Forecast Method for Audit Data Analysis by Modified Liquid State Machine

Tatiana Neskorodieva[1[0000-0003-2474-7697]], Eugene Fedorov[2[0000-0003-3841-7373]], Ivan Izonin[3[0000-0002-9761-0096]]

[1] Donetsk National University named Vasyl Stus, Vinnitsa, Ukraine
[2] Cherkasy State Technological University, Cherkasy, Shevchenko blvd., 460, 18006, Ukraine
[3] Lviv Polytechnic National University, Lviv, Ukraine

t.neskorodieva@donnu.edu.ua
fedorovee75@ukr.net
ivanizonin@gmail.com

Abstract. The forecast problem is considered for the audit data analysis automation. A forecast neural network model based on a modified liquid state machine is proposed. To choose the criterion of efficiency estimation of forecast neural network model and to offer the method of parametric identification of forecast neural network model. This allows you to increase the forecast efficiency by reducing computational complexity and improving the forecast accuracy. Software has been developed that implements the proposed method. The developed software is studied when solving the problem of forecasting indicators for data checking of the "paid-received" display.

Keywords: Audit Data, Automatic Analysis, "Paid-Received" Display, Forecast Method, Neural Network, Modified Liquid State Machine.

1 Introduction

In the process of development of international and national economies and industry of IT in particular, it is possible to distinguish the following basic tendencies: realization of digital transformations, forming of digital economy, globalization of socio-economic processes and of IT accompanying them [1]. These processes result in the origin of global, multilevel hierarchical structures of heterogeneous, multivariable, multifunction connections, interactions and cooperation of managing subjects (objects of audit), the large volumes of information about them have been accumulated in the informative systems of account, management and audit. Thus, the intercommunications mentioned above, have a network structure at every level.

In relation to the enterprises of Ukraine [2] it is marked that in the conditions of swift development of infrastructure and deepening of informatization of economic processes efficiency of activity of enterprises, establishments and organizations are all more depend on the information technologies (IT) used in management system. Now environment of information technologies (IT-environment) as a structural constituent of organization is the difficult system, that unites various informative, programmatic, technical, human and other types of resources for the achievement of enterprise aims.

Currently, the scientific and technical problem of modern information technologies in the financial and economic sphere is the formation of a design methodology [3] and the creation of decision support systems (DSS) for enterprise audit based on the automated analysis of large volumes of data on financial and economic activities and the state of enterprises in order to expand functional capabilities, increasing the efficiency and versatility of IT audit [4 - 6].

2 Related Works

One of the analysis element among the audit tasks is a forecast of economic indicators. Among them methods of short-term forecast, such as regressive [7], structural [8, 9], logical [10 - 12]; methods of long-term forecast, such as autoregressive [13], exponential smoothing out [14]. A compromise between the above-mentioned groups of methods is connectionist [15-17], that can use neural networks both for a short-term and for long-term forecasts. At the same time connectionist methods usually use parametric identification based on local search, that reduces forecast accuracy [18].

Regressive methods [7] conduct a forecast based on regressive linear and nonlinear model. The advantages of these methods are simplicity of construction of model, design transparency. The disadvantages of these methods are high computational complexity of parametric identification. Structural methods [8, 9] conduct a forecast based on Markov chain. The advantages of these methods are simplicity of construction of model, design transparency. Logical methods [10 - 12] conduct a forecast based on regressive tree. The advantages of these methods are design transparency, speed of process of construction of tree. The disadvantages of these methods are the problem of construction of optimal tree. The disadvantages of these method groups are absence of possibility of long-term forecast, that results in insufficient forecast accuracy.

Autoregressive methods [13] conduct a forecast based on autoregressive linear model. The advantages of these methods are simplicity of construction of model, design transparency. The disadvantages of these methods are high computational complexity of parametric identification, absence of ability of design of nonlinear processes, that results in insufficient forecast accuracy. Methods of the exponential smoothing [14] conduct a forecast based on linear model with one (single smoothing), two (double smoothing) or by three (triple smoothing) parameters. The advantages of these methods are simplicity of construction of model, design transparency, a result can be got quicker, than at the use of other models. The disadvantages of these methods are a subzero adaptivity, absence of ability of design of nonlinear processes, that results in insufficient forecast accuracy.

In the last few years among analytical procedures of exposure of financial fraud the class of procedures, based on the methods of intellectual analysis of data, was formed [15]. In practice different methods of extraction of data, namely: K-nearest neighbors, decision tree [16], fuzzy logic [17], logistic model, Bayesian belief networks, naive Bayes algorithm, Beneish M-Score, Benford's law, Altmann Z-Score, are being used for the improvement of accuracy of the fraud finding out [18]. Connectionist methods [19, 20] conduct a forecast based on nonlinear model of neural network. The advantages of these methods are scalability, high adaptivity. The disadvantages of these methods are absence of design transparency; complexity of choice of model structure; hard requirements to training sample; problem of choice of method of parametric identification; that results in insufficient forecast accuracy high computational complexity of parametric identification.

The general feature of all the methods mentioned above is that they possess a high computational complexity and/or do not give high forecast accuracy.

Therefore, an actual task is an increase of forecast efficiency by reducing computational complexity and improving forecast accuracy. The aim of study is to increase the efficiency of the forecast method due to the modification of model of artificial neural network and method of its parametric identification.

For the achievement of the aim it is necessary to solve the following tasks:

- to offer the forecast neural network model;
- to choose the criterion of efficiency estimation of forecast neural network model;
- to offer the method of parametric identification of forecast neural network model;
- to conduct numeral researches on audit data for checking of the "paid-received" display.

3 Modified Liquid State Machine

As well as in the traditional liquid state machine (LSM) [21, 22] in the proposed modified liquid state machine (MLSM) the hidden layer corresponds to the reservoir or liquid, and output layer correspond to the weekend to the layer of multi-layered perceptron (MLP). Unlike the traditional LSM in the offered MLSM: for the increase of forecast accuracy the method of pseudoinverse matrix, was used instead of the method of backpropagation, like the echo-state network (ESN) [23, 24]; for the reduction of computation complexity the hidden layer was done 1D, but not 3D.

Pulse neural networks are the third generation of artificial neural networks and, from the point of view of physiology, is the most realistic model of ANNs. Since the traditional LSM is based on pulsed neurons, the LIF (Leaky Integrate and Fire) model of the neuron, which has the least computational complexity in comparison with other models, is selected as the hidden layer neuron model. The LIF neuron model is presented in a kind

$$\tau \frac{du}{dt} = u_{rest} - u(t) + I(t)R, \tag{1}$$

where:

τ – time constant, $\tau = C \cdot R$,

C – capacity,

R – resistance,
$u(t)$ –potential (voltage),
$I(t)$ – input current,
u_{rest} – resting potential.

Firing time of LIF neuron is certain in a kind $t^f : u(t^f) \ge \theta$, where θ – threshold value. After the firing time of LIF neuron voltage is drop in a constant u_r, thus $u_r < \theta$, and during a refractory period t^r saves a value u_r. After completion of refractory period of LIF neuron continues to function to the new firing.

Taking into account (1) model of the modified liquid state machine is certain in a next kind (2)-(5):

$$\tilde{u}_j(n\Delta t) = \frac{\Delta t}{\tau} u_{rest} + \left(1 - \frac{\Delta t}{\tau}\right) u_j(n\Delta t - \Delta t) +$$
$$+ \Delta t \frac{R}{\tau}\left(\sum_{i=0}^{M} w_{ij}^{in-h} y^{in}(n-i) + \sum_{i=1}^{N^h} w_{ij}^{h-h} u_i(n\Delta t - \Delta t)\right), \; j \in \overline{1, N^h}, \tag{2}$$

$$u_j(n\Delta t) = \begin{cases} u_r, & (t_j^f + t_I^r > n\Delta t \wedge j \in I) \vee (t_j^f + t_E^r > n\Delta t \wedge j \in E) \\ \tilde{u}_j(n\Delta t), & else \end{cases}, \; j \in \overline{1, N^h},$$

$$u_j(n\Delta t) = \begin{cases} u_r, & \tilde{u}_j(n\Delta t) \ge \theta \\ \tilde{u}_j(n\Delta t), & else \end{cases}, \; t_j^f = \begin{cases} n\Delta t, & \tilde{u}_j(n\Delta t) \ge \theta \\ id(t_j^f), & else \end{cases}, \; j \in \overline{1, N^h}, \tag{3}$$

$$id(v) = v, \; inc(v) = v + 1, \tag{4}$$

$$y^{out}(n) = f^{out}(s^{out}(n)), \; s^{out}(n) = \sum_{i=0}^{N^h} w_i^{h-out} u_i(n\Delta t), \; j \in \overline{1, N^h}, \tag{5}$$

where:
I is numbers set of inhibitory neurons of the hidden layer,
E is numbers set of exciting neurons of the hidden layer,
Δt is a time sampling step,
M is an amount of unit delays of input layer,
N^h is an amount of hidden layer neurons,
w_{ij}^{in-h} are the weights between an input and hidden layer,
w_{ij}^{h-h} are the weights between the hidden layer neurons,

w_{ij}^{h-out} are the weights between the hidden and output layer.

4 Choice of Criterion for Estimation of Efficiency of Modified Liquid State Machine Model

In the work for training the LSM model (2)-(5), the goal function was chosen in according (6), that means the choice of such values of the parameter vector $W = (w_1^{h-out}, ..., w_{N^h}^{h-out})$, that deliver a minimum of mean-square error (differences of output on a model and test output)

$$F = \frac{1}{P}\sum_{\mu=1}^{P}(y_\mu^{out} - d_\mu)^2 \to \min_W , \qquad (6)$$

where:

y_μ^{out} is μ-th output signal on a model,

d_μ is μ-th test output signal.

5 Method of Parametric Identification of Modified Liquid State Machine Model

The method includes thr following steps:

1. Initializing of weights between an input and hidden layer

If $U(0,1) < P_{in-out}$, than $w_{ij}^{in-h} = U(-1,1)$, $i \in \overline{1,M}$, $j \in \overline{1,N^h}$.

Initializing of weights between the hidden and output layer $w_i^{h-out}(n) = U(-1,1)$, $i \in \overline{1,N^h}$, where $U(a,b)$ is an uniform distribution on a segment $[a,b]$,

P_{in-out} is a probability of weights between an input and hidden layer.

2. To form the set of numbers of hidden layer inhibitory (I) and excitatory (E) neurons as follows:

2.1. $I = \varnothing$, $E = \varnothing$.

2.2. If $U(0,1) < P_I$, then $I = I \bigcup \{j\}$, otherwise $E = E \bigcup \{j\}$, $j \in \overline{1,N^h}$,

where:

P_I is a probability that a neuron is inhibitory.

3. To calculate weights between the hidden layer neurons w_{ij}^{h-h}, $i, j \in \overline{1, N^h}$, as follows:

3.1. $w_{ij}^{h-h} = 0$;

3.2. if $i \in E, j \in E$, $i \neq j$, $P_{EE} = C_{EE} \exp\left(-\left(d_{ij} / \sigma\right)^2\right)$, $U(0,1) < P_{EE}$, then $w_{ij}^{h-h} = w_{EE}$;

3.3. if $i \in E, j \in I$, $P_{EI} = C_{EI} \exp\left(-\left(d_{ij} / \sigma\right)^2\right)$, $U(0,1) < P_{EI}$, then $w_{ij}^{h-h} = w_{EI}$;

3.4. if $i \in I, j \in E$, $P_{IE} = C_{IE} \exp\left(-\left(d_{ij} / \sigma\right)^2\right)$, $U(0,1) < P_{IE}$, then $w_{ij}^{h-h} = w_{IE}$;

3.5. if $i \in I, j \in I$, $i \neq j$, $P_{II} = C_{II} \exp\left(-\left(d_{ij} / \sigma\right)^2\right)$, $U(0,1) < P_{II}$, then $w_{ij}^{h-h} = w_{II}$,

where:

C_{EE}, C_{EI}, C_{IE}, C_{II} – coefficients for connections EE, EI, IE, II respectively,

d_{ij} is an Euclidean distance between two neurons,

σ is an constant,

P_{EE}, P_{EI}, P_{IE}, P_{II} are the probabilities that connection is EE, EI, IE, II respectively,

w_{EE}, w_{EI}, w_{IE}, w_{II} are the weights of connections EE, EI, IE, II respectively.

4. A learning set is given, $\left\{\left(x_\mu, d_\mu\right) \middle| x_\mu \in R, d_\mu \in R\right\}$, $\mu \in \overline{1, P}$, where x_μ is the μ-s learning set input value, d_μ is the μ-s learning set output value, P is power of learning set number. Number of values from a learning set $\mu = 1$. Number of iterations of learning set $n = 1$.

5. Initial calculation of output signal of input layer

$y^{in}(n-i) = 0$, $i \in \overline{1, M}$.

6. Initial calculation of output signal of the hidden layer

$u_i(0) = 0$, $i \in \overline{1, N^h}$.

7. Initial calculation of firing time of hidden layer neurons:

if $j \in I$, then $t_j^{fn} = -t_I^r$, $j \in \overline{1, N^h}$, if $j \in E$, then $t_j^{fn} = -t_E^r$, $j \in \overline{1, N^h}$,

where t_I^r, t_E^r are the refractory period for inhibitory (I) and excitatory (E) neurons respectively.

8. Calculation of output signal of input layer

$$y^{in}(n) = x_\mu, \; y^{in}(n) = \exp\left(-\frac{(x_\mu - m)^2}{2\sigma^2}\right),$$

where:

m is an expected value,

σ is an standard deviation.

9. Calculation of output signal for the hidden layer:

$$\tilde{u}_j(n\Delta t) = \frac{\Delta t}{\tau} u_{rest} + \left(1 - \frac{\Delta t}{\tau}\right) u_j(n\Delta t - \Delta t) +$$

$$+\Delta t \frac{R}{\tau}\left(\sum_{i=0}^{M} w_{ij}^{in-h} y^{in}(n-i) + \sum_{i=1}^{N^h} w_{ij}^{h-h} u_i(n\Delta t - \Delta t)\right), \; j \in \overline{1, N^h}.$$

10. If a refractory period proceeds, then an output signal for the hidden layer is drop in a constant

$$u_j(n\Delta t) = \begin{cases} u_r, & (t_j^f + t_I^r > n\Delta t \wedge j \in I) \vee (t_j^f + t_E^r > n\Delta t \wedge j \in E) \\ \tilde{u}_j(n\Delta t), & else \end{cases}, \; j \in \overline{1, N^h}.$$

11. If firing of neuron, then an output signal for the hidden layer is drop in a constant and fixed firing time:

$$u_j(n\Delta t) = \begin{cases} u_r, & \tilde{u}_j(n\Delta t) \ge \theta \\ \tilde{u}_j(n\Delta t), & else \end{cases}, \; t_j^f = \begin{cases} n\Delta t, & \tilde{u}_j(n\Delta t) \ge \theta \\ id(t_j^f), & else \end{cases}, \; j \in \overline{1, N^h},$$

12. Calculation of output signal for an output layer:

$$y^{out}(n) = f^{out}(s^{out}(n)), \; s^{out}(n) = \sum_{i=0}^{N^h} w_i^{h-out}(n) u_i(n\Delta t), \; j \in \overline{1, N^{out}},$$

where:

f^{out} is a sigmoid function of activating of neurons of output layer.

It is considered that $w_0^{h-out}(n) = b^{h-out}(n), u_0(n\Delta t) = 1$.

13. To modify weights of output layer based on method of pseudoinverse matrix:

13.1. To create a matrix $U = \left[u_i(n\Delta t) \right]$, $n \in \overline{1, P}$, $i \in \overline{0, N^h}$.

13.2. To create a vector $T = \left((f^{out})^{-1}(d_1), \ldots, (f^{out})^{-1}(d_p) \right)$.

13.3. To calculate a vector $W = (b^{h-out}(n), w_1^{h-out}(n), ..., w_{N^h}^{h-out}(n))$, $W = U^+ T$,

where U^+ is a pseudoinverse matrix.

6 Experiments and Results

The numerical experiments were conducted with the use of package of MATLAB. The probability of weights between an input and hidden layer $P_{in-out} = 0.3$. The probability of that a neuron is inhibitory $P_I = 0.2$. Coefficients for connections $C_{EE} = 0.3$, $C_{EI} = 0.2$, $C_{IE} = 0.4$, $C_{II} = 0.1$. Weights of connections w_{EE} = w_{EI} = w_{IE} = w_{II} $= 0.4$. Constant σ =2, Resistance of $R = 1$ Om, time constant $\tau = 30$ ms, capacity $C = 30$ nF, resting potential $u_{rest} = 0$. Refractory period for inhibitory neurons t_I^r =2 ms, refractory period for excitatory neurons t_E^r =3 ms. Thresholding $\theta = 1.5$ mV, constant $u_{rest} = 0$ mV. Amount of unit delays M =10, amount of neurons of the hidden layer $N^h = 2M$. For the determination of forecast model structure on the basis of the modified liquid state machine (MLSM) the row of experiments were done, the results of that are presented on the fig. 1.

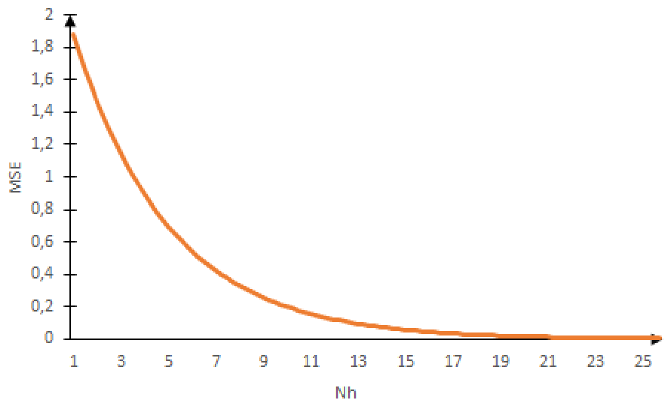

Fig. 1. Chart of dependence of mean-square error of forecast from the amount of the hidden neurons

As the input data for determination of parameters values of forecast neural network model the indexes of delivery and payment of supplies of machine-building enterprise were used with the two-year sampling period with daily allowance temporal intervals, value of indexes present a commercial secret and they have been scaled.

The criterion of choice of neural network model structure was minimum mean-square error of forecast. As be obvious from a fig. 1, with the increase of amount of the hidden neurons the value of error reduces. For a forecast it is enough to use 10 time delay in an input layer and 20 hidden neurons, as at the further increase of amount of delays and hidden neurons the change of value of error is insignificant.

Neural networks were researched in the given paper for a forecast on a criterion minimum mean-square error (MSE) of forecast. The following neural networks were used in the experiments (tabl.1): JNN (Jordan neural network), ENN (Elman neural network) also called SRN (Simple recurrent network), NARMA (nonlinear auto-regressive-moving average), BRNN (bidirectional recurrent neural network), LSTM (long short-term memory), GRU (gated recurrent unit), ESN (echo state network), LSM (liquid state machine), proposed by the authors MLSM (modified liquid state machine).

Table 1. Comparative features of neural networks for a forecast

Network	JNN	ENN (SRN)	NARMA	BRNN	LSTM	GRU	ESN	LSM	MLSM
Minimum MSE of forecast	0.17	0.16	0.13	0.14	0.8	0.10	0.05	0.07	0.05

According to the table 1, MLSM and ESN have the most forecast accuracy, however ESN requires a greater computational complexity due to the relations between an input and output layer and between the neurons of output layer. It is because of that the neural network of MLSM and ESN do not use a local search, that reduces probability of hit in a local extremum.

The components of the technical solution are the liquid state machine and the LIF model of the neuron (2) - (5). There is a process of parametric identification of the forecast model described in section 5. Limitations of the parametric identification method of the MLSM model - for the pseudoinversion method of matrix, in the case of a very large amount of data, difficulties arise in calculating the inverse matrix and the complexity of matrix multiplications. In addition, in the presence of noise, the matrix pseudo-inversion method should be modified. In the future, it is planned to use CUDA parallel processing technology for block matrix multiplication to accelerate matrix calculations.

7 Conclusions

In the article the problem of increasing the efficiency of the forecast method for audit data is examined due to an offer of modified liquid state machine (MLSM). The scientific contribution is to improve the model and method of parametric identification of a liquid state machine. Compared with the traditional model, advanced model of the liquid state machine, that is based on the model of LIF (Leaky Integrate and Fire) of neuron, is improved, and limited to the 1D hidden layer, that allows to reduce computational complexity. Compared to the traditional method, advanced method of parametric identification of MLSM needs further development, that is based on the method of pseudoinverse matrix, that improves forecast accuracy, as a local search that reduces probability of hit in a local extremum is not used. Software realizing an offered method was worked out and researched on the indexes of delivery and payment of supplies of machine-building enterprise with the two-year sampling period with daily allowance of temporal intervals. The conducted experiments confirmed the capacity of the worked out software and allow to recommend it for the use in practice in the subsystem of the automated analysis of DSS of audit. The proposed method was used by Ekol Ukrane, a logistics company, to forecast the amount of freight traffic and for the forecast of indicators in the audit task of display "paid - received" calculations with suppliers of the machine-building enterprise. The prospects of further researches are grounded on the proposal to check the offered methods for the wide set of test databases.

References

1. The World Bank: World Development Report 2016: Digital Dividends. https://www.worldbank.org/en/publication/wdr2016 (2016). Accessed 12 February 2020.
2. The State Audit Service of Ukraine: Praktychna metodolohiia IT-audytu. (Practical methodology of IT-audit). http://dkrs.kmu.gov.ua/kru/doccatalog/ document (2015). Accessed 12 February 2020.
3. Neskorodieva, T.V. Postanovka elementarnykh zadach audytu peredumovy polozhen bukhhalterskoho obliku v informatsiinii tekhnolohii systemy pidtrymky rishen (Formulation of elementary tasks of audit subsystems of accounting pro-visions precondition IT DSS). Modern information systems. 3(1), 48-54. (2019) doi:10.20998/2522-9052.2019.1.08.
4. Zhu, B. Research on the Application of Big Data in Audit Analysis Program. International Seminar on Automation, Intelligence, Computing, and Networking. Francis Academic Press, UK (2019).
5. Bidiuk, P.I., Prosiankina-Zharova, T.I., Terentieev, O.M., Lakhno, V.A., Zhmud, O.V.: Intellectual technologies and decision support systems for the control of the economic and financial processes. Journal of Theoretical and Applied Information Technology. 96(1), 71-87 (2019).
6. Ahmad, S., Mehdi, G., Mohammed, F.: Data mining techniques for anti money laundering. International Journal of Applied Engineering Research. 12(20), 10084-10094 (2017).
7. Khrystyianivsky, V.V., Neskorodieva, T.V., Polshkov, Yu.N.: Ekonomiko-matematicheskie metodyi i modeli: praktika primeneniya v kursovyih i diplomnyih rabotah (Economic and mathematical methods and models: application practice in term papers and dissertations). DonNU, Donetsk (2013).
8. Alevizos E., Artikis A., and Paliouras G. Event forecasting with pattern Markov chains. In Proceedings of ACM International Conference on Distributed Event-Based Systems, Barcelona, Spain, 12 p. doi: 10.1145/3093742.3093920 (2017).
9. Anastasios, P., Vasilis, S., Dionysios, M., Aristotelis, K. A combined statistical framework for forecasting default rates of Greek financial institutions’ credit portfolios. Athens, Bank of Greece (2018).
10. Lytvynenko, T.I.: Problem of data analysis and forecasting using decision trees method. Programming problems. 2, 220-226 (2016).

11. Cornel, L., Mirela, L. Using the Method of Decision Trees in the Forecasting Activity. Economic Insights. Trends and Challenges. 4 (67), No. 1, pp. 41–48 (2015).
12. Hovorushchenko, T. Information technology for assurance of veracity of quality information in the software requirements specification. In: Shakhovska,, N., Stepashko, V. (eds) Advances in Intelligent Systems and Computing II. CSIT 2017. Advances in Intelligent Systems and Computing, vol 689, pp. 166-185. Springer, Cham (2018) doi:10.1007/978-3-319-70581-1.
13. Baillie, R. T., Kapetanios, G., Papailias, F.: Modified information criteria and selection of long memory time series models. Computational Statistics and Data Analysis. 76. 116–131 (2014).
14. Bidyuk,, P., Prosyankina-Zharova,, T., Terentiev, O.: Modelling nonlinear nonsta-tionary processes in macroeconomy and finances. In: Hu, Z., Petoukhov, S., Dychka, I., He M. (eds) Advances in Computer Science for Engineering and Edu-cation. Advances in Intelligent Systems and Computing, vol 754, pp. 735-745. Springer, Cham (2019). doi: 10.1007/978-3-319-91008-6_72.
15. Zgurovsky, M.Z., Zaychenko, Y.P.: The fundamentals of computational intelligence: system approach. Springer International Publishing. Switzerland (2017).
16. Alex, G., Pereira, G., Pappa L. A customized classification Algorithm for Credit card Fraud Detection. Engineering Applications of Artificial Intelligence, vol. 72: pp. 21-29 (2018).
17. Vlasenko, A., Vlasenko, N., Vynokurova, O., Bodyanskiy, Y., Peleshko, D.: A novel ensemble neuro-fuzzy model for financial time series forecasting. Data 4(3), 126. (2019) 10.3390/data4030126.
18. Tkachenko, R., Izonin, I., Greguš ml., M., Tkachenko, P., Dronyuk, I.: Committee of the SGTM neural-like structures with extended inputs for predictive analytics in insurance. In: Younas, M., Awan, I., Benbernou, S. (eds) Big Data Innovations and Applications. Innovate-Data 2019. Communications in Computer and In-formation Science. vol. 1054. pp. 121-132. Springer, Cham (2019) doi:10.1007/978-3-030-27355-2.
19. Tkachenko, R., Tkachenko, P., Izonin, I., Vitynskyi, P., Kryvinska, N., Tsymbal, Y. Committee of the Combined RBF-SGTM Neural-Like Structures for Prediction Tasks. In: Awan, I., Younas, M., Ünal, P., Aleksy, M. (eds) Mobile Web and Intelligent Information Systems. Lecture Notes in Computer Science, vol 11673, pp. 267-277. Springer, Cham (2019) doi:10.1007/978-3-030-27192-3_21.
20. Leoshchenko, S., Oliinyk, A., Subbotin, S., Zaiko, T.: Using recurrent neural net-works for data-centric business. In: Ageyev, D., Radivilova, T., Kryvinska, N. (eds) Data-Centric Business and Applications. Lecture Notes on Data Engineering and Communications Technologies. 42, pp. 73-91. Springer, Cham (2020) doi:10.1007/978-3-030-35649-1_4.
21. Wang, Q., Li, P. D-lsm: Deep liquid state machine with unsupervised recurrent reservoir tuning, in pattern recognition. 23-rd International Conference. Cancun, IEEE. 2652–2657 (2016).
22. Haykin, S.S.: Neural networks and learning machines. Pearson, Delhi (2016).
23. Bengio, Y. Goodfellow, I.J., Courville, A.: Deep learning. MIT Press (2016) http://www.deeplearningbook.org.
24. Zhiteckii, L.S., Solovchuk, K.Yu.: Pseudoinversion in the problems of robust stabilizing multivariable discrete time control systems of linear and nonlinear static objects under bounded disturbances. Automation and Information Sciences. 3, 57-70 (2017).