JOURNAL OF SECURITY AND SUSTAINABILITY ISSUES
ISSN 2029-7017 print/ISSN 2029-7025 online
2019 December Volume 9 Number 2
http://doi.org/10.9770/jssi.2019.9.2(15)

TRANSPARENT COGNITIVE TECHNOLOGIES TO ENSURE SUSTAINABLE SOCIETY DEVELOPMENT

Aleksy Kwilinski[1]*, Volodymyr Tkachenko[2], Aleksandra Kuzior[3]

*[1]*The London Academy of Science and Business, 3rd Floor, 120, Baker Street, London, W1U 6TU, England*
[2]The London Academy of Science and Business, 3rd Floor, 120, Baker Street, London, W1U 6TU, England
[2]Kyiv National University of Construction and Architecture, 31, Povitroflotsky Avenue, 03680, Kyiv, Ukraine
[3]Silesian University of Technology, 26 Roosevelta Street, Zabrze, 41-800, Poland

E-mail: [1]koaduep@gmail.com (corresponding author)*

Received 11 January 2019; accepted 25 September 2019; published 15 December 2019

Abstract. The article formalizes theoretical and methodological foundations of the use of parametric artificial intelligence technologies to ensure the security of sustainable society development. An algorithm for using an artificial neuron to describe a model of social development is proposed. Optimization of the processes of using neural networks in creating an expert system for forecasting safe social development is conducted.

Keywords: operation security; social development; artificial intelligence; artificial neuron model; macroeconomic indicators; system adaptability; "window method"

Reference to this paper should be made as follows: Kwilinski, A., Tkachenko, V., Kuzior, A. 2019. Transparent cognitive technologies to ensure sustainable society development. *Journal of Security and Sustainability Issues* 9(2): 561–570.
http://doi.org/10.9770/jssi.2019.9.2(15)

JEL Classifications: C10; M14

1. Introduction

Modern real systems (technical, economic, social, environmental, etc.) in the system of global world order are imperfect due to the complexity of internal relationships and the influence of a large number of parametric factors, which cannot be always predicted and taken into account. At the same time, systems of society development can change a mode (in a planned way or randomly), structure of elements, which identifies new states of a system and its security, which qualitatively differ from previous ones, defining unstable and unsteady development of all social processes. The above problems do not allow to describe in detail the processes using traditional approaches, in particular, causation in the form of comparative systems and theoretical models.

Today a new scientific trend is actively developing based on the representation of multidimensional social and public processes in the form of cognitive models and connections. Their use allows to describe the dynamics of complex social systems and to predict their future behavior and safe development.

2. Literature Survey

The methodological basis of our study is determined by the interpretation of forecasting methods, and features and patterns of the studied processes. We emphasize the following methods we need: 1) Formalized thinking.

The essence of the method is that the determining value of the ratio of the horizon of forecasting (warning period) Δt and the evolutionary period (retrospective period) of the development of a social process t_x is determined by the formula (Beatty, 1995):

$$\tau = \frac{\Delta t}{t_x} \tag{1}$$

If *(τ<<1)* (the horizon of forecasting fits within the evolutionary cycle) then it is recommended to use formalized methods. With (*t~1*) the possibility of dramatic changes in development, intuitive methods are significant and more effective.

1) According to the scientific works (Belkin and Niyogi, 2002; Krippendorff, 2004; Dalevska, N., Khobta, V., Kwilinski, A., & Kravchenko, S., 2019), formalized methods can be used before and after turning events. If several evolutionary periods fit within a social study period (τ>>*1*) then intuitive methods are used to develop forecasts (Kwilinski, A., 2019a,b).

2) Intuitive methods (Fernández-Rodríguez, et. al. 2000; Krizhevsky, A., Sutskever, Hinton, 2012; Watts, 1999). Intuitive methods are used when the object of forecasting is either too simple or so complex and unpredictable that it is almost impossible to analytically take into account the influence of many factors. Individual and collective peer reviews obtained in such cases are used as final forecasts or as initial data in integrated systems for forecasting safe social development. The content of intuitive forecasting methods consists in the intuitive choice of the most important and decisive ones from the numerous circumstances (Bilan, Y., Lyeonov, S., Luylyov, O., Pimonenko T., 2019).

3) The methods based on nonlinear models are thoroughly presented in the works (Jang, et. al. 1996; Jin, et. al. 2017; Poteete, et. al. 2010), remove the limitations inherent in statistical methods and satisfy the above requirements. Most of these methods belong to the category of artificial intelligence technologies. These are artificial neural networks and the latest means of optimization in determining the development and security of social processes.

3. Methods

The studies of the properties of macroeconomic systems (Goodfellow and Courville, 2016; Bikas, Saponaitė, 2018; Ostrom, 2009; Tkachenko, V., Kwilinski, A., Klymchuk, M., & Tkachenko, I., 2019; Baltgailis, 2019; Selivanova-Fyodorova et al., 2019; Sriyana, 2019; Kuzmin et al., 2019; Kaluge, 2019; Vinogradova et al, 2019) under study indicate that it is possible to identify models of behavior of local, recurring social systems and to use them to forecast preserving or reversing a trend. For the macroeconomic systems under study, it makes sense to develop forecasting models that are able to "remember" past social situations and consequences (that is, their continuation) that are relevant to them, in order to further compare them with the situations that happen in the evolutionary development of society.

4. Results

A possible solution to the set task may be a database into which you can record social situations and manifestations encoded in a certain way. In order to make a forecast, one would have to review all the records, which must be very numerous in order to have a forecast of safe development with required accuracy. This idea is not constructive because of the complexity of data access and information matching criteria, and more. The ability to "remember" is inherent in technologies that are combined under the name Computational Intelligence (Laurier, et. al. 2016; Vasylieva, T., Lyeonov, S., Lyulyov, O., & Kyrychenko, K., 2018) allowing to obtain continuous or discrete solutions as a result of modeling based on available data.

One of the subclasses of the discussed group of methods is neural networks (NN) using stochastic algorithms to forecast and manage the secure development of social processes through self-organization (Coppin, 2004; Lakhno, V., Malyukov, V., Bochulia, T., Hipters, Z., Kwilinski, A., & Tomashevska, O., 2018). These methods do not imply any restrictions on the nature of the input public information. These can be indicators of this interim series as well as information about the behavior of other public objects.

The processed information on social process data is numerical in nature allowing the use of NN, for example, as a model of systems with completely unknown characteristics. NN is a set of neurons connected in a certain way. A neuron is an elementary conversion component with a non-empty multitude of inputs that receive signals x_1, x_2,...,x_n (Fig. 1), a summation block, a block of signal conversion using an activation function and a single output – *Y*.

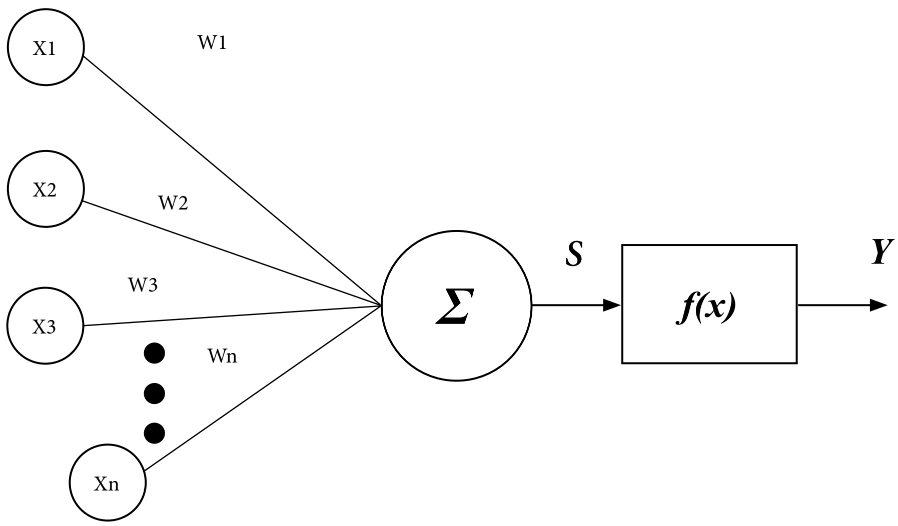

Figure 1. An artificial neuron to describe a model of social development

Each input has its own “weight” w_i corresponding to the “strength” of the synaptic connection. The neuron works in two cycles. In the first cycle in the summation block the amount of excitation obtained by the neuron is calculated:

$$S = \sum_{i=1}^{n} x_i \times w_i = (X, W) \tag{2}$$

which can be conveniently represented as a scalar vector of inputs to a vector of weights. In the second cycle the total excitation is passed through the activation (conversion) function *F,* which determines the output signal *Y=f(S).*

The multilayer network can form an arbitrary multidimensional function at the output at the appropriate choice of the number of layers, the range of signal changes and the parameters of neurons. The neural network implements the following conversion of the initial function:

$$y = f(x) = F\left\{\sum_{iN} w_{i_N j_N N} ... \sum_{i2} w_{i_2 j_2 2} F\left\{\sum_{i1} w_{i_1 j_1 1} \times x_{i_l j_l 1} - \theta_{j_1 1}\right\} - \theta_{j_2 2} ... \theta_{j_N N}\right\} \tag{3}$$

where:

i – input number;
j – neuron number in a layer;
l – layer number;

N – number of layers;
x_{ijl} – input signal i of neuron j in layer l;
w_{ijl} – weight factor of input signal i of neuron j in layer l;
θ_{jl} – threshold of neuron j in layer l.

Through the alternate calculation of linear combinations and nonlinear conversions, the approximation of an arbitrary multidimensional function is achieved with the appropriate choice of network parameters.

At the same time, adaptability refers to the process of changing the parameters and structure of the formed model at the initial uncertainty in working conditions, which has a volatile nature based on current input management information in order to achieve a certain condition characterized by a given threshold of accuracy. Mechanism of adaptation of models formed with the help of artificial intelligence system (artificial intelligence system – AIS). At the same time, as a rule, the topology of the network is considered to be unchanged, and tunable parameters are usually related to the parameters of neurons and the magnitude of synaptic weights.

Currently, there are many variations of neural networks capable of performing various operations with initial information. The most appropriate paradigm for forecasting the dynamic state of non-stationary macroeconomic systems is AIS with the following features (Gevrey, et. al. 2003):

a) by the method of learning – models with social direction or development vectors, to identify internal potential based on analysis of the history of society.

b) by the nature of propagation in information networks – recurrent networks based on the algorithm of propagation of error signals from the outputs of the neural network to its inputs, in the direction opposite to the direct propagation of signals in the normal mode of operation.

The above paradigm allows to use neural networks as a "black box", which is "presented" the task input data and the response that corresponds to these data, previously discovered, when forming the parameters of social model development. AIS itself, in the process of safe development, must build within the "black box" the process under study (identify the dynamics) in order to produce the response that matches the correct one (Selsam, et. al. 2019). The more different pairs of the "initial data" on secure social development – the "response" will be given to NN, it will create the more adequate logical target decision-making function within the model of social development.

The significance of such a neural network concept regarding the task of forecasting the security of development is determined by the general principles of operation of multilayer perceptrons and includes three stages: 1) collection and preliminary processing of input data; 2) perceptron learning; 3) recognition (forecast) of the model of safe development of society (Hamill, 2017; Pająk, K., Kvilinskyi, O.; Fasiecka, O., & Miśkiewicz, R., 2017).

The pattern of the solution of the task of forecasting macroeconomic and social processes based on security principles can be presented in the form of a sequence of stages (Fig. 2).

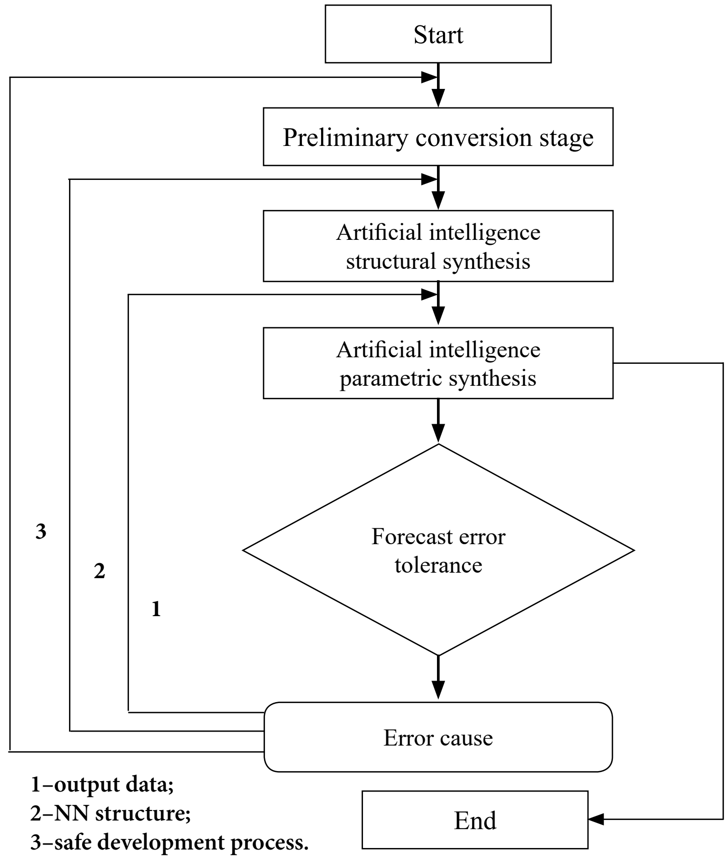

Figure 2. An algorithmic scheme for solving the task of forecasting the safe development of society using the AIS apparatus

At the initial stage, NN restores the target function using multiple sets of macroeconomic samples, that is, solves the task of interpolation of safe development. At the stage of using the formed NN model (forecasting), the network will use the restored dependency for forecasting, i.e. solve the task of extrapolation.

The ability to abstract at the stage of preliminary conversion allows AIS to ignore the secondary properties of the data set under study and to identify the main ones within the model of safe society development. However, these properties, given the set task of forecasting, can be a disadvantage, because sometimes a small property of the studied non-stationary processes in the rapidly changing economic situations can have a significant impact on social development and security characteristics in the future (Metelenko, et. al. 2019). In addition, the parameter setting process (parametric synthesis stage) of the neural network model is non-deterministic by nature, does not always sum up, requires the use of a large number of different heuristic tricks, depends significantly on the complexity of the initial data, the selected network architecture (NN structural synthesis stage) and computational resources.

The stages of preliminary conversion and parametric synthesis of NN determine the main points, keeping track of which allow you to create expert systems of forecasting with the help of the apparatus of artificial neural networks.

The stage of preliminary conversions is necessary for the neural network to solve the problem of extrapolation of initial values by solving the problem of interpolation of converted values of factors. It should be noted that the important stage of neural network computing is the stage of preliminary data conversion. The speed of modern learning algorithms, the ability of the neural network to remember (selection of characteristic patterns in instructive data) and the generalization (adequate processing of unused input signals for development security) depend exactly on what form the data is presented in, how their preliminary selection is performed. In addition, preliminary conversion allows ensuring the invariance of feature sets, as determined by the fact that the signals distributed over the neural network must be limited by the space determined by the asymptotic interval of the activation functions of the network neurons in the current model of social development.

The values of the signals of the first NN output layer may be in the interval [- 2, 2]. The conversions performed in the second layer in the space of activation functions in the interval [- 1, 1] "cut off" the informative part of the signal values above or below this interval. At the same time, the values that did not fall within this interval are approximated by the neural network with the values of the asymptotic activation functions (Kashima, et. al. 2003).

The above problems generally impose determinative constraints on the input and output samples of the input values given for the NN operation and as a whole determine the ability of the NN to make general conclusions – the NN can forecast the behavior of a particular social model only in the space of the activation function. At the same time, the multitude must contain the behavior of the indicator throughout the space. Only taking into account these constraints the NN is able to make general conclusions and consequently make forecasts. Thus, at the stage of preliminary conversions it is necessary to ensure invariance of the feature set so that they are located in the space of the activation function (Scarselli, et. al. 2009).

Let us consider a simple way of forming invariant images. The basic concept here is "window" ("immersion depth"), that is, the number of time periods (or other parameter by which extrapolation is conducted) into which vectors fall that are formed at the input and output of the network, for which *n* input neurons and *m* output neurons are alloted accordingly.

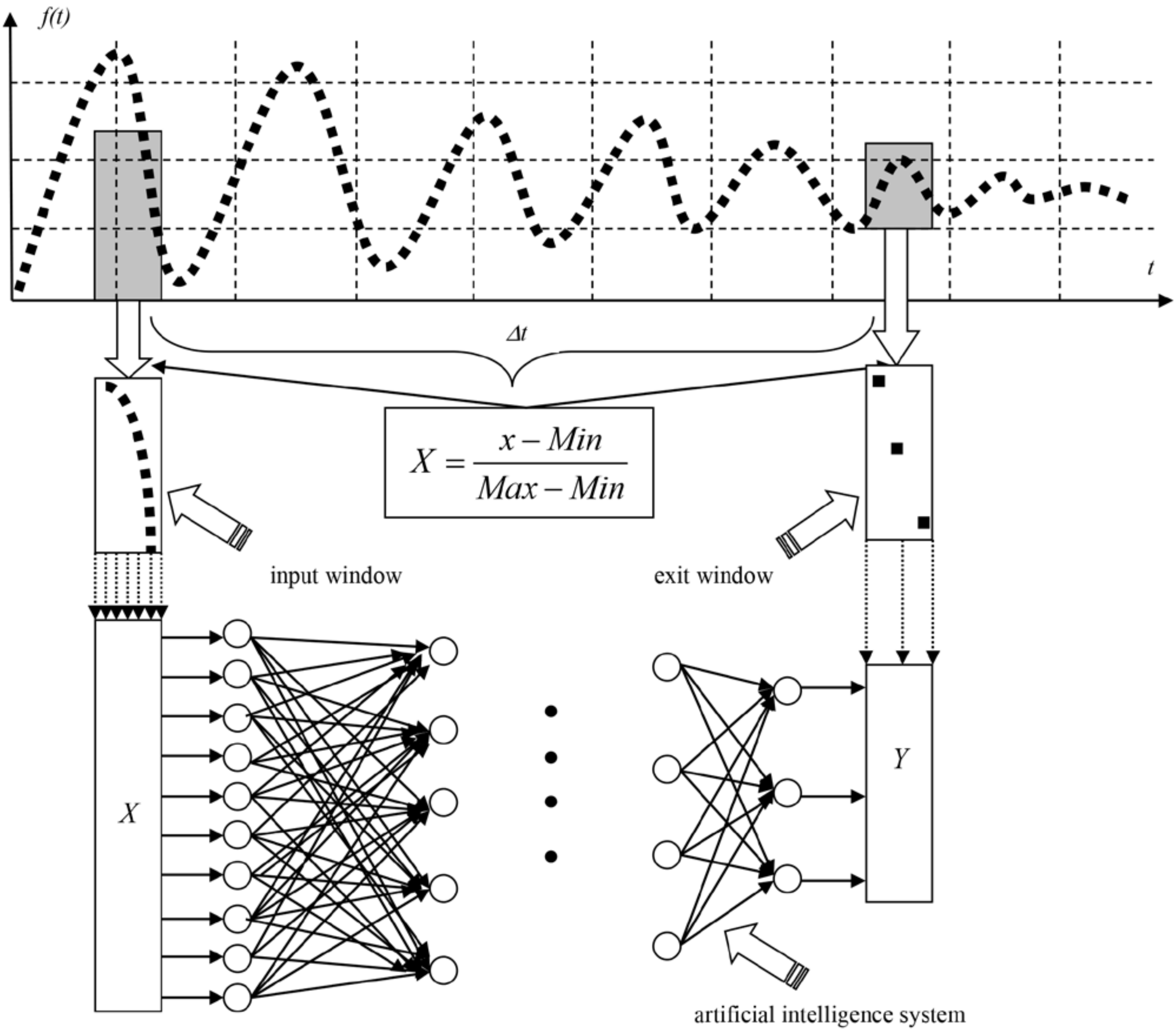

Figure 3. The method of normalizing input and output images of the initial sample to ensure development security based on the parameter of elementary ≪windows≫

The data of each of these vectors is limited by a range [*Min...Max*]. The simplest way to form the "window" in the space of the activation function of an artificial neuron would be to transform by the formula:

$$\widehat{X} = \frac{x - Min}{Max - Min} \tag{4}$$

where:

x – initial vector;

$\widehat{X}$ – scaled vector;

Max and Min – respectively maximum and minimum values of the "window".

After such transformation, each vector consisting of *n(m)* consecutive values is normalized so that all its values lie in the range from 0 to 1. In this case, the values of the input and output images fit into the hypercubes of dimension $[0,1]^n$ and $[0,1]^m$ (Fig. 3).

While the above transformation by the formula (4) guarantees the invariance of the initial vectors of instructive samples, it is not optimal. The activation function that determines the specified values in the end must also be symmetrical. Thus, the initial magnitude of the features must be translated into space {–1,1} (Zhang and Chen, 2018). Scaling is as follows:

$$\widehat{X} = (x - m) \times c \tag{5}$$

the appropriate choice of the scale factor *c* allows you to perform the specified transformation; *m* – the average value of the set of input data.

However, when using the following formula 6 it is necessary to select the value of the scale factor, which is not convenient in most cases. The research used the empirical formula 5, which scales a vector from *[MinR, MaxR]* to *[MinC, MaxC]:*

$$\widehat{X} = MinR + \frac{(x - MinC)}{(MaxC - MinC)} \times (MaxR - MinR) \tag{6}$$

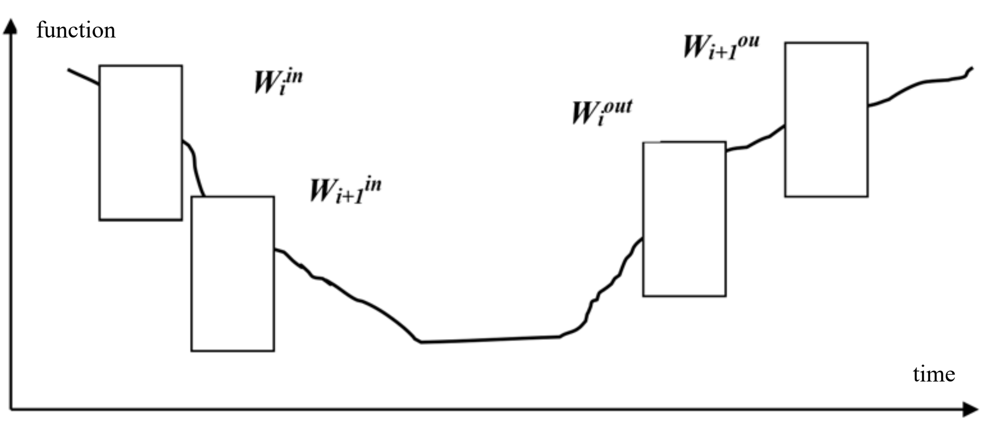

Figure 4. The process of secure social development through the "window method"

The transformation by the formula (6) eliminates the above disadvantages of the formulae (4) and (5) and can be recommended when calculating the parameters of safe development. It should be noted during scaling the interval of the sample image should not coincide with the asymptotic interval of the activation functions. It is necessary to select a slightly smaller value of the window interval (in practice limited by 5% barrier) – this action allows to improve the quality of NN use, since the activation function in this case will not try to approximate the values lying on the asymptote of the activation functions (Kipf and Welling, 2016).

Thus, forecasting based on elementary "windows" involves the use of two windows W^{in} i W^{out} (Fig. 4) with fixed sizes *n* and *m* respectively.

These windows, which are able to move in certain increment by a sequence of features, starting with the first element of the sample under study, and are intended to access time series data, with the first W^{in} window that receives such data transmitting them to the input of the neural network and the second W^{out} window to its output. Thus, at each step, W^{in}/W^{out} pairs form a set of secure system development sample.

Assuming the presence of latent dependencies in the sample sequence as a multiple of observations, then by instructing NN based on these observations you can obtain the necessary dependence, which can be used to build a forecasting model of artificial intelligence for the security of society development.

5. Discussion

Recommendations for further research are determined by the very structure of the cognitive network based on the procedure of back propagation of the network error, the pattern of signal distribution is identified, the error criteria are proposed increasing the quality of the network performance. It is promising to work in the area of evaluating the impact of modification of the basic back propagation algorithm on the speed and quality of development security of social systems and formations, in particular in the direction of introducing the accumulation of cumulative gradient by the sample of indicators and minimizing the cumulative quality criterion for all errors of individual development images, which will allow to increase the speed of convergence by 4-5 times compared to the basic algorithm and accelerate the methods neural network optimization and learning.

Conclusions

Thus, the use of artificial neural network apparatus allows to create functional models for forecasting the safe development of society, which are not set in advance but generated by the data itself – the sets used by the network to learn, but at the same time, there is a number of disadvantages not allowing to fully use NN in forecasting non-stationary macroeconomic and social processes, which are determined by a significant distortion of the results at the stages of model setting.

The developed recommendations touch upon the main stages of determining the quality of the created models to forecast the security of development based on the apparatus of AIS. The creation by means of "window" transformation operations and discrete differentiation of invariant images determines the possibility of extrapolation (forecasting) for the investigated non-stationary samples. The use of anti-gradient network setting methods based on nonlinear optimization algorithms allows you to successfully approximate the target function of NN in the points of local minima of the error function, which increases the quality of the model formed by the network.

References

Baltgailis, J. (2019). The issues of increasing the effectiveness of teaching comparative economics. Insights into Regional Development, 1(3), 190-199. https://doi.org/10.9770/ird.2019.1.3(1)

Beatty, Ian D. (1995). Neural Network Dynamics, Complexity, and Cognition, Physics Education Research Group, University of Massachutes. URL: http://umperg.physics.umass.edu/perspective/

Belkin, M. and Niyogi, P. (2002). Laplacian eigenmaps and spectral techniques for embedding and clustering. In Advances in Neural Information Processing Systems: 585-591.

Bikas, E., Saponaitė, V. (2018). Behavior of the Lithuanian investors at the period of economic growth. Entrepreneurship and Sustainability Issues, 6(1), 44-59. http://doi.org/10.9770/jesi.2018.6.1(4)

Bilan, Y., Lyeonov, S., Luylyov, O., Pimonenko T. (2019). Brand management and macroeconomic stability of the country. Polish Journal of Management Studies, 19(2), 61-74. https://doi.org/10.17512/pjms.2019.19.2.05

Coppin, Ben. (2004). Artificial Intelligence Illuminated. Mississauga, Canada: Jones and Bartlett Publishers, Inc.

Dalevska, N., Khobta, V., Kwilinski, A., & Kravchenko, S. (2019). A model for estimating social and economic indicators of sustainable development. Entrepreneurship and Sustainability Issues, 6(4), 1839-1860. https://doi.org/10.9770/jesi.2019.6.4(21)

Dalevska, N., Khobta, V., Kwilinski, A., Kravchenko, S. (2019). A model for estimating social and economic indicators of sustainable development. Entrepreneurship and Sustainability Issues, 6(4), 1839-1860. http://doi.org/10.9770/jesi.2019.6.4(21)

Fernández-Rodríguez, F., C. González-Martel, and S. Sosvilla-Rivero. (2000). On the profitability of technical trading rules based on artificial neural networks: evidence from the Madrid stock market. Economics Letters 69: 89-94. http://dx.doi.org/10.1016/S0165-1765(00)00270-6

Gevrey, M., I. Dimopoulos, and S. Lek (2003). Review and comparison of methods to study the contribution of variables in artificial neural network models. Ecological Modelling 160(3), 249-264. http://dx.doi.org/10.1016/S0304-3800(02)00257-0

Goodfellow, Bengio and Courville. (2016). Deep Learning. Massachusetts, USA: Massachusetts Institute of Technology.

Hamill, Jasper (2017). Artificial muscle could make robots 15 times stronger than humans. New York Post. Last modified September 19, 2017. URL: https://nypost.com/2017/09/19/artificial-muscle-could-make-robots-15-times-stronger-than-humans/

Jang, J.S., Sun, C.T., Mitzuni, E. (1996). Neuro-Fuzzy and Soft Computing, Prentice-Hall.

Jin, K. H., McCann, M. T., Froustey, E., Unser, M. (2017). Deep convolutional neural network for inverse problems in imaging. IEEE Transactions on Image Processing, 26, 4509–4522

Kaluge, D. (2019). Multifactor on macroeconomic fundamentals to explain the behavior of sectoral indices in the Indonesian stock exchange. Entrepreneurship and Sustainability Issues, 7(1), 44-51. http://doi.org/10.9770/jesi.2019.7.1(4)

Kashima, H., Tsuda, K., and Inokuchi, A. (2003). Marginalized kernels between labeled graphs. In International Conference on Machine Learning, 321-328.

Kipf, T. N. and Welling, M. (2016). Variational graph auto-encoders. arXiv preprint arXiv:1611.07308.

Krippendorff, K. (2004). Content Analysis: An Introduction to its Methodology. SAGE, Thousand Oaks / London / New Delhi

Krizhevsky, A., Sutskever, I., Hinton (2012). in Advances in neural information processing systems (2012): 1097-1105.

Kuzmin, E.A., Vinogradova, M.V., Guseva, V.E. (2019). Projection of enterprise survival rate in dynamics of regional economic sustainability: case study of Russia and the EU Entrepreneurship and Sustainability Issues, 6(4), 1602-1617. https://doi.org/10.9770/jesi.2019.6.4(4)

Kwilinski, A., Dalevska, N., Kravchenko, S., Hroznyi, I., Kovalenko, I. (2019b). Formation of the entrepreneurship model of e-business in the context of the introduction of information and communication technologies. Journal of Entrepreneurship Education, 22(1S), 1528-2651-22-S1-337: 1-7. Retrieved from https://www.abacademies.org/articles/Formation-of-the-entrepreneurship-model-of-e-business-1528-2651-22-S1-337.pdf

Lakhno, V., Malyukov, V., Bochulia, T., Hipters, Z., Kwilinski, A., & Tomashevska, O. (2018). Model of managing of the procedure of mutual financial investing in information technologies and smart city systems. International Journal of Civil Engineering and Technology, 9(8), 1802-1812. Retrieved from http://www.iaeme.com/MasterAdmin/UploadFolder/IJCIET_09_08_181/IJCIET_09_08_181.pdf

Laurier, E., Brown, B., McGregor, M. (2016). Mediated Pedestrian Mobility: Walking and the Map App. Mobilities 11: 117–134. http://doi.org/10.1080/17450101.2015.1099900

Metelenko, N.G., Kovalenko, O.V., Makedon, V., Merzhynskyi, Y.K., Rudych, A.I. (2019). Infrastructure security of formation and development of sectoral corporate clusters. Journal of Security and Sustainability Issues 9(1): 77-89. http://doi.org/10.9770/jssi.2019.9.1(7)

Ostrom, E. (2009). A general framework for analyzing sustainability of social-ecological systems. Science 325:419-422. http://dx.doi.org/10.1126/science.1172133

Pająk, K., Kvilinskyi, O.; Fasiecka, O., & Miśkiewicz, R. (2017). Energy security in regional policy in Wielkopolska region of Poland. Economics and Environment, 2(61), 122-138.

Poteete, A. R., M. Janssen, and E. Ostrom. (2010). Working together: collective action, the commons, and multiple methods in practice. Princeton University Press, Princeton, New Jersey, USA.

Retrieved from https://www.ekonomiaisrodowisko.pl/uploads/eis%2061/11_pajak.pdf

Scarselli, F., Gori, M., Tsoi, A. C., Hagenbuchner, M., and Monfardini, G. (2009). The graph neural network model. IEEE Transactions on Neural Networks, 20(1): 61-80

Selivanova-Fyodorova, N., Komarova, V., Lonska, J, Mietule, I. (2019). Differentiation of internal regions in the EU countries. Insights into Regional Development, 1(4), 370-384. https://doi.org/10.9770/ird.2019.1.4(7)

Selsam, D., Lamm, M., Bunz, B., Liang, P., de Moura, L., and Dill, D. L. (2019). Learning a sat solver from singlebit supervision. International Conference on Learning Representations

Sriyana, J. (2019). What drives economic growth sustainability? Evidence from Indonesia. Entrepreneurship and Sustainability Issues, 7(2), 906-918. http://doi.org/10.9770/jesi.2019.7.2(8)

Tkachenko, V., Kwilinski, A., Klymchuk, M., & Tkachenko, I. (2019). The economic-mathematical development of buildings construction model optimization on the basis of digital economy. Management Systems in Production Engineering, 27(2), 119-123. http://doi.org/10.1515/mspe-2019-0020

Vasylieva, T., Lyeonov, S., Lyulyov, O., & Kyrychenko, K. (2018). Macroeconomic Stability and Its Impact on the Economic Growth of the Country. Montenegrin Journal of Economics, 14(1), 159-170.

Vinogradova, N.P., Popov, A.N. (2019). Methodological basis of economic decision-making. Entrepreneurship and Sustainability Issues, 6(4), 1798-1806. http://doi.org/10.9770/jesi.2019.6.4(18)

Watts, D. J. (1999). Networks, dynamics, and the small-world phenomenon. American Journal of sociology, 105(2), 493-527.

Zhang, M. and Chen, Y. (2018). Link prediction based on graph neural networks. Advances in Neural Information Processing Systems https://papers.nips.cc/paper/7763-link-prediction-based-on-graph-neural-networks.pdf

Kwilinski, A. (2019a). Implementation of Blockchain Technology in Accounting Sphere. Academy of Accounting and Financial Studies Journal, 23(SI2), 1528-2635-23-SI-2-412: 1-6.

Aleksy KWILINSKI, Ph.D. (Economics), The London Academy of Science and Business, London, England
ORCID ID: orcid.org/0000-0001-6318-4001

Volodymyr Tkachenko, Ph.D., Doctor of Science of History, Professor, The London Academy of Science and Business, London, England Kyiv National University of Construction and Architecture, Ukraine
ORCID ID: orcid.org/0000-0003-2114-7194

Aleksandra KUZIOR, Ph.D., Doctor of Science of Humanities, Associate Professor, Faculty of Organization and Management, Silesian University of Technology
ORCID ID: orcid.org/0000-0001-9764-5320