Neural Network Model for the Multiple Factor Analysis of Economic Efficiency of an Enterprise

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Abstract. The paper proposes a neural network model for assessing the impact of financial instruments and organizational forms on the growth of efficiency within the industry based on the case study of such a high-technology company as the Rosatom State Atomic Energy Corporation. A large holding that is a monopoly state corporation (Rosatom SC) manages more than 300 large enterprises which it owns (either fully or partially, through joint ventures, such as JSCs), or controls directly, such as FSUEs (Federal state unitary enterprises) and FSBIs (Federal state budgetary institutions). Objective: To explain the degree of impact of financial instruments and their groups on the overall economic efficiency using a non-recurrent neural network-based analysis, and to build a neural network-based profit generation model. The main criterion for the economic efficiency of the head enterprise of Rosatom group is its combined profit for the year. Since 2007, Rosatom group has used EBITDA as the main indicator of the company's performance. The Rosatom's order portfolio exceeds \$133 billion, which is 67% of the global nuclear power plant construction market. The present paper suggests a methodology for evaluating the economic efficiency of existing organizational forms, financial instruments and support institutions for Rosatom. The paper proposes an algorithm for building a neural network model for evaluating an enterprise's efficiency.

Keywords: Neural network model · Algorithm · Artificial intelligence · Multiple factor analysis

1 Introduction

We will assess the performance of Rosatom group companies and evaluate what factors and financial instruments have influenced the growth of the holding's economic efficiency. To do this, we propose a method for evaluating the economic efficiency of an enterprise.

The methodology for evaluating the economic efficiency of an enterprise involves the following aspects:

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1. **Formalization of the efficiency measure.** At this stage, the form and type of efficiency measurement are determined. The form of measurement should be determined by a mathematical formula that expresses the ratio of positive and negative aspects of the evaluated parameter. Let us suggest a formula for calculating technological efficiency. Technological efficiency can be measured by such indicators as 1) the number of patents; 2) economic impact of the introduction of new technology that reflects the positive aspect of this parameter and 3) R&D costs, 4) technology introduction costs and 5) organizational costs that reflect the negative aspect of this parameter. Let us derive the ratio of these indicators, which will characterize the measure of technological efficiency (TE).

$$TE = \frac{\text{number of patents} \times \frac{\text{economic impact of the introduction}}{number\ of\ introductions}}{\text{R\& D costs} + \text{introduction costs} + \text{organizational costs}} \quad (1)$$

   To measure economic performance, specialists often use such indicators as EBITA and EBITDA that exclude the tax and political components as well as depreciation and amortisation.
2. **Formalization of evaluation components.** At the next stage, we need to formalize the components of the evaluation by determining their type, data sources, and, if necessary, methods of normalization and reduction to a unified scale.
3. **Deductive analysis. Building a tree of components and factors.** At this stage, the process of forming the evaluation factor is deduced to the level of finite elements related to organizational forms, financial instruments and support institutions, after which a deductive tree is constructed.
4. **Formalization of the deductive tree of components.** After building a deductive tree, it is necessary to formalize all its components including formula descriptions and group allocation with respect to organizational forms and financial instruments, as well as to determine the sources, types, and completeness of data along with methods of its normalization and reduction to a unified economic scale.
5. **Collection and normalization of data.** At the fifth stage, it is necessary to obtain the requisite data and verify its reliability with the eventual application of significance coefficients, and then normalize it to reach a unified economic scale, e. g. XDR in the case of monetary funds, or another generally accepted measure in other cases.
6. **The choice and construction of the model.** At the next stage, depending on the volume of data (sample size), preferred deviations (absolute or relative), and established methodologies, it is necessary to select and apply a standardized method for building a linear statistical, variance-analytical, or neural mathematical model. The selection stage is followed by a formal mathematical description of the model, including all its components, dependencies and constraints of its organizational structures and parameters.
7. **Selection of optimization criteria.** In this case, one of three typical criteria is selected: Bayesian (the smallest integral of the difference between

model results and empirical data), Fischer's (the highest frequency of agreement between model results and empirical data), or the Neyman-Pearson approach, which determines the minimum MSE (mean square error).

8. **Calculation of the optimal coefficients of the model.** Depending on the selected criterion, we determine the optimal coefficients for the equation described in paragraph 6, using the gradient Newton method, or combined stochastic gradient methods (Newtonian Monte Carlo).
9. **Empirical testing of the model quality.** After determining the optimal coefficients, we wait for further results, check them, and, if necessary, adjust the model.

2 Objective Setting. Neural Network Model for the Multiple Factor Analysis of Economic Efficiency of an Enterprise

While applying neural network modelling as a method of the multiple factor analysis of an enterprise's economic efficiency, it is necessary to define some key issues related to the characteristics of the factors under study:

- To determine the network architecture, it is necessary to know exactly the number of groups and subgroups, the factors under study, and their cross-impact structure. All the factors used must be strictly formalized, and the cross-impact must be represented in the form of a tree structure.
- There are factors of economic inertia. It is necessary to determine the possibility of the autocorrelation of the actual performance indicators analyzed. If the presence of autocorrelation or inertia is determined explicitly or at least partially, an autocorrelation branch must be added to the generated structure.
- It is necessary to account for the eventual impact of the studied factors on the ultimate efficiency value in cases where their weights differ significantly and play various roles in shaping the final result. In this case, it is necessary to determine the boundary values of the output coefficients related to these factors of neurons, in order to avoid their unjustified increase for factors that actually make a small contribution, but have a good correlation with the resulting efficiency value.
- If the natural fluctuations of the resulting value are inconsiderable, and there are no significantly correlating factors, instead of taking the actual normalized values of the initial factors as the initial analytical data, it is recommended to use their differentials, which will increase the sensitivity of the network not so much to the measure of the standard deviation, but to the general direction of growth or decline in economic efficiency.
- Another important step is to choose a technique for evaluating the quality of the trained network, both for overfitting and for compliance of the network model dynamics with the dynamics of real performance data. In some cases, it is necessary to introduce additional estimates that correspond to both the degree of

overfitting based on the assumed mean values and the degree of Bayesian likelihood. For a common evaluation of the network quality, we will use a generalized parameter that is the product of the standard deviation by the sum of differences between the differentials of the model and real data [1–3].

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As an example, let us consider the generation of an analytical neural model of economic efficiency for a real enterprise.

As input data, let us take an enterprise whose economic efficiency is presumably influenced by two groups of factors, two factors in each. It is understood that the enterprise is profitable and invests a part of its profit in its own fixed and intangible assets, which means it has economic inertia. To construct a simple non-recurrent convolutional network, we define a tree structure of cross-impact of efficiency elements for the two-year depth of impact (see Fig. 1)

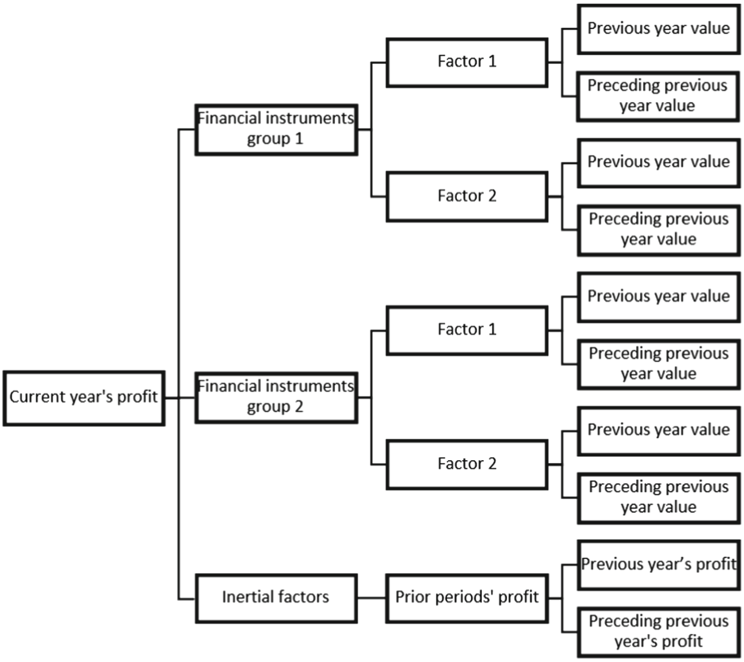

Fig. 1. Hierarchy of the system.

Having this structure, we can define the architecture of the neural network (see Fig. 2).

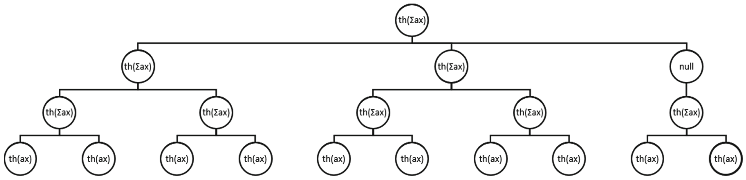

Fig. 2. Structure of the neural network.

Next, having the complete structure of the neural network, we formalize the calculation of the economic efficiency function, expressed as the current year's profit:

$$E = a\sum\nolimits_{g=1}^{g} a_g \,\mathrm{th} \sum\nolimits_{s=1}^{s} a_s \,\mathrm{th}\, a_n x, \tag{2}$$

where

E — output of neural network (current year's profit);
a — coefficient for the highest level neuron;
a_g — coefficients of the second level neurons;
a_s — coefficients of the third level neurons;
a_n — coefficients of neurons of the subsequent levels;
th — activation function of neural network th $= \frac{e^x - e^{-x}}{e^x + e^{-x}}$.

As an optimization criterion for this network, we select a generalized indicator of the form:

$$\text{Total network error} \qquad (S) = MSE * \sum\nolimits_{x=x_1}^{x_n} \left| \frac{sy_m}{dx} - \frac{dy_d}{dx} \right|, \tag{3}$$

where $\frac{dy_d}{dx}$ — the differential for the output parameter (d) of the neural network;
$\frac{dy_m}{dx}$ — the differential for the input parameter (m) of the neural network;
MSE — mean square error of the neural network at time t;

The total error of the neural network (S) is a parameter of neural network optimization that needs to be minimized.

If the difference of derivatives $\frac{dy_m}{dx} - \frac{dy_d}{dx}$ is close to one, then the total network error (S) will tend to the value of the stand-ard error (MSE). Therefore, the greater the difference between the derived input and output parameters of the neural network, the smaller should be the coefficient of impact of the network's input parameter on the output of the network. Conversely, the smaller the difference between the derivatives of the input and output parameters of a neural network, the greater the coefficient of impact of the input parameter of the network on the output parameter of the network [6,7].

When optimizing the total network error to a minimum, using any of conventional methods, we get a trained neural network, the weights of coefficients in which are distributed according to the degree of impact of factors and their groups on the final economic efficiency [8,9]. However, it should be borne in mind that insignificant factors may have a good correlation with the output data and therefore artificially limit the output coefficients of neurons as and ag according to the assumed share of the factor' contribution to the final result (usually 3–5 times the weight).

3 Development of a Neural Network Model for the Multiple Factor Analysis of Economic Efficiency Based on a Case Study of Rosatom

Let us propose an algorithm for building a neural network model for evaluating an enterprise's efficiency:

- Objective statement. We define the input and output elements of the system to build a model of financial flows representing the movement of finance from input to output.
- Grouping elements by factors. For instance, an enterprise's financial instruments influencing its economic efficiency can be divided into two groups: financial instruments related to joint-stock ownership (JSC) and financial instruments related to state ownership (federal state unitary enterprise).
- Analysis of the hierarchy of factors influencing economic efficiency.
- Collecting raw information from public sources.
- Creating a neural network based on a grouped tree. Development of a mathematical model.
- Determination of optimal model coefficients.
- Estimation and interpretation of the network coefficient values.

Objective Statement. To explain the degree of impact of financial instruments and their groups on the overall economic efficiency of the enterprise using a non-recurrent neural net-work-based analysis, and to build a neural network-based profit generation model. The main criterion for the economic efficiency of the head enterprise of Rosatom group is its combined profit for the year (EBITDA). Thus, the output elements of the system are the EBITDA data for 2007–2018. The collected data is formalized, cleared of inflation, and brought to XDR to ensure a unified measurement scale. As input elements, we will use three financial indicators that affect the enterprise's total profit (EBITDA), such as a) subsidies; b) loans; c) security issue.

Grouping Elements by Factors. Let us describe the component tree. The component tree consists of three levels. At the first level, we highlight one component — the EBITDA performance indicator. At the second level, we distinguish two components (organizational forms of incorporation):

- federal ownership (Rosatom SC, as well as FSUEs and FSBIs affiliated with Rosatom);
- collective (joint-stock) ownership (JSCs affiliated with Rosatom).

At the third level, we allocate three components (three financial instruments): a) instruments of state influence (subsidies); b) lending; c) issue of securities.

Each of these instruments can be related to both federal and joint-stock forms of ownership.

The general model of the problem can be described as finding the relationship between the profitability of the enterprise and each of the independent groups (organizational forms), as well as subgroups in each group (financial instruments).

Analysis of the Hierarchy of Factors Influencing Economic Efficiency. Let us build a hierarchy diagram of the impact of financial instruments on the enterprise's profit (see Fig. 3).

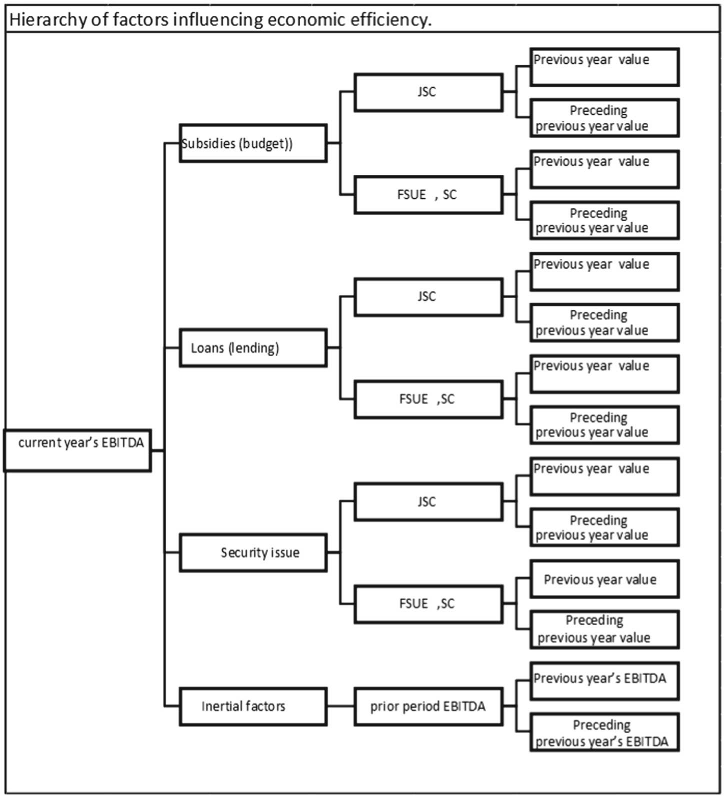

Fig. 3. Hierarchy of factors.

Collecting Raw Information From Open Sources. Data for building the model are obtained from official public sources. Data on subsidies received by Rosatom in the period 2007–2018 were taken from the website of the Ministry of Finance of the Russian Federation.

Since Rosatom group incorporates more than 360 enterprises including nuclear weapons enterprises, research establishments, and the nuclear icebreaker fleet, we classify these enterprises by sector. Table 1 shows data on subsidies for 2017.

Table 1. Subsidies received by Rosatom holding in 2017.

Rosatom holding enterprises	Form of ownership	bln rubles
Rosatom	Federal	2.883644
Operation	Federal	0.25
Supervision	Federal	4,841428
Export	Federal	7,107074
Operation	Federal	3,608192
R&D	Federal	0
R&D	Federal	1,64655
Operation	Joint-stock	0.0668
R&D	Joint-stock	1.3187
Production	Joint-stock	0
Operation	Joint-stock	0
Production	Joint-stock	0
Operation	Joint-stock	0
Operation	Joint-stock	6,039757

Table 2 presents aggregated data on subsidies to enterprises of the Rosatom holding for the years 2007–2018.

Table 3 shows data on the issue of bonds of Rosatom group.

After collecting, processing, and summarizing data from public sources, the in-formation for each of the model elements is expressed in XDR. Thus, we reduce the impact of fluctuations and plummeting of exchange rates. Table 4 shows con-solidated indicators for building the model, expressed in XDR.

Development of Mathematical Model. Since the numbers of groups of ownership forms and subgroups of financial instruments are clearly defined, this problem can be solved using a convolutional neural network [10]. In this case, the coefficients of convolutional neurons will correspond to the efficiency weights of groups of ownership forms and subgroups of financial instruments (see Fig. 4).

Determination of Optimal Model Coefficients. Table 5 shows the results of the neural network. The neural network selects coefficients that determine the degree of impact of financial instruments on the company's profit.

Table 2. Subsidies for Rosatom.

	Subsidies for joint-stock companies of Rosatom group (bln rub)	Subsidies for federal enterprises of Rosatom group (bln rub)
2007	7,425257	20,336888
2008	60,0267	109,719681
2009	66,800266	185,730887
2010	8,294913	167,364135
2011	34,67569	161,36264
2012	7,808726	196,333049
2013	7,265003	168,561916
2014	1,748965	161,36407
2015	5,016797	195,062353
2016	16,288606	95,747481
2017	15,821427	91,394533
2018	3,790242	111,973298

Table 3. Issue of bonds of Rosatom State Corporation.

Date	Amount, bln rub	Rosatom holding enterprises	Form of ownership
May 2007	1.5	Atomstroyexport	JSC
November 2009	30	Atomenergoprom	JSC
November 2009	30	Atomenergoprom	JSC
November 2009	5	Atomenergoprom	JSC
August 2010	10	Atomenergoprom	JSC
November 2011	12.5	Atomredmetzoloto	JSC
December 2011	16.5	Atomredmetzoloto	JSC
August 2013	12.5	Atomredmetzoloto	JSC
July 2015	15	Rosatom SC	FED
July 2015	10	Atomenergoprom	JSC
July 2015	10	Atomenergoprom	JSC
December 2015	10	Atomenergoprom	JSC
December 2015	10	Atomenergoprom	JSC
November 2016	15	Atomenergoprom	JSC
December 2016	15	Atomenergoprom	JSC

Table 4. Summary data for the model.

	Financial instruments						Profit
Year	JSC subsidies	FED subsidies	JSC issue	FED issue	JSC loans	FED loans	EBITDA
2007	0,192	0,524	0,039	0	1,140	0	2,69
2008	1,313	2,399	0	0	0	0	2,6
2009	1,407	3,913	1,369	0	0	0	2,87
2010	0,178	3,582	0,214	0	0	0	3,87
2011	0,704	3,275	0,589	0	13,099	0	3,24
2012	0,167	4,193	0	0	0	0	3,01
2013	0,144	3,333	0,247	0	7,403	0,316	3,07
2014	0,021	1,98	0	0	4,522	4,908	2,46
2015	0,05	1,927	0,39	0,15	18,2	0,079	2,4
2016	0,20	1,178	0,369	0	20,1	0	3,21
2017	0,193	1,117	0	0	25,86	0,789	3,74
2018	0,039	1,159	0	0	3,33	0	3,65

Table 5. Calculation of neural network coefficients.

Neurons	Output neuron	JSC input	Joint-stock ownership			FED input	Federal ownership			
			Subsidies	Issue	Loans		Subsi	Issue	Loans	
Network Coeff	6.64	1,31	8,42	0,6	0,0	0,7	0,02	41,19	1,8	Preced, Previous year
	77.7	55,82	13,4	0,0	0,0	20,6	0,0	0,002	0,0	Previous Year

Table 6. Interpretation of neural network coefficients.

Neurons	Output neuron	JSC in	Joint-stock ownership			FED input	Federal ownership			
			Subsidies	Issue	Loans		Subsidies	Issue	Loans	
Network coeff	6,64	67%	93%	7%	0%	33%	0,04%	95,73%	4,24%	Preced previous year (2017)
	77.7	73%	100%	0,0%	0%	27%	0,0%	100,0%	0%	Previous year (2018)

Estimation and Interpretation of Neural Network Coefficient Values. To interpret the coefficients of the neural network, we express them as a percentage. Table 6 provides the network's estimated coefficients as a percentage.

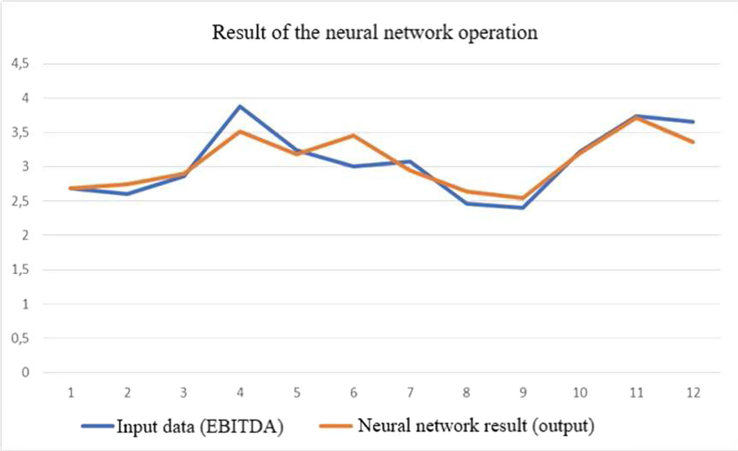

Fig. 4. Output of neural network.

4 Conclusion

The results showed that in 2018, the group of financial instruments of joint-stock enterprises of Rosatom group affected the holding's profit (EBITDA) to a degree of 73%, while the degree of impact of financial instruments of federal enterprises of the holding equalled to 27%. Hence, it may be noted that financial instruments (subsidies, loans, issue of securities) allocated to joint-stock companies of the Rosatom group had a greater impact on the profit of the group compared to financial instruments allocated to federal enterprises of Rosatom group. The same results were obtained when we evaluated the impact of financial instruments on the profit of Rosatom group for the year 2017.

Let us consider which financial instruments have the greatest impact on the company's total profit (EBITDA). The evaluation of financial instruments of joint-stock enterprises showed that the greatest contribution (impact) to the profit of Rosatom group is made by subsidies. The degree of impact of subsidies in the financial instruments group comprised 93% in the year 2017 and 100% in the year 2018. Thus, we can conclude that subsidies from the federal budget granted to joint-stock companies of Rosatom group make the greatest impact on the total profit (EBITDA) of Rosatom State Corporation.

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