ECONOMIC ANNALS-XXI
ISSN 1728-6239 (Online)
ISSN 1728-6220 (Print)
https://doi.org/10.21003/ea
http://www.soskin.info/ea/

Volume 183 Issue (5-6)'2020

Citation information:
Astanakulov, O. (2020). National projects and government programmes: functional algorithm for evaluating and modelling using the Data Science methodology. *Economic Annals-XXI, 183*(5-6), 51-59. doi: https://doi.org/10.21003/ea.V183-05

UDC: 332.05

Olim Astanakulov
PhD (Economics), Associate Professor,
Academy of Public Administration under President of Republic of Uzbekistan (APA)
45 Islam Karimov Str., Tashkent, 100066, Republic of Uzbekistan
astanakulov@gmail.com
ORCID ID: https://orcid.org/0000-0002-0536-1214

National projects and government programmes: functional algorithm for evaluating and modelling using the Data Science methodology

Abstract
Programme and target planning procedures in Russia have a lot of shortcomings, related to the selection of priority goals, establishment of criteria for evaluating the effectiveness of target programmes, as well as achievement of goals, development of a system of performance indicators, and so on. In addition, the problem of the lack of a high-quality theoretical and legislative framework for the transition to budget expenditures planning in accordance with the principles of result-oriented budgeting remains urgent.
The purpose of this paper is to develop a functional fuzzy computing algorithm for modelling the evaluation of government programmes using neural networks.
As a part of this work, we obtained stable results in the form of creating a neural network that can analyze government projects using a multi-criteria method, taking into account the root-mean-square error, with an accuracy of up to 95%. The analysis criteria cover all effective areas for predicting the correct use of the government projects by implementing them in the government systems.
Keywords: Support; Solution; System; Building; Model; Neural Network; Government Programme; Data Science
JEL Classification: C81; H52
Acknowledgements and Funding: The author received no direct funding for this research.
Contribution: The author contributed personally to this work.
DOI: https://doi.org/10.21003/ea.V183-05

Астанакулов О. Т.
кандидат економічних наук, доцент,
Академія державного управління при Президентові Республіки Узбекистан, Ташкент, Узбекистан
Національні проекти й державні програми: функціональний алгоритм оцінки та моделювання з використанням методології Data Science
Анотація
Процедури програмно-цільового планування в Росії мають масу недоліків, які пов'язані з вибором пріоритетних цілей, встановленням критеріїв оцінки ефективності цільових програм, а також з оцінкою досягнення поставлених цілей, розробкою системи показників ефективності. Актуальною залишається проблема відсутності якісної теоретичної та законодавчої бази для переходу до планування бюджетних витрат відповідно до принципів бюджетування, орієнтованого на результат.
Метою статті є розробка функціонального нечіткого обчислювального алгоритму для моделювання оцінки державних програм із використанням нейронних мереж.
У рамках цієї роботи ми отримали стабільні результати в вигляді створення нейронної мережі, здатної аналізувати державні проекти багатокритеріальним методом із урахуванням середньоквадратичної помилки з точністю до 95%. Критерії аналізу охоплюють усі ефективні галузі прогнозування правильного використання державних проектів шляхом їх впровадження в державні системи.
Ключові слова: підтримка; рішення; система; побудова; модель; нейронна мережа; державна програма; Data Science.

Астанакулов О. Т.
кандидат экономических наук, доцент,
Академия государственного управления при Президенте Республики Узбекистан, Ташкент, Узбекистан

Национальные проекты и государственные программы: функциональный алгоритм оценки и моделирования с использованием методологии Data Science

Аннотация. Процедуры программно-целевого планирования в России имеют множество недостатков, которые связаны с выбором приоритетных целей, установлением критериев оценки эффективности целевых программ, а также оценкой достижения поставленных целей, разработкой системы показателей эффективности и так далее. Низкое качество средне- и долгосрочного макроэкономического прогнозирования, а также недостаточная ответственность субъектов бюджетного планирования за достижение целей программно-целевого планирования также сдерживают развитие программно-целевого планирования.

Целью данной статьи является разработка функционального нечеткого вычислительного алгоритма для моделирования оценки государственных программ с использованием нейронных сетей.

В рамках данной работы мы получили устойчивые результаты в виде создания нейронной сети, способной анализировать правительственные проекты, используя многокритериальный метод, с учетом среднеквадратической ошибки, с точностью до 95%. Критерии анализа охватывают все эффективные области для возможности прогнозирования правильного использования правительственных проектов, реализуя их в правительственных системах.

Ключевые слова: поддержка; решение; система; здание; модель; нейронная сеть; правительственная программа; Data Science.

1. Introduction

Programme-based planning is an important part of public economic management systems. Distinctive features of the programme-target method are (Abadi et al., 2016):

- ensuring the reciprocity of interests, goals and objectives of government bodies and business entities, as well as planned periods of different duration;
- indicative nature of programmes, the timing of implementation of which is directly dependent on the availability of programmes with the necessary material and financial resources;
- systematic nature of the main goals and objectives of programmes to solve complex (intersectoral and interregional) problems of economic and social development in the region at various levels;
- the ability to use the multiplier effect in the targeted use of budget funds, own funds, bank loans and other attracted funds of investors.

The attention paid to improving programme-oriented planning in Russia and abroad is due to the fact that this method of managing budget expenditures best meets the modern requirements of state financial regulation of socio-economic processes, as it orients authorities and organizations, first of all, to achieve the goal. strategic goals and tactical objectives, as well as the expected socio-economic results of ministries, agencies, services and organizations, are a reference point in the distribution of budget funds, including the formation of targeted programmes.

2. Brief Literature Review

Evaluation of the effectiveness of target programmes based on the leading foreign experience in implementing the programme-target method, determining the factors affecting this effectiveness, as well as determining the methodological principles of programme-target planning (Abadi et al., 2016).

The main feature of the programme-target approach is that it allows you to solve complex tasks that stand at the intersection of departmental and sectoral competencies, powers and areas of responsibility of business entities, executive and municipal authorities (Bengio et al., 2007), by coordinating joint efforts to solve the problem (Laskov & Srndic, 2014). Accordingly, there should be organizational mechanisms for such connections. So, the key feature of software management - is that the tasks solved using the programme-target method cannot be solved using standard «routine» management procedures of government bodies, municipal administration and commercial structures (Pei, Cao, Yang, & Suman, 2017). So, one of the main features of the programme-targeted approach is its complexity and the availability of appropriate organizational forms for implementing programmes (Khalign-Razavi & Kriegeskorte, 2014).

To date, the Russian Federation has adopted at least 40 methods for evaluating targeted programmes, most of which are formal in nature and have no real implementation experience (Pencheva et al., 2018).

Most processes in demography, ecology, economics and finance today are non-linear and non-stationary, or partially linear and stationary (Güçlü & van Gerven, 2015). Processes are characterized by the presence of stochastic or deterministic trends that depend on specific random disturbances and factors of influence (Abdelhack & Kamitani, 2018). Many of the processes under study are heteroscedastic or integral, meaning that their conditional variance or expected variance changes over time (Deng et al., 2009). Usually, non-stationary processes exhibit various kinds of non-linearity (non-linearity with respect to variables or parameters) (Simonyan & Zisserman, 2014). A deterministic trend can be formally described by a quadratic, cubic, or higher-order function, exponent, spline, or harmonic function (Yosinski et al., 2015). Models of heteroscedastic processes include an equation that describes the amplitude of the process (Sun & Medaglia, 2019), and an equation that describes the dynamics of its dispersion (Nguyen et al., 2016). The nonlinear dispersion model is very useful in many applications (Gorgolewski et al., 2016).

3. Materials and Methods

To solve the objectives set, the neural network methods and methods of the theory of automatic control are used for management, optimization, and object-oriented programming testing.

The main provisions of the work are obtained on the basis of reliable knowledge of applied mathematics with mathematically rigorous calculations. The obtained theoretical results are confirmed by experiments using the computational methods.

4. Results

Currently, the following Federal government projects are being implemented in the Russian Federation: the Health project, the Education project, the Demography project, the Culture project, the Safe and high-quality roads project, the Housing and urban environment project, the Ecology project, the Science project, the Small and medium-sized businesses and support for individual entrepreneurship, labour productivity and employment support, international cooperation and export, Digital economy of the Russian Federation, comprehensive plan for modernization and expansion of the main infrastructure

One of the important points in modelling the dynamics of a system is to identify and determine the type of possible uncertainties (Figure 1). Uncertainties are considered as factors that negatively affect the modelling process, lead to various errors, and reduce the quality of the final results (Sun & Medaglia, 2019).

A linear process can be non-stationary if it contains a linear trend. As a rule, nonlinear processes can be piecewise stationary, mainly in a stable mode of operation. Nonlinear non-stationary processes (NPS) are most commonly found in all the above-mentioned areas of research. (Thierer et al., 2017).

Consequently, adaptive forecasting of nonlinear non-stationary processes is a very important task of our time, due to the fact that most processes in economics, finance, ecology and technological processes belong to this class.

Let us consider some well-known mathematical models for this purpose.

- ***Polynomial regression***

One of the most common methods of describing trends is polynomial regression of this type:

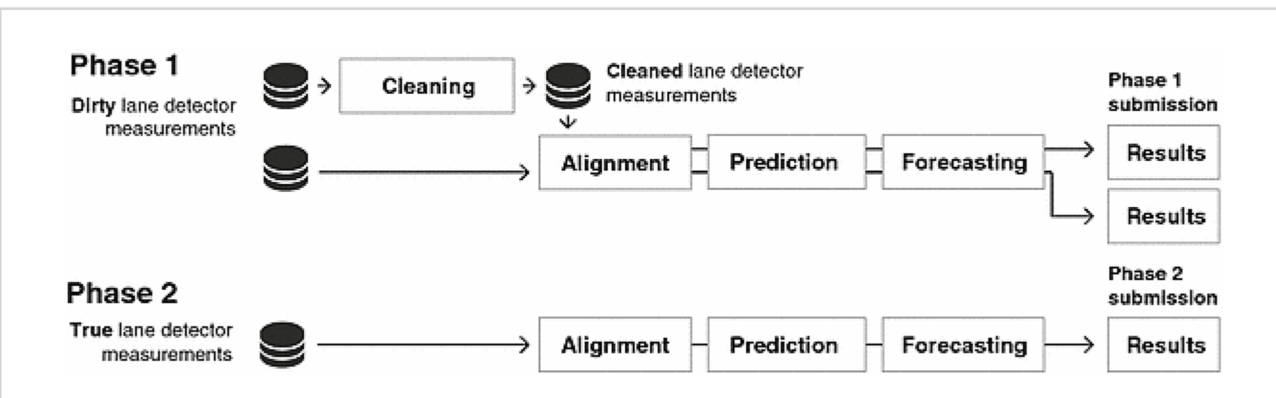

Figure 1:
The pre-pilot evaluation of the task workflow
Source: Author's development

$$y(k) = a_0 + a_1 k + a_2 k^2 + \ldots + a_m k^m + \varepsilon(k)\,, \tag{1}$$

where:

$y(k)$ is the main (dependent) process variable;

$k = 0,1,2,\ldots$ is discrete time, which is associated with the real continuous time t for the period of discretization of changes T_s: $t = kT_s$;

a_i, $i = 0,\ldots\, m$ are coefficients (parameters) of the model;

m is the order of a polynomial that is defined by the number of derivatives that can be calculated based on an adequate polynomial model of the process;

$\varepsilon(k)$ is a random process, the appearance of which is caused by the presence of random external disturbances, measurement errors, methodological errors in estimating the parameters of the model, and errors in evaluating the structure.

Arbitrary-order polynomials (1) are quite often used in practice due to the simplicity of defining the model structure and the ability to use the least squares method (OLS) to estimate its parameters (Valle-Cruz, 2019).

Autoregression with a trending component, on this basis, is as follows:

$$y(k) = a_0 + \sum_{i=1}^{p} a_i y(k-i) + \sum_{j=1}^{m} b_j k^j + \varepsilon(k)\,. \tag{2}$$

Autoregression with an integrated moving average:

$$y(k) = a_0 + \sum_{i=1}^{p} a_i y(k-i) + \sum_{j=1}^{q} b_j v(k-j) + \varepsilon(k)\,. \tag{3}$$

Formulas (2) and (3) describe the trend and the fluctuations that are imposed on it if there is at least one single root of the characteristic equation that is written for the autoregressive AR-parts (Nguyen et al., 2016).

Since such processes are quite typical for production technologies, economics, finance, ecology and other industries, they need to be given considerable attention. Non-stationary processes of this type are particularly common in the transition economy, where related financial activities have high non-stationary dynamics of development.

• *Splines for describing quadratic, cubic, and higher-order trends*

A first-order spline is a function $f(x)$ that is continuous on the segment $[a, b]$ and linear on each partial segment $f(x)$. It is designated $S_1(x)$. The interpolation function $f(x)$ is called a spline that satisfies the conditions $S_1(x) = y_j$, $i = 0,\ldots, m$. The graph of a linear interpolation spline $S_1(x)$ is a polyline that passes through the specified points. Let $x \in [x_i, x_{i+1}]$, then, the formula for a spline $S_1(x)$ over such a span is as follows:

$$S_1(x) = y_i \frac{x_{i+1} - x}{h_i} + y_{i+1} \frac{x - x_i}{h_i}\,, \tag{4}$$

where:

$S_1(x)$ is a first-order spline;

$y_i = f(x_i), i = 0,\ldots, m,\ a = x_0 < \ldots < x_n = b$ are the given values;

$h_i = x_{i+1} - x_i$.

To approximate data, a ***Hermite spline*** is often used. It is a third-order spline, a derivative of which takes specified values at the nodes of the spline.

Cubic spline. Some function $f(x)$ is defined on the interval $[a, b]$, which is divided into parts $[x_{i-1}, x_i]$, $a = x_0 .. < x_n = b$. A cubic spline is called the function which on each of the segments $[x_{i-1}, x_i]$ is a polynomial no higher than the third order; has continuous first and second derivatives on the entire segment $[a, b]$; at points x_i, the equality $S(x_i) = f(x_i)$ holds (Monzon et al., 2010).

This function looks as follows:

$$S_i(x) = a_i + b_i(x - x_i) + \frac{c_i}{2}(x - x_i)^2 + \frac{d_i}{6}(x - x_i)^3\,, \tag{5}$$

where:
$S_i(x)$ is the cubic spline;
$a_i = S_i(x_i) = f(x_i)$;
$b_i = S_i'(x_i) = \frac{f_i - f_{i-1}}{h_i} - \frac{h_i(2c_i + c_{i-1})}{6}$;
$h_i = S_i''(x_i)$;
$d_i = \frac{C_i - C_{i-1}}{h_i}$.

• ***Using an exponent***

An exponential trend is a trend that is written using the following equation:

$$y(k) = ap^k + \varepsilon(k)\,, \tag{6}$$

where:
$y(k)$ is the main (dependent) process variable;
a is the free term of the exponent, equal to the aligned trend, i.e., the level of the trend at the moment or time period that is taken as the beginning of the countdown ($k = 0$);
p is the main parameter of the exponential trend, which characterizes the rate of change in the level. The value $p > 1 >$ corresponds to a positive trend with increasing acceleration. If $p < 1$, then such a trend reflects the trend of a constant level of amplitude, that is, a reduction in levels (Pencheva et al., 2018).

The exponent has no extremum and at $k \to \infty$ tends to infinity at $p > 1 >$ or $k \to \infty$ at $p < 1$. An exponential trend is characteristic of processes that develop in an environment that does not create any restrictions on the growth of the level. Expression (6) is often used in a converted form (Güçlü & van Gerven, 2015):

$$y(k) = \exp(\ln(a) + \ln(pk)) + \varepsilon(k)\,. \tag{7}$$

• ***A combination of periodic functions***

In the presence of periodic processes, the trend k is described by a combination of trigonometric functions:

$$y(k) = a_0 + \sum_{i=1}^{p} a_i sin(\omega_0 i) + \sum_{j=1}^{q} b_j\, cos(\omega_0 i) + \varepsilon(k)\,, \tag{8}$$

where:
$y_n(k)$ is the main (dependent) variable;
a_0, $\{a_i, a_i\}$, $i = 1,\ldots,n$ are the coefficients (parameters) of the model;
a_n, b_n are senior coefficients of the model;
n is the order of the model.

To describe a trend, you can use any deterministic function that corresponds to the nature of the trend change over time.

• ***Heteroscedastic processes***

Heteroscedastic processes are processes that have a time-varying variance, i.e.:

$$var[\varepsilon(k)] = \sigma_\varepsilon^2 \neq const\,, \tag{9}$$

where:
$\varepsilon(k)$ is a random variable.

- ***ARCH (Auto Regressive Conditional Heteroscedasticity)*** model is used in econometrics to analyze time series (primarily financial ones), where the conditional variance of a series depends on the past values of the series, the past values of these variances, and other factors. (Monzon et al., 2010).

Autoregressive conditionally heteroscedastic equation has the form:

$$\hat{\varepsilon}^2(k) = \alpha_0 + \alpha_1\hat{\varepsilon}^2(k-1) + \alpha_2\hat{\varepsilon}^2(k-2)+\ldots+\alpha_q\hat{\varepsilon}^2(k-q) + v(k)\,, \tag{10}$$

where:
$\hat{\mathcal{E}}^2(k)$ are the squares of the estimates of the model's residuals (errors);
a_0 is the coefficient of delay;
$a_1,\ldots,a_q$ are the parameters;
$v(k)$ is a zero, mean: white noise process for an adequate model.

Residues (perturbations) of $\varepsilon(k)$ can be obtained from regression, autoregression, or autoregression equations with a low-order moving average.

In addition to the formula (10), you can also choose more complex forms of describing the behaviour of variance. For example, it is almost never known in advance whether perturbations affect the process additively or multiplicatively. Therefore, it can be entered in the model in multiplicative form:

$$\varepsilon^2(k) = v^2(k)[\alpha_0 + \alpha_1\varepsilon^2(k-1)]\,, \tag{11}$$

where:
$v(k)$ are the multiplicative disturbances in the form of white noise, with $\{v(k)\} \sim (0.1)$, that is, it has a zero mean and a single variance;
$\varepsilon(k-1)$ and $v(k)$ are statistically independent (uncorrelated) values.

One of the key problems in determining the structure of the model is to establish the fact of the presence of non-linearities in the process under study and their type. To avoid this problem, you should use visual data analysis and formal tests for the presence of non-linearities. For an experienced modeler, visual analysis gives the ability to quickly identify the presence of fragments with a linear or nonlinear trend, - heteroscedasticity and significant peaks (pulses) that significantly affect the quality of the model (Khaligh-Razavi & Kriegeskorte, 2015).

In addition, there are a number of formal ***tests for detecting non-linearity***. Consider the following simple test for non-linearity. It can be used if you can select multiple groups (samples) of observations for the same process:

$$\hat{F} = \frac{\frac{1}{m-2}\sum_{i=1}^{m} n_i\,(\bar{y}_i-\hat{y}_i)^2}{\frac{1}{n-m}\sum_{i=1}^{m}\sum_{j=1}^{n_i}(y_{ij}-\bar{y}_i)^2}\,, \tag{12}$$

where:
$\bar{y}_i$ is the average value for i-th group (sample or group) of data;
$\hat{y}_i$ is the average for linear data approximation;
m is the number of data groups;
n_i is the number of measurements in i-th group;
n is the total number of dimensions.

If the statistics $\hat{F}$ with degrees of freedom $v_1 = m-2$ and $v_2 = n-m$ reach or exceed equal significance, then the hypothesis of lignity should be rejected. The disadvantage of this approach is that it requires several (at least three) groups of data for the same process, which can be obtained as a result of repeated experiments (Abadi et al., 2016).

The presence of non-linearity can also be established by using selective ***nonlinear correlation functions (NCF)*** - correlation functions calculated from samples of experimental (statistical) data. For example, if a discrete NCF is:

$$r_{yx^2}(s) = r_{y(k)x^2(k-s)} = \frac{1}{N}\,\frac{\sum_{k=s+1}^{N}\{\,[y(k)-\bar{y}]\,[x(k-s)-\bar{x}]^2\,\}}{\sigma_y\sigma_x^2}\,,\ s = 0,1,2,3,\ldots, \tag{13}$$

where:
$y(k)$ is the main (dependent) process variable.

If the process contains values that differ significantly from zero in a statistical sense, then the process contains a quadratic non-linearity relative to the x regressor.

The model adequacy criteria allow us to evaluate separately the significance of the coefficients of the mathematical model in a statistical sense, to determine the integral error of the model, establish the presence of a correlation between the values of the model error (they must not be correlated), and also determine the degree of adequacy of the model to the physical process as a whole. This set includes the following statistical parameters:

- ***Visual representation of the model's error graph***

$$e(k) = y(k) - \hat{y}(k), \tag{14}$$

where:

$\hat{y}(k)$ is the estimate of the variable obtained using the constructed model.

The graph should not contain significant outliers or long intervals where the error takes on large values (i.e., long intervals of significant inadequacy). In the case of recursive estimation methods, the greatest errors will occur in the transition process, when the information matrix does not yet contain enough information about the process.

- ***t - student statistics.*** The significance of each regression coefficient in a statistical sense is determined using t-statistics calculated by all statistical software packages using the formula:

$$t_a = \frac{\hat{a} - a_0}{SE_{\hat{a}}}, \tag{15}$$

where:

$\hat{a}$ is the coefficient estimate obtained using the package;

a_0 is a null hypothesis (initial hypothesis) for the value of this coefficient. Statistical theory suggests putting forward a null hypothesis, which is the opposite of the desired result, that is, a lightweight coefficient $H_0 : a_0 = 0$ is given, but the option is $H_0 : a_0 \neq 0$ possible. This makes it possible to correctly determine the significance of coefficient estimates and significantly simplify calculations;

$SE_{\hat{a}}$ is the standard error of estimating the coefficient, calculated in a package (Abdelhack & Kamitani, 2018).

Using the created neural network (Figure 2), we will analyze the project «labour productivity and employment support» (Figure 3).

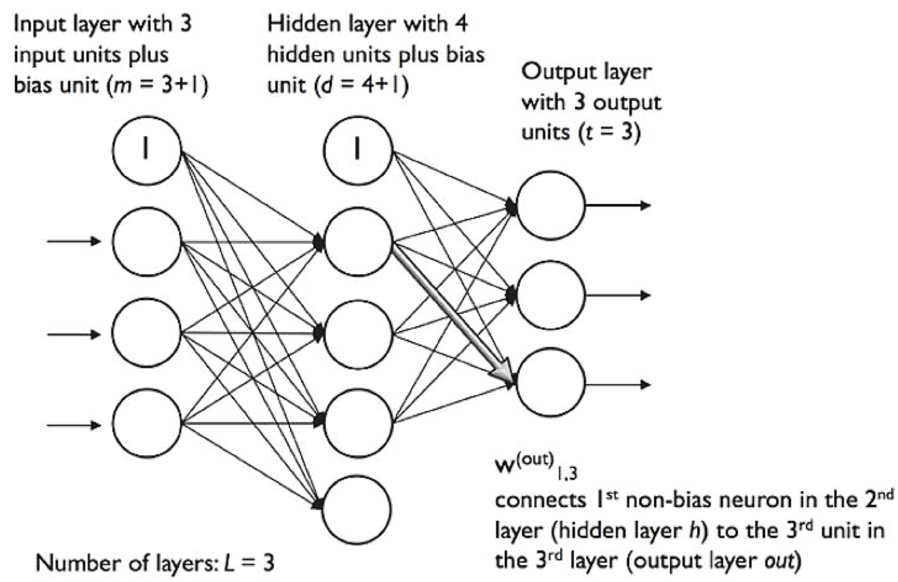

Figure 2:
Multilayer neural network to analyze a government project
Source: Author's development

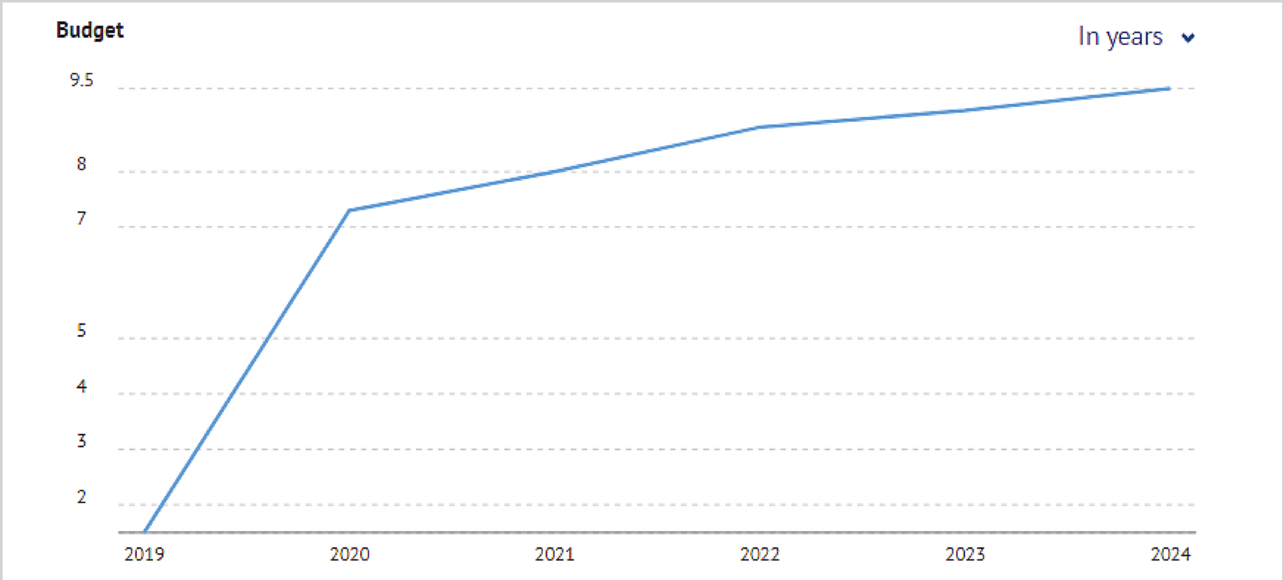

Figure 3:
Volume of financial support by year of implementation, billion rubles in project «labour productivity and employment support»
Source: https://futurerussia.gov.ru (2020)

The neural network analyzed 27 input parameters of this project, as well as 13 internal ones. The output was an analysis of the project's funding, and with an accuracy of 83%, the correlation of the required funding with the final expected effect is correct.

It is obvious that the smaller the value of the standard error, the better the score ratio model.

5. Conclusion

Within the framework of the conclusions to this scientific study, we can give an accurate definition of the need to use a neural network in government programmes in order to study the further effectiveness and comprehensive assessment of each project. As a methodological and mathematical apparatus, a neural universal neural network was created, suitable for any task with the required number of variables and unknowns.

A neural network can simultaneously explore 10 factors of one project in the form of 10 variables; at the same time, by studying the values of these 10 factors (they can be either economic and empirical or theoretical factors), the neural network evaluates the project.

Experiments on modelling and forecasting using an adaptive Kalman filter with the estimation of model parameters using the maximum likelihood method and a granular filter were conducted.

Three algorithms of granular filtration methods are constructed and implemented in the programming.

For methods of the government projects evaluating, we used mathematical modelling and neural network evaluation, with the results obtained in the form of a ready-made algorithmic neural network.

As part of this work, we obtained stable results in the form of creating a neural network that can analyze government projects using a multi-criteria method, taking into account the root-mean-square error, with an accuracy of up to 95%. The analysis criteria cover all effective areas for predicting the correct use of government projects by implementing them in government systems.

References

1. Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., ... Zheng, X. (2016). Tensorflow: Large-scale machine learning on heterogeneous distributed systems. *arXiv*, *preprint arXiv:*1603.04467. Retrieved from https://arxiv.org/abs/1603.04467
2. Abdelhack, M., & Kamitani, Y. (2018). Sharpening of hierarchical visual feature representations of blurred images. *Eneuro, 5*(3), doi: https://doi.org/10.1523/ENEURO.0443-17.2018
3. Bengio, Y., Lamblin, P., Popovici, D., & Larochelle, H. (2007). *Greedy layer-wise training of deep networks.* Retrieved from https://papers.nips.cc/paper/2006/file/5da713a690c067105aeb2fae32403405-Paper.pdf

4. Deng, J., Dong, W., Socher, R., Li, L., Li, K., & Fei-Fei, L. (2009) Imagenet: A large-scale hierarchical image database. *IEEE CVPR.* doi: https://doi.org/10.1109/CVPR.2009.5206848
5. Gorgolewski, K. J., Auer, T., ... Poldrack, A. (2016). The brain imaging data structure, a format for organizing and describing outputs of neuroimaging experiments. *Scientific Data, 3,* 160044. doi: https://doi.org/10.1038/sdata.2016.44
6. Güçlü, U., & van Gerven, M. A. J. (2015). Deep neural networks reveal a gradient in the complexity of neural representations across the ventral stream. *Journal of Neuroscience, 35*(27), 10005-10014. doi: https://doi.org/10.1523/JNEUROSCI.5023-14.2015
7. Hamblin, A., Wordsworth, S., Fermont, J. M., ... Schuh, A. (2017). *Clinical applicability and cost of a 46-gene panel for genomic analysis of solid tumours: retrospective validation and prospective audit in the UK National Health Service.* doi: https://doi.org/10.1371/journal.pmed.1002230
8. Khaligh-Razavi, S. M., & Kriegeskorte, N. (2014). Deep supervised, but not unsupervised, models may explain IT cortical representation. *Plos Computational Biology.* doi: https://doi.org/10.1371/journal.pcbi.1003915
9. Laskov, P., & Srndic, N. (2014). *Practical evasion of a learning-based classifier: A case study.* Retrieved from https://personal.utdallas.edu/~muratk/courses/dmsec_files/srndic-laskov-sp2014.pdf
10. Monzon, F. A., Medeiros, F., Lyons-Weiler, M., & Henner, W. D. (2010). Identification of tissue of origin in carcinoma of unknown primary with a microarray-based gene expression test. *Diagnostic Pathology, 5*(3). doi: https://doi.org/10.1186/1746-1596-5-3
11. Nguyen, A., Yosinski, J., & Clune, J. (2016). *Multifaceted feature visualization: Uncovering the different types of features learned by each neuron in deep neural networks.* Retrieved from https://arxiv.org/abs/1602.03616
12. Pei, K., Cao, Y., Yang, J., & Suman J. (2017). *DeepXplore: Automated Whitebox Testing of Deep Learning Systems.* Retrieved from http://www.cs.columbia.edu/~junfeng/papers/deepxplore-sosp17.pdf
13. Pencheva, I., Esteve, M., & Jankin Mikhaylov, S. (2018). Big Data and AI-A transformational shift for government: So, what next for research? *Public Policy and Administration, 35*(1), 24-44. doi: https://doi.org/10.1177%2F0952076718780537
14. Simonyan, K., & , A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv,* 1409.1556 Retrieved from https://arxiv.org/abs/1409.1556v6
15. Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly, 36*(2), 368-383. doi: https://doi.org/10.1016/j.giq.2018.09.008
16. Thierer, A., Castillo, A., & Russell, R. (2017). *Artificial intelligence and public policy.* Retrieved from https://www.mercatus.org/system/files/thierer-artificial-intelligence-policy-mr-mercatus-v1.pdf
17. Valle-Cruz, D. (2019). Public value of e-government services through emerging technologies. *International Journal of Public Sector Management*, *32*(5). doi: https://doi.org/10.1108/IJPSM-03-2018-0072
18. Yosinski, J., Clune, J., Nguyen, A., Fuchs, T., & Lipson, H. (2015). Understanding neural networks through deep visualization. *arXiv,* 1506.06579. Retrieved from https://arxiv.org/abs/1506.06579

Received 19.02.2020
Received in revised form 20.03.2020
Accepted 26.03.2020
Available online 4.06.2020