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Analysis of efficiency factors of companies in Serbia based on artificial neural networks

Анализа фактора ефикасности предузећа у Србији на бази вештачких неуронских мрежа

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Abstract: This paper investigates the influence of certain factors on the efficiency of companies in Serbia using artificial neural networks. According to the results of empirical research using artificial neural networks, the significance of some observed factors on the efficiency of companies in Serbia is as follows: net profit 55.5%, operating revenues 59.4%, operating assets 52.8%, capital 59.6 %, loss 100% and number of employees 51.3%. In order to improve the efficiency of companies in Serbia in the future, it is necessary, in the first place, to manage profits as efficiently as possible (i.e. to reduce losses as much as possible). This is also achieved with the most efficient management of sales, assets, capital and human resources (training, rewarding, job advancement, and flexible employment). Accelerated digitalization of the entire business certainly plays a significant role in that.

Keywords: efficiency, factors, artificial neural networks, Serbian companies
JEL classification: L81, M31, M41, O32

Сажетак: У овом раду се истражује утицај појединих фактора на ефикасност предузећа у Србији коришћењем вечтачких неуронских мрежа. Према добијеним резултатима емпиријског истраживања коришћењем вештачких неуронских мрежа значај појединих посматраних фактора на ефикасност предузећа у Србији је следећи: нето добитак 55.5%, пословни приходи 59.4%, пословна имовина 52.8%, капитал 59.6%, губитак 100% и број запослених 51.3%. У циљу побољшања ефикасности предузећа у Србији у будућности неопходно је, на првом месту, што ефикасније управљати профитом (тј. у што већој мери смањити губитак). То се постиже, исто тако, и са што ефикаснијим управљањем продајом, активом, капиталом и људским ресурсама (тренинг, награђивање, напредовање на послу, флексибилно И запошљавање). Значајну улогу у томе има свакако и убрзана дигитализација целокупног пословања.

Кључне речи: ефикасност, фактори, вештачке неуронске мреже, предузећа Србије
ЈЕЛ класификација: L81, M31, M41, O32

Introduction

In principle, the problem of researching the efficiency of companies based on artificial neural networks is very challenging (Rezaei et al., 2019; Sustrova, 2016; Machovál & Vochozkal, 2019; Wanchoo, 2019; Sabau-Popa etal., 2021; Hafez etal., 2021). With this in mind, the subject of research in this paper are the efficiency factors of companies in Serbia using artificial neural networks. The goal and purpose of this is to investigate this issue as comprehensively as possible in order to improve the efficiency of companies in Serbia through better control of key factors and the implementation of relevant measures.

The research of the problem treated in this paper is based on the hypothesis that the basic premise for improving the efficiency of companies (in this case in Serbia) is knowledge of critical factors (net profit, business revenues, business assets, capital, loss and number of employees) and their better control, as well as effective control of relevant measures taken in that direction. The given critical factors were chosen because, in our opinion, they determine the efficiency and financial performance of the company well. Input elements are: when measuring efficiency, number of employees, business assets, capital and output elements are: business revenues, loss and net profit.

The use of artificial neural networks plays a significant role in this. Artificial neural networks make it possible to see the impact of critical factors (net profit, business revenues, business assets, capital, loss and number of employees) on the success of a company's business. Their knowledge is a prerequisite for improving the business performance of companies through more efficient control. For these reasons, they are used in this paper.

The research of enterprise efficiency factors in Serbia using artificial neural networks is based on original empirical data for 25 companies from different sectors (5 companies each from the sectors: manufacturing, construction, wholesale and retail trade, J-Information and communication and public companies) collected from the Agency for Business Registers of the Republic of Serbia. The data are in line with relevant international standards and there are no limitations in terms of comparability at the domestic and international level.

1.Theoretical background

The As is well known, the literature dedicated to the assessment of the efficiency of companies based on artificial neural networks is becoming richer (Abiodun etal., 2018; Azarnoush & Arash, 2016; Beer etal., 2020; Gao et al., 2009; Hafez etal., 2021; Hasti etal., 2015; Liu, 2015; Huang etal., 2020; Lantz, 2019; Hütsch, 2021; Penpece & Elma, 2014; Sihem & Younes, 2017; Zhou & Gumbo, 2021, Shalev-Schwartz & Ben-David, 2014). However, there are very few, almost no complete works, as far as we know, dedicated to the analysis of the efficiency of companies in Serbia using artificial neural networks. This gap should be filled to some extent by this paper, and in particular, among other things, its scientific and professional contribution is reflected in it. Research through the literature in this paper, especially on the application of artificial neural networks in economics, serves as a theoretical, methodological and empirical basis for the analysis of the problem treated in this paper.

Motivations for adopting an artificial neural network include its flexibility in increasingly complex data structures, in creating extraordinary in conditions of sufficiently missing data, multicollinearity, and nonlinearity (Merkel etal., 2018). The advantage of artificial neural networks lies in their versatility, because they can be applied to almost any learning task (Leo etal., 2019). Numerous examples of successful practical application of artificial neural networks have been presented in the literature (Croda etal., 2019; Strandberg & Alas, 2019; Droomer & Bekker, 2020; Penpece & Elma, 2014).

2. Research methodology

The research methodology of the treated problem in this paper is based on artificial neural networks. In mathematical form, artificial neural networks can be expressed as:

$$O = \sum_{i=1}^{n} w_i x_i + b \qquad (1)$$

wherein x_i i – input-layer of the artificial neural network, w_i – weight i-th inputs, n – the number of inputs, a – bias term and O – output layer.

The following types of neural networks are used in the experiment: single-layer Perceptron, multilayer Perceptron, Feed Forward Backpropagation neural network and Radial Basis Function Network.

3. Research results

A **multilayer Perceptron** (MLP), known as a multilayer transmission network, was used in this study (Lantz, 2019). The paper uses artificial neural networks to investigate the impact of the following factors on the efficiency of companies in Serbia, namely: net profit, operating revenues, operating assets, capital, loss and number of employees. Their efficiency control can certainly significantly affect the achievement of the target efficiency of companies in Serbia. Table 1 shows the initial data for 2019.

Table 1. Initial data

	Net profit VAR00001	Business revenues VAR00002	Business assets VAR00003	Capital VAR00004	Loss VAR00005	Number of employees VAR00006	Efficiency* VAR00007
TIGAR TYRES DOO PIROT	9.025	103.463	52.604	12.322	0	3.530	1.00
PHILIP MORRIS OPERATIONS AD NIŠ	4.659	22.598	24.408	15.997	0	575	1.00
AD IMLEK PADINSKA SKELA	4.380	21.246	45.408	8.633	5.940	935	1.00
HEMOFARM AD VRŠAC	3.979	35.899	48.841	34.906	0	2.666	1.00
COCA-COLA HBC-SRBIJA DOO ZEMUN	3.642	33.035	49.658	40.798	0	837	1.00
PREDUZEĆE IVAN MILUTINOVIĆ - PIM AD BEOGRAD	3.867	119	1.339	813	8.488	180	1.00
IDC DOO BEOGRAD	3.087	78.206	3.077	3.077	10	643	1.00
Beograd na Vodi	1.840	10.784	6.967	6.967	2.657	71	1.00

DOO Beograd							
INCOP Doo Čuprija	1.763	4.890	1.803	1.803	0	78	1.00
OAO Beltruboprovodstvoj ogranak Beograd	1.710	6.413	1.710	1.710	0	142	1.00
DELHAIZE SERBIA DOO BEOGRAD	5.175	104.869	86.264	58.851	0	12.579	1.00
JT INTERNATIONAL AD SENTA	1.918	19.271	15.275	4.374	4.056	282	1.00
AGROMARKET DOO KRAGUJEVAC	1.811	16.986	23.751	15.030	0	417	1.00
JUGOIMPORT-SDPR JP BEOGRAD	1.782	19.526	48.757	19.865	0	373	1.00
SPORT VISION DOO BEOGRAD	1.531	11.949	11.368	6.699	0	1.223	1.00
TELENOR DOO BEOGRAD	10.526	45.294	43.191	32.279	0	672	1.00
TELEKOM SRBIJA AD BEOGRAD	3.477	86.230	324.079	145.159	0	6.767	1.00
VIP MOBILE DOO BEOGRAD	3.381	33.496	50.283	0	60.416	1.151	.00
SBB DOO BEOGRAD	3.319	27.784	64.757	20.856	22.621	1.624	1.00
PRVA TELEVIZIJA DOO BEOGRAD	1.076	5.063	6.318	1.920	0	207	1.00
JP SRBIJAGAS NOVI SAD	4.772	91.487	202.556	118.797	0	1.021	1.00
JKP BEOGRADSKE ELEKTRANE BEOGRAD	4.018	28.770	57.886	42.459	298	2.004	.00
JP EPS BEOGRAD	3.662	279.637	973.624	674.555	119.720	24.966	.00
JP POŠTA SRBIJE BEOGRAD	1.932	25.291	30.505	24.638	0	14.922	1.00
JUGOIMPORT-SDPR JP BEOGRAD	1.782	19.526	48.757	19.865	0	373	1.00

Note: The data are expressed in millions of dinars (employees as an integer).
* The authors' assessment (efficiency is marked with the number 1.00, and inefficiency with the number .00. Companies with losses are treated as inefficient).

Source: Agency for Business Registers of the Republic of Serbia

When determining the significance of independent variables (i.e. efficiency factors of companies in Serbia) based on artificial neural networks, a **multilayer perceptron networks** was used, as already mentioned. The calculation was performed using the SPSS software program. The obtained results are shown in Table 2 - 7, and annex 1, as well as in Figures 1-4.

```
EXECUTE.
* Multilayer Perceptron Network.
MLP VAR00007 (MLEVEL = N) BY VAR00001 VAR00002 VAR00003 VAR00004 VAR00005 VAR00006
  / PARTITION TRAINING = 7 TESTING = 3 HOLDOUT = 0
  / ARCHITECTURE AUTOMATIC = YES (MINUNITS = 1 MAXUNITS = 50)
  / CRITERIA TRAINING = BATCH OPTIMIZATION = SCALEDCONJUGATE LAMBDAINITIAL =
0.0000005
    SIGMAINITIAL = 0.00005 INTERVALCENTER = 0 INTERVALOFFSET = 0.5 MEMSIZE = 1000
  / PRINT CPS NETWORKINFO SUMMARY CLASSIFICATION SOLUTION IMPORTANCE
  / PLOT NETWORK ROC GAIN LIFT PREDICTED
  / STOPPINGRULES ERRORSTEPS = 1 (DATA = AUTO) TRAININGTIMER = ON (MAXTIME = 15)
MAXEPOCHS = AUTO
    ERRORCHANGE = 1.0E-4 ERRORRATIO = 0.001
/ MISSING USERMISSING = EXCLUDE.
```

Table 2. Case Processing Summary

Case Processing Summary			
		N	Percent
Sample	Training	20	95.2%
	Testing	1	4.8%
Valid		21	100.0%
Excluded		4	
Total		25	

Source: the authors' own research

Case processing summary shows the number of cases included and excluded in the analysis. In the specific case, out of 25 analysed, 4 companies were excluded in the data processing process. 20 companies were trained (95.2%), and 1 company was tested (4.8%).

Table 3. Network information

Network information			
Input layer	Factors	1	VAR00001
		2	VAR00002
		3	VAR00003
		4	VAR00004
		5	VAR00005
		6	VAR00006
	Number of units [a]		109
Hidden layer (s)	Number of hidden layers		1
	Number of units in hidden layer 1 [a]		7
	Activation function		Hyperbolic tangent
Output layer	Dependent variables	1	VAR00007

	Number of units	2
	Activation function	Softmax
	Error function	Cross-entropy
a. Excluding the bias unit		

Source: the authors' own research

Network information shows information about the neural network (Input layer, Hidden layer, Output layer). They are useful for ensuring that the specifications are correct. In the analysed case, there is only 1 hidden layer with 7 units.

Table 4. Model Summary

Model Summary		
Training	Cross entropy error	1.347E-5
	Percentage of incorrect predictions	0.0%
	Stopping rule used	Training error ratio criterion (.001) achieved
	Training time	0: 00: 00.01
Testing	Cross entropy error	8.546E-8
	Percentage of incorrect	0.0%
Dependent variable: VAR00007		

Source: the authors' own research

Model summary shows the percentage of incorrect predictions. In this case: the percentage of incorrect predictions is 0.0%.

(*Annex 1* shows the parameter estimates. The table parameter estimates primarily specify the weights and biases more precisely. In this case: the estimate of, say, parameter H (1: 7) in category 0.00 (inefficient) is .877 (87.7%) and in category 1.00 (efficient) -.96.4 (-96.4%). The accuracy is therefore at a satisfactory level.)

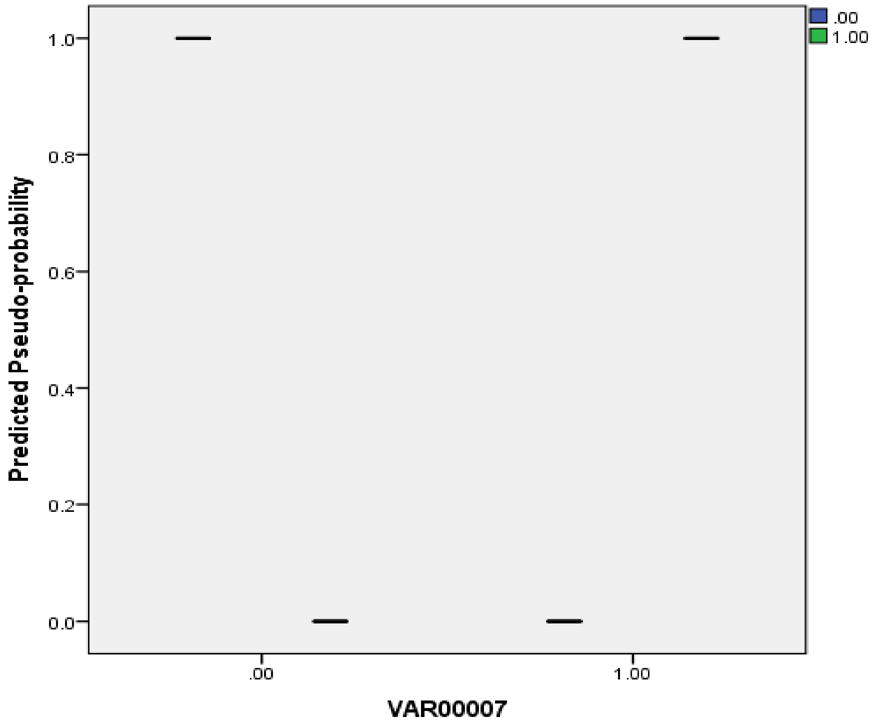
Table 5. Classification

Classification				
		Predicted		
Sample	Observed	.00	1.00	Percent correct
Training	.00	3	0	100.0%
	1.00	0	17	100.0%
	Overall percent	15.0%	85.0%	100.0%
Testing	.00	0	0	0.0%
	1.00	0	1	100.0%
	Overall percent	0.0%	100.0%	100.0%
Dependent variable: VAR00007				

Source: the authors' own research

The classification table shows the results of the use of neural networks. The values on the diagonal are correct and the predictions below are incorrect. Neural network performance is determined by generalizing missing as well as predicting unused data during network training. So, for example, 3 inefficient companies (15.0%) and 17 efficient companies (85.0%) were trained. Only 1 efficient company (100%) was tested. Insight into the field training sample and testing sample shows that all values are outside the diagonal 0, indicating 100% prediction accuracy. The conclusion is that the predictions are correct.

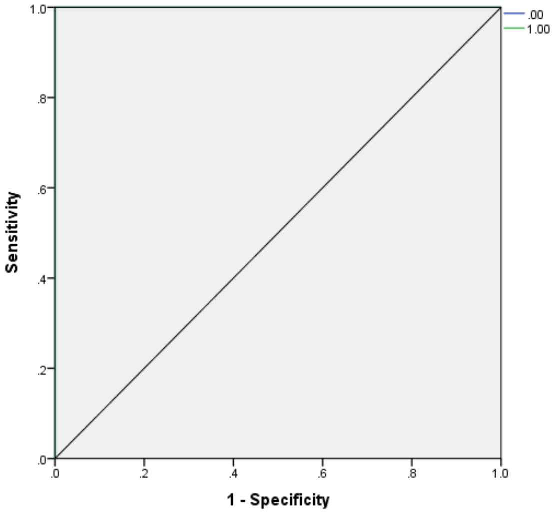
Figure 1. Predicted - observed chart



Source: the authors' image

The Predicted by observed chart shows the predicted values for each dependent variable. For categorical dependent variables, clustered boxplots of predicted pseudo probabilities are displayed for each response category, with the observed response category as the cluster variable. The scattering diagram is displayed for variable dependent variables.

Figure 2. ROC Curve



Source: the authors' image

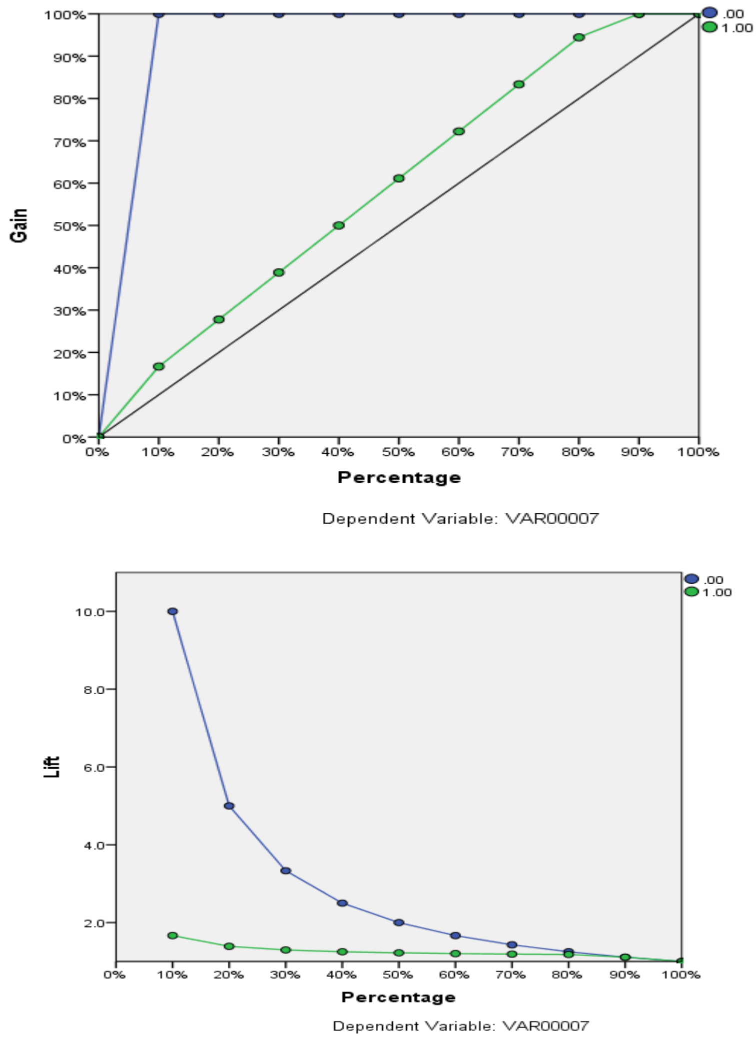
Table 6. Area under the curve

Area under the curve		
		Area
VAR00007	.00	1,000
	1.00	1,000

Source: the authors' own research

RCO (Receiver Operating Characteristic) is displayed for each category dependent variable. The table shows the area below each curve. The ROC curve chart reveals the percentage of "false" positives, i.e. efficient units. Thus, for example, in a specific case, at a point on the reference line with 20% of sensitive and 20% of specifics, 80% (100% - 20%) of inefficient units can be expected. The explanation is similar for other percentages (points) on the reference line.

Figure 3. Cumulative Gain and Lift



Source: the authors' image

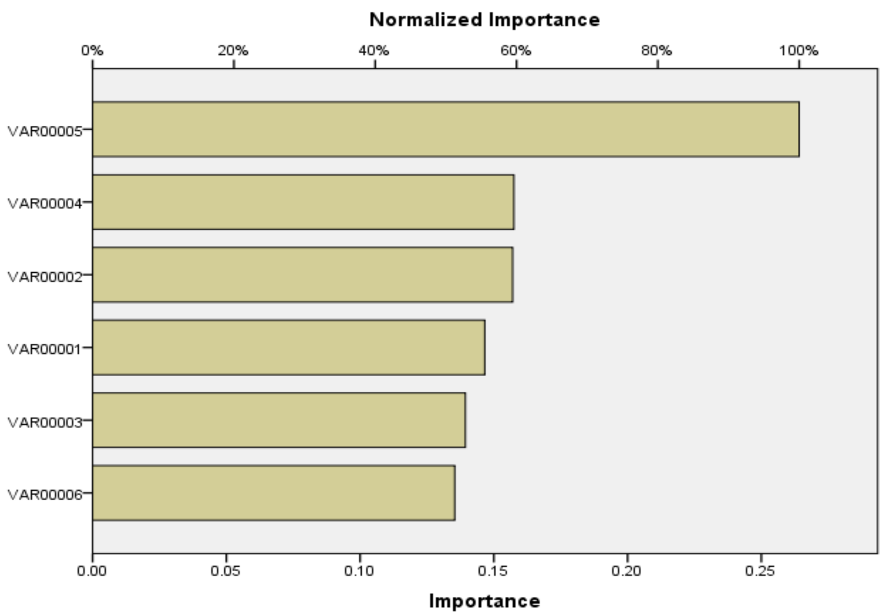
The cumulative gains chart shows the cumulative gains for each category-dependent variable. The lift chart shows the lift for each category dependent variable. They are used to assess the performance of the classification model, and supplement the RCO curve. Metrics are very popular in marketing analytics. They can be successfully used for risk modelling, supply chain analysis, to find the best predictive model among multiple challenger models, etc. Thus, for example, according to the presented chart of cumulative gain category 1.00 (efficient): for 10% of effective cases it can be (according to the probability test) expected to be approximately 20% ineffective; 50% of effective cases can be expected to be 60% ineffective; 90% of effective cases can be expected to be 100% ineffective; etc. The Lift chart is derived from the cumulative gain chart. Thus, for example, according to the presented chart for category 1.00 (effective) the ratio of cumulative gain for percentages of 10%, 40%, 90% is: 20/10% = 2; 50% / 40% = 1.25; 100% / 90% = 1.11; etc.

Table 7. Independent Variable Importance

	Independent Variable Importance		
		Importance	Normalized Importance
Net profit	VAR00001	.147	55.5%
Business revenues	VAR00002	.157	59.4%
Business assets	VAR00003	.139	52.8%
Capital	VAR00004	.157	59.6%
loss	VAR00005	.264	100.0%
Number of employees	VAR00006	.135	51.3%

Source: the authors' own research

Figure 4. Normalized Importance



Source: the authors' image

Normalized importance chat illustrates the importance of the analysed factors.

4. Discussion

According to the obtained results of empirical research using artificial neural networks, the importance of certain observed independent variables (factors), expressed as a percentage, for the efficiency of companies in Serbia is as follows: net profit 55.5%, operating revenues 59.4%, operating assets 52.8%, capital 59.6%, loss 100% and number of employees 51.3%.

In order to improve the efficiency of companies in Serbia in the future, it is necessary, primarily, to manage profits as efficiently as possible (i.e. to reduce losses as much as possible). This is also achieved with the most efficient management of sales, assets, capital and human resources (training, rewarding, job advancement, flexible employment, health and pension insurance). Accelerated digitalization of the entire business certainly plays a significant role in that.

Research in this paper has shown that artificial neural networks are excellent for determining the impact of certain factors on the efficiency of enterprises in Serbia. Because they enable the perception of complex connections between input and output elements. Considering that, in addition to other methods, artificial neural networks should be used in the analysis of company efficiency factors in Serbia.

Conclusion

Based on the obtained results of empirical research using artificial neural networks, it can be stated that the importance of certain observed factors (expressed as a percentage) on the efficiency of companies in Serbia is as follows: net profit 55.5%, operating revenues 59.4%, operating assets 52.8%, capital 59.6%, loss 100% and number of employees 51.3%.

All in all, in order to improve the efficiency of companies in Serbia in the future, it is necessary to manage profits as efficiently as possible (i.e. to reduce losses as much as possible). This is also achieved with the most efficient management of sales, assets, capital and human resources (training, rewarding, job advancement, flexible employment). In any case, the accelerated digitalization of the entire business has a significant role in that.

As far as the effects of the implication are concerned, we can say the following: research in this paper has clearly shown that the very effective application of artificial neural networks in identifying the strength of the influence of factors on the efficiency of enterprises in Serbia. Therefore, the use of artificial neural networks is recommended, especially in combination with other related statistical techniques and multicriteria decision-making methods.

When researching the efficiency factors of companies in Serbia using artificial neural networks, one should keep in mind the extent to which empirical data are accurate. In this respect, they certainly differ from one company to another "due to a certain haircut" from certain (for example, increasing profits to obtain a bank loan), despite the fact that relevant international standards are applied.

Generally speaking, the limiting factor of application in economics and management, in this case in the analysis of the efficiency factors of companies in Serbia, is still insufficient knowledge of the theoretical, methodological and empirical significance of artificial neural networks. In the future, thanks to a better knowledge of the essence, the importance of the application of artificial neural networks in general in economics and management in various research areas (for example, credit risk assessment) will become even more important.

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ANNEX

Annex 1. Parameter estimates

Parameter estimates										
		Predicted								
		Hidden layer 1							Output layer	
Predictor		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	[VAR00007=.00]	[VAR00007=1.00]
Input layer	(Bias)	.098	.583	.366	.791	-.501	.010	-.579		
	[VAR00001=1.08]	.145	.426	-.347	-.101	.169	-.072	-.122		
	[VAR00001=1.53]	.479	-.062	.401	.149	-.174	-.097	.016		
	[VAR00001=1.71]	-.305	.315	.406	.445	-.500	-.272	.211		
	[VAR00001=1.78]	.363	.135	.382	-.042	-.334	.036	-.438		
	[VAR00001=1.81]	.437	-.006	-.063	.433	.046	.422	.182		
	[VAR00001=1.84]	.195	.326	.443	-.081	.032	.329	.268		
	[VAR00001=1.92]	.360	.316	-.255	.047	.139	.156	-.469		
	[VAR00001=1.93]	-.216	.144	.519	.342	.013	.219	-.436		
	[VAR00001=3.09]	-.293	.071	.564	.610	.243	-.148	.145		
	[VAR00001=3.32]	.024	.282	.355	.386	.293	.160	-.352		
	[VAR00001=3.38]	.097	-.550	-.176	-.564	.051	-.311	.658		
	[VAR00001=3.48]	.134	.382	.519	.179	.243	-.393	.254		
	[VAR00001=3.64]	.345	-.111	.043	.548	.312	.126	.115		
	[VAR00001=3.66]	-.565	-.449	-.158	-.669	.017	-.115	.346		
	[VAR00001=3.98]	-.247	.132	-.231	.487	.217	-.363	.450		
	[VAR00001=4.02]	-.655	-.515	-.209	-.052	.621	.306	.402		
	[VAR00001=4.38]	-.062	.040	.494	.437	-.039	-.244	.394		
	[VAR00001=4.77]	-.154	.325	.409	.355	-.202	.081	.289		
	[VAR00001=5.18]	-.188	-.177	.088	.291	-.128	-.039	.082		
	[VAR00001=10.53]	.296	-.236	.309	.422	-.292	-.425	.336		
	[VAR00002=5.06]	-.436	.204	.235	.081	.061	-.152	-.482		
	[VAR00002=6.41]	.217	.511	-.161	-.266	-.390	.132	.280		
	[VAR00002=10.78]	.254	-.086	.503	.019	.258	-.361	-.326		

	[VAR00002=11.95]	.565	.054	.199	.439	.020	.273	.071		
	[VAR00002=16.99]	.347	-.074	.263	.332	-.035	-.304	-.209		
	[VAR00002=19.27]	.156	-.285	.282	-.239	-.274	-.185	-.506		
	[VAR00002=19.53]	.478	-.110	-.306	.026	-.501	-.251	-.109		
	[VAR00002=21.25]	.211	.231	.204	-.008	.015	-.214	-.345		
	[VAR00002=25.29]	.292	-.398	.085	-.315	.425	-.310	-.057		
	[VAR00002=27.78]	.247	.107	.461	.268	-.303	.290	-.308		
	[VAR00002=28.77]	-.139	.154	-.181	-.456	.308	.031	.137		
	[VAR00002=33.04]	-.024	-.040	-.070	.070	-.028	-.149	-.256		
	[VAR00002=33.50]	-.230	.198	-.137	-.731	.430	.191	.496		
	[VAR00002=35.90]	-.330	.352	.292	.336	.056	.438	.069		
	[VAR00002=45.29]	-.062	.326	-.406	.406	.413	.025	-.335		
	[VAR00002=78.21]	.290	-.330	.541	-.192	-.006	-.488	-.619		
	[VAR00002=86.23]	.489	.364	.302	.394	.284	.207	-.444		
	[VAR00002=91.49]	.354	.283	.226	.438	-.115	-.520	.349		
	[VAR00002=104.87]	-.048	-.408	.179	.434	-.414	.051	.184		
	[VAR00002=279.64]	.203	-.577	-.678	-.266	.845	.145	.643		
	[VAR00003=1.71]	-.261	-.111	-.288	-.043	-.247	.022	-.241		
	[VAR00003=3.08]	-.287	-.280	.010	.149	-.050	.281	-.075		
	[VAR00003=6.32]	.471	.092	.014	-.046	-.449	-.075	.151		
	[VAR00003=6.97]	.364	-.049	-.108	.592	.145	-.454	.201		
	[VAR00003=11.37]	.044	-.380	.458	.038	.373	.460	-.412		
	[VAR00003=15.28]	.167	-.140	.132	.092	-.088	-.243	-.154		
	[VAR00003=23.75]	-.366	-.102	.262	-.072	-.001	-.173	-.159		
	[VAR00003=30.51]	.159	.393	.477	-.143	.205	-.357	-.390		
	[VAR00003=43.19]	.065	-.328	.280	-.142	-.371	.330	.370		
	[VAR00003=45.41]	.029	-.022	.439	.391	-.033	-.406	.259		
	[VAR00003=48.76]	-.002	-.021	.524	-.171	-.092	.119	.058		
	[VAR00003=48.84]	.137	.061	-.084	.215	-.279	-.265	-.097		
	[VAR00003=49.66]	-.005	.483	-.232	.171	.369	-.054	-.217		

	[VAR00003=50.28]	-.446	-.434	-.003	.038	.665	.387	.269		
	[VAR00003=57.89]	-.189	-.339	-.070	-.663	.286	.313	.716		
	[VAR00003=64.76]	-.159	.536	-.066	-.033	.021	-.031	.207		
	[VAR00003=86.26]	.026	-.217	.163	.416	.244	.254	-.481		
	[VAR00003=202.56]	-.151	-.394	-.174	-.104	.312	.297	.207		
	[VAR00003=324.08]	-.251	.161	-.415	-.274	.397	-.319	.362		
	[VAR00003=973.62]	-.004	-.117	-.176	-.304	.598	.286	-.092		
	[VAR00004=.00]	-.526	-.266	-.208	-.591	.685	.298	.604		
	[VAR00004=1.71]	-.057	.211	-.321	.318	.236	.146	.397		
	[VAR00004=1.92]	.108	-.247	.336	-.029	-.074	.295	-.476		
	[VAR00004=3.08]	.643	.520	-.105	-.073	-.301	-.083	-.448		
	[VAR00004=4.37]	-.023	.039	-.263	.136	.025	-.277	-.052		
	[VAR00004=6.70]	-.409	.249	-.224	-.356	.341	-.238	.149		
	[VAR00004=6.97]	.119	-.189	.028	.202	.225	.113	-.511		
	[VAR00004=8.63]	-.098	-.307	-.089	-.076	-.468	-.442	-.179		
	[VAR00004=15.03]	.414	-.012	-.412	-.307	-.160	.456	.184		
	[VAR00004=19.87]	-.328	-.007	.458	.126	.002	-.291	.267		
	[VAR00004=20.86]	.561	-.311	-.144	.011	-.128	.002	.040		
	[VAR00004=24.64]	.468	-.284	.015	.341	-.514	.152	-.405		
	[VAR00004=32.28]	-.016	-.210	.466	.122	.324	.196	.114		
	[VAR00004=34.91]	-.226	.453	-.350	.101	.320	-.278	-.485		
	[VAR00004=40.80]	.250	.038	-.113	-.336	.018	.159	.118		
	[VAR00004=42.46]	.074	-.335	-.559	-.418	.683	.445	-.147		
	[VAR00004=58.85]	.214	.077	.084	.253	-.143	.234	-.277		
	[VAR00004=118.80]	.517	-.264	-.265	-.311	-.143	.296	.209		
	[VAR00004=145.16]	-.261	-.050	.182	.201	-.198	-.442	-.388		
	[VAR00004=674.56]	-.324	.092	-.554	-.475	.760	.305	.689		
	[VAR00005=.00]	.977	.767	.641	.469	-.984	-.498	-.745		
	[VAR00005=2.66]	.150	.584	-.069	.367	-.533	-.075	-.002		

	[VAR00005=4.06]	.637	.466	.667	.431	.029	-.336	.301		
	[VAR00005=5.94]	.442	.506	.166	-.157	.297	-.193	.211		
	[VAR00005=10.00]	.408	.089	-.081	.108	-.143	.418	.207		
	[VAR00005=22.62]	-.117	-.190	.331	.236	.084	-.012	-.438		
	[VAR00005=60.42]	-.357	-.505	.131	-.197	.282	.346	.095		
	[VAR00005=119.72]	-.491	-.233	-.475	-.633	.602	-.268	.009		
	[VAR00005=298.00]	.015	-.010	-.374	-.379	.183	-.117	.171		
	[VAR00006=1.02]	-.167	.075	-.374	.585	.035	-.021	.221		
	[VAR00006=1.15]	-.096	-.522	-.464	-.320	.482	-.095	.356		
	[VAR00006=1.22]	-.267	-.269	-.380	.370	.083	-.266	.318		
	[VAR00006=1.62]	.124	.069	.322	-.049	-.439	-.572	-.391		
	[VAR00006=2.00]	.028	-.330	-.162	-.475	.021	.034	.801		
	[VAR00006=2.67]	-.314	.065	.367	.019	-.485	-.356	.231		
	[VAR00006=6.77]	.269	.337	-.319	-.069	-.515	-.034	-.099		
	[VAR00006=12.58]	.222	.284	-.386	-.120	.023	-.051	.246		
	[VAR00006=14.92]	-.349	-.150	-.447	-.289	-.474	-.449	-.264		
	[VAR00006=24.97]	-.707	.044	-.578	-.080	.261	.300	.726		
	[VAR00006=71.00]	.187	.080	.021	-.029	.343	-.259	.072		
	[VAR00006=142.00]	-.305	-.113	.227	.192	.239	.099	-.457		
	[VAR00006=207.00]	.202	.402	-.188	.527	-.220	.189	.375		
	[VAR00006=282.00]	-.250	.097	-.316	.665	-.647	.000	-.110		
	[VAR00006=373.00]	-.375	.275	-.260	.060	.272	-.034	.222		
	[VAR00006=417.00]	.321	.468	.140	-.090	-.155	-.068	.214		
	[VAR00006=643.00]	.199	.292	.152	-.219	-.119	-.422	.029		
	[VAR00006=672.00]	.439	.202	.205	-.111	.020	.185	.358		
	[VAR00006=837.00]	-.093	-.172	-.081	-.146	-.498	.054	-.237		
	[VAR00006=935.00]	.019	.279	.233	-.327	-.508	-.069	-.421		
Hidden layer	(Bias)								-.802	.670
	H(1:1)								-.872	1.058

1	H(1:2)								-1.022	.862
	H(1:3)								-.775	.412
	H(1:4)								-2.865	2.338
	H(1:5)								.930	-1.420
	H(1:6)								1.658	-1.135
	H(1:7)								.877	-.964

Source: the authors' own research