications of A.G. Ivakhnenko's method, and mainly such examples are presented in publications by scientists from former Soviet republics, although there are instances of its use by foreign researchers as well (Marateb, 2023).

In 2024, an elementary image of the Kolmogorov-Gabor polynomial (hereinafter referred to as the EI) was proposed, which serves as a simplified model of polynomial (4) (Svetunkov, 2024). In general form, the EI can be represented as follows:

$$\hat{y} = c_0 + \sum_{j=1}^{m} c_j (b_0 + \sum_{i=1}^{m} b_i x_i)^j \tag{5}$$

where c_i and b_i is coefficients.

The essence of the model and the method for estimating its parameters is revealed by another form of recording:

$$\hat{y}' = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_m x_m \tag{6}$$

$$\hat{y} = c_0 + c_1 \hat{y}' + c_2 (\hat{y}')^2 + \ldots + c_m (\hat{y}')^m \tag{7}$$

As can be seen, the first equation (6) represents a simple linear one-factor model, the coefficients b_i of which can be easily estimated from statistical data on the values of *y* and x_i corresponding to the characteristics of the stochastic process using a statistical method, such as the method of least squares (MLS).

The second equation contains only one influencing factor, namely, the calculated values of the linear multifactor model (6). These calculated values are used as a factor in the polynomial of degree m. The values of the coefficients of this polynomial c_i can also be easily determined from the data on *y* and x_i using a chosen statistical method.

If (6) is substituted into (7), and the brackets are expanded and grouped, a polynomial will be obtained that structurally, in form, and in the number of terms completely coincides with the Kolmogorov-Gabor polynomial. However, unlike it, constructing (5) requires estimating a significantly smaller number of unknown coefficients: for instance, with the number of factors m equal to 11, constructing the Kolmogorov-Gabor polynomial requires estimating 705,432 unknown coefficients, whereas for constructing the elementary image, only 24 coefficients need to be estimated—12 unknown coefficients for model (6) and then 12 unknown coefficients for (7).

It is clear that model (5) is simpler than model (4), which means it is less accurate than polynomial (4), of which it is a simplified version. However, as research has shown, the EI has proven to be a surprisingly accurate model for describing various nonlinear economic processes. It effectively describes exponential, power, and trigonometric trajectories, as well as various superpositions of these nonlinear functions, sometimes yielding better results than those of artificial neural network models (Svetunkov, 2024). It can also be used to solve the problem posed in our study. Let us demonstrate how this can be done.

A simple autoregression of order $p = m$ can be represented as a linear multifactor model:

$$\hat{y}'_t = b_0 + b_1 y_{t-1} + b_2 y_{t-2} + ... + b_m y_{t-m} \tag{8}$$

and it can be considered as the first part of EI (6).

Then, substituting the calculated values of the autoregression (8) into (7), we obtain the second nonlinear part of the autoregression:

$$\hat{y}_t = c_0 + c_1 \hat{y}'_t + c_2 (\hat{y}'_t)^2 + ... + c_m (\hat{y}'_t)^m \tag{9}$$

Since the model is universal and describes various nonlinear forms, the question of selecting the type of nonlinear function for the autoregressive model is resolved — the nonlinearity is generated automatically by fitting the coefficients of polynomial (9).

For practical application of the nonlinear autoregression (8) — (9), it is necessary to find an answer to the question of how to choose the order of autoregression for each series. We proposed the following hypothesis to answer this question: the order of the best nonlinear autoregression (8) — (9) corresponds to the order of the best linear autoregression.

To test this hypothesis, an algorithm was developed in Python to compute the coefficients of linear autoregressions of various orders from the first order up to p, where the order p can be any number but should not exceed 1/3 N, with N being the number of observations. Since these autoregressions form the basis for constructing the nonlinear autoregression, an algorithm was also developed to construct the corresponding polynomials (9) for each autoregression (8).

Both linear and nonlinear autoregressions were tested for the accuracy of data approximation, where the measure of accuracy was the values of the approximation error variance. To understand how much worse or better the nonlinear autoregression describes the nonlinear processes of the data compared to the linear autoregression, the relative error of the EI was calculated in comparison with the autoregression.

The calculation algorithm was carried out as follows: first, a first-order autoregression was constructed, and its statistical characteristics (including variance) were calculated for all data. Then the data was reduced by one unit, and the statistical characteristics of the first-order autoregression were recalculated. This process was repeated by reducing the data by one unit each time. The variance values for the autoregression, depending on the number of used values in the series, were recorded. After that, a second-order autoregression was built on all the datasets, and its statistical characteristics were determined. The database was then reduced by one unit, and the calculations were repeated. As a result, a kind of “map” of the series was created, showing, on one hand, how the variance of the approximation error of the autoregressive model changed for fixed data as the order of autoregression increased, and on the other hand, how stable the best model in terms of minimum variance approximation was when the number of used data points decreased.

The recorded values of the coefficients from the linear autoregressions served as the basis (8) for constructing nonlinear autoregressions (9) using the EI. Nonlinear autoregressions were also computed based on the lag of the autoregression and the number of observations, similar to how it was done for linear autoregressions. “Maps” of the series were created for them as well.

To visualize the obtained results, “heat maps” of the error variances and relative errors were constructed based on numerical values, allowing for a visual comparison of the areas of best and worst performance of the models at various lags and degrees.

Results and Discussion

A comparative analysis of linear and nonlinear autoregressive models was conducted using the M3C database from the International Institute of Forecasters (Makridakis, 2000). Monthly series numbered 2830, 2834, 2835, 2836, 2837, 2838, 2839, 2840, 2841, and 2842 were selected for this analysis.

The results showed that the optimal order of autoregression, which has the minimum approximation error variance, remains consistent as the sample size decreases. This indicates that the modeled process exhibits the characteristics of autoregression of this specific order. For example, for series number 2830, the optimal autoregression is of order p=29.

As indicated by the results of the statistical characteristics of the nonlinear autoregressions, the order of the optimal nonlinear autoregression generally coincides with that of the linear autoregression. This means that a researcher, having determined the order of the best linear autoregression and estimated its coefficients based on statistical data, can use (9) to compute its nonlinear form and can reasonably expect that this nonlinear autoregression will be the best in its class for the given series.

As expected, nonlinear autoregressions consistently provided better approximations of the data series than linear autoregressive models. For instance, for series number 2830, the optimal linear autoregression has a variance of about 6700, while the error variance of the nonlinear autoregressive model is equal to 5200.

It is well known that the best model for approximation is not necessarily the best for forecasting (Fildes, 1985; Makridakis, 1982). Although autoregressive models are tools for modeling stochastic processes (Chen, 2023; Kulkarni, 2009), they are primarily used for forecasting tasks (Athanasopoulos, 2023; Hyndman, 2008; Kwiatkowski, 1992). Therefore, it is essential to assess the feasibility of using nonlinear autoregressions for short-term forecasting tasks. This assessment was conducted on the same M3C database but for different data series. The existing series was divided into a training set and a testing set. Statistical characteristics of the autoregressions were evaluated on the training set, while the forecast error variance was computed on the testing set. For data series number 1402, the optimal model on the training set turned out to be a third-order autoregression. It predicted data on the testing set with a forecast error variance of 810.01. The nonlinear autoregression on the testing set yielded a forecast error variance of 711.39. For another data series number 1429, the optimal linear autoregression is of fourth order, providing a forecast error variance of 497.44. The nonlinear autoregression of the same order has a forecast error variance of 437.29.

Conclusion

We demonstrated that the elementary image of the Kolmogorov-Gabor polynomial, which has proven effective in modeling complex nonlinear economic dependencies, can be applied as a formal model of nonlinear autoregression. Our research indicated that the process of constructing this autoregression should begin with the search for the best linear autoregression, as the order of the optimal linear autoregression generally coincides with that of the optimal nonlinear autoregression.

In randomly selected data series, it was shown that nonlinear autoregressions provide more accurate forecasts in short-term forecasting of stochastic processes compared to linear autoregressions.

We examined the simplest of the autoregressive models, namely the AR (p) model, and demonstrated how to form a nonlinear autoregression based on it using the Kolmogorov-Gabor polynomial. It seems that our approach can also be extended to more complex autoregressive models, such as the ARIMA (p, d, q) model:

$$\hat{y}_t = \sum_{i=1}^{p} a_i y_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j} \tag{10}$$

we should first calculate the estimated values y'_{1t} and y'_{2t}:

$$y'_{1t} = \sum_{i=1}^{p} a_i y_{t-i}, \quad y'_{2t} = \sum_{j=1}^{q} b_j \varepsilon_{t-j} \tag{11}$$

Then form a nonlinear ARIMA(p,d,q):

$$\hat{y}_t = \sum_{i=1}^{p} c_i (y'_{t-i})^i + \sum_{j=1}^{q} d_j (y''_{t-j})^j \tag{12}$$

But these are tasks for future scientific research. Similarly, other types of autoregressive models can also be transformed into nonlinear forms.

Nonlinear models constructed using the elementary image of the Kolmogorov-Gabor polynomial will always provide better approximations of stochastic processes than the original autoregressions. This can be explained by the way they are constructed: if the linear autoregression perfectly describes the modeled process, then fitting it into the nonlinear form (9) using the least squares method will result in all coefficients (9) being equal to zero, except for the coefficient c_i. In this case, a linear autoregression will be used.

REFERENCES

Athanasopoulos G., Kourentzes N. 2023. On the evaluation of hierarchical forecasts. International Journal of Forecasting 39, 1502-1511. doi:10.1016/j.ijforecast.2022.08.003

Bhattacharya R. 2021. Random Walk, Brownian Motion, and Martin-gales, 396.

Chen N. 2023. Stochastic Methods for Modeling and Predicting Complex Dynamical Systems: Uncertainty Quantification, State Estimation, and Reduced-Order Models, 199.

Fildes R. 1985. Quantitative Forecasting—the State of the Art: Econometric Models. Journal of Oper. Res. Soc. 36, 549-580. doi:10.1057/jors.1985.99

Gabor D., Wilby W.R., Woodcock R.A. 1961. A universal nonlinear filter, predictor and simulator which optimizes itself by a learning process. Proc. Inst. Electr. Engrs. 108 (40), 85-98. doi:10.1049/pi-b-2.1961.0070

Hyndman R.J., Khandakar Y. 2008. Automatic Time Series Forecasting: The forecast Package for R. Journal of Statistical Software 27, 1-22. doi:10.18637/jss.v027.i03

Ivakhnenko A.G. 1963. Self-learning systems with positive feedback.

Ivakhnenko A.G. 1971. Systems of heuristic self-organization in technical cybernetics. Technology, 372. doi:10.1016/0005-1098(70)90092-0

Ivakhnenko A.G. 1975. Long-term forecasting and control of complex systems. Technology, 312.

Kolmogorov A.N. 1956. On the representation of continuous functions of several variables by superpositions of continuous functions of a smaller number of variables. Reports of the USSR Academy of Sciences 108 (2), 179-182.

Kulkarni V.G. 2023. Modeling and Analysis of Stochastic Systems, 544.

Kwiatkowski D., Phillips P.C.B., Schmidt P., Shin Y. 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? Journal of Econ-ometrics 54, 159-178. doi:10.1016/0304-4076(92)90104-Y

Makridakis S., Andersen A., Carbone R., Fildes R., Hibon M., Lewandowski R., Newton J., Parzen E., Winkler R. 1982. The accuracy of extrapolation (time series) methods: Results of a

forecasting competition. Journal of Forecasting. 1, 111–153. doi:10.1002/for.3980010202
Makridakis S., Hibon M. 2000. The M3–Competition: results, conclusions and implications. International journal of forecasting 16, 451-476. doi:10.1016/S0169-2070(00)00057-1
Marateb H., Norouzirad N., Tavakolian K., Aminorroaya F., Mohebbian M., Macanas M. A., Lafuente S.R., Sami R., Mansourian M. 2023. Predicting COVID-19 Hospital Stays with Kolmogorov–Gabor Polynomials: Charting the Future of Care. Information, 14 (11), 590. doi:10.3390/info14110590
Markov A.A. 1900. Probability calculus, 279.
Svetunkov S.G. 2024. Elementary image of the Kolmogorov-Gabor polynomial in economic modeling. Technoeconomics 2 (9), 4-21. doi:https://doi.org/10.57809/2024.3.2.9.1
Svetunkov S.G. 2024. Polynomial networks instead of neural networks. Technoeconomics 3 (10), 57–71. doi:10.57809/2024.3.3.10.6
Volterra V. 1930. Theory of Functionals and of Integral and Integro-differential Equations, 226.
Wiener N. 1958. Nonlinear problems in random theory, 138.

СПИСОК ИСТОЧНИКОВ

Athanasopoulos G., Kourentzes N. 2023. On the evaluation of hierarchical forecasts. International Journal of Forecasting 39, 1502-1511. doi:10.1016/j.ijforecast.2022.08.003
Bhattacharya R. 2021. Random Walk, Brownian Motion, and Martin-gales, 396.
Chen N. 2023. Stochastic Methods for Modeling and Predicting Complex Dynamical Systems: Uncertainty Quantification, State Estimation, and Reduced-Order Models, 199.
Fildes R. 1985. Quantitative Forecasting—the State of the Art: Econometric Models. Journal of Oper. Res. Soc. 36, 549-580. doi:10.1057/jors.1985.99
Gabor D., Wilby W.R., Woodcock R.A. 1961. A universal nonlinear filter, predictor and simulator which optimizes itself by a learning process. Proc. Inst. Electr. Engrs. 108 (40), 85-98. doi:10.1049/pi-b-2.1961.0070
Hyndman R.J., Khandakar Y. 2008. Automatic Time Series Forecasting: The forecast Package for R. Journal of Statistical Software 27, 1-22. doi:10.18637/jss.v027.i03
Ivakhnenko A.G. 1963. Self-learning systems with positive feedback.
Ivakhnenko A.G. 1971. Systems of heuristic self-organization in technical cybernetics. Technology, 372. doi:10.1016/0005-1098(70)90092-0
Ivakhnenko A.G. 1975. Long-term forecasting and control of complex systems. Technology, 312.
Kolmogorov A.N. 1956. On the representation of continuous functions of several variables by superpositions of continuous functions of a smaller number of variables. Reports of the USSR Academy of Sciences 108 (2), 179-182.
Kulkarni V.G. 2023. Modeling and Analysis of Stochastic Systems, 544.
Kwiatkowski D., Phillips P.C.B., Schmidt P., Shin Y. 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? Journal of Econ-ometrics 54, 159-178. doi:10.1016/0304-4076(92)90104-Y
Makridakis S., Andersen A., Carbone R., Fildes R., Hibon M., Lewandowski R., Newton J., Parzen E., Winkler R. 1982. The accuracy of extrapolation (time series) methods: Results of a forecasting competition. Journal of Forecasting. 1, 111–153. doi:10.1002/for.3980010202
Makridakis S., Hibon M. 2000. The M3–Competition: results, conclusions and implications. International journal of forecasting 16, 451-476. doi:10.1016/S0169-2070(00)00057-1
Marateb H., Norouzirad N., Tavakolian K., Aminorroaya F., Mohebbian M., Macanas M. A., Lafuente S.R., Sami R., Mansourian M. 2023. Predicting COVID-19 Hospital Stays with Kolmogorov–Gabor Polynomials: Charting the Future of Care. Information, 14 (11), 590. doi:10.3390/info14110590
Markov A.A. 1900. Probability calculus, 279.
Svetunkov S.G. 2024. Elementary image of the Kolmogorov-Gabor polynomial in economic modeling. Technoeconomics 2 (9), 4-21. doi:https://doi.org/10.57809/2024.3.2.9.1
Svetunkov S.G. 2024. Polynomial networks instead of neural networks. Technoeconomics 3 (10), 57–71. doi:10.57809/2024.3.3.10.6

Volterra V. 1930. Theory of Functionals and of Integral and Integro-differential Equations, 226.

Wiener N. 1958. Nonlinear problems in random theory, 138.

INFORMATION ABOUT AUTHORS / ИНФОРМАЦИЯ ОБ АВТОРАХ

LUPAREV Kirill A. – student.
E-mail: luparev_ka@spbstu.ru
ЛУПАРЕВ Кирилл Алексеевич – студент.
E-mail: luparev_ka@spbstu.ru

SVETUNKOV Sergey G. – Professor, Doctor of Economic Sciences
E-mail: sergey@svetunkov.ru
СВЕТУНЬКОВ Сергей Геннадьевич – профессор, д.э.н.
E-mail: sergey@svetunkov.ru
ORCID: https://orcid.org/0000-0001-6251-7644

Статья поступила в редакцию 05.03.2025; одобрена после рецензирования 06.03.2025; принята к публикации 11.03.2025.

The article was submitted 05.03.2025; approved after reviewing 06.03.2025; accepted for publication 11.03.2025.