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ASSESSING THE IMPACT OF THE NON-ECONOMIC FACTORS ON GDP PER CAPITA USING MLRA AND ANNs

Abstract. *This study presents the results of assessing the impact of non-economic factors: science and higher education (number of papers in IF journals, number of citations, number of citations per paper, number of universities on the ARWU list, number of most cited people in the top 500), and innovation index on GDP per capita in European countries, as well as Turkey and Israel, which are relatively close geographically and mentally. Multiple linear regression analysis (MLRA) and artificial neural networks (ANNs) were applied in which the measured value of GDP per capita was used as an output of the statistical process (dependent variable). The obtained results indicate that the elements of science and higher education quality significantly impact the size of GDP per capita in the considered countries.*

Keywords*: Science quality, Education quality, GII, GDP per capita, MLRA, ANNs.*

JEL Classification: C53

1. Introduction

Gross Domestic Product (GDP) per capita represents the total production of goods and services in the national economy (regardless of ownership) per capita (Todaro and Smith, 2011), and as such is one of the reliable indicators for the country's development (Tümer and Akkuş, 2018). It has been found that people's satisfaction with their quality of life is higher in countries with higher values of

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GDP per capita (Dipietro and Anoruo, 2006). Also, a significant correlation was found between GDP per capita and the size of the air quality index (AQI) (Živković and Panić, 2020a), CO_2 emissions (Kumar and Muhuri, 2019; Munir et al., 2020), SO_2 (Zhao et al., 2021), which directly affects human health (EU, 2008).

Higher education is in direct correlation with the development of science: there is no science without higher education, as well as quality higher education without quality science (Živković et al., 2017; Živković and Panić, 2020a). A significant correlation was found between the quality of primary education (results of the PISA test – Programme for International Student Assessment) and the quality of science (the results of the number of published papers and realized citations) (Živković and Panić, 2020a).

People with the highest educational and scientific competencies in a given country work in higher education and science (Lendel, 2010; Živković et al., 2017). Verification of the level of education and scientific achievement is measured by achieved scientific results: verified publications in leading scientific journals on the Clavirate Analytics list and in the SCOPUS database (Živković and Panić, 2020b). Published paper in a visible journal with impact factor (IF), gives the author the opportunity to verify the level of his scientific work, give the possibility for international cooperation (Živković and Panić, 2020a). A research paper that has not been published in a visible journal is practically non-existent. Based on the achieved scientific results, universities are ranked on the prestigious ARWU (Academic Ranking of World Universities) list (Docampo, 2013; Živković et al., 2017).

The development of the education system in a country, and especially higher education and science, depends on the attitude of the state administration towards these disciplines, whose role is the creation of human capital and the development of the country. Due to the attitude of the ruling elite in developing countries towards education and science as consumption, a low value of human potential is created, which affects the living standard of the majority to be low and the standard of the ruling minority to be high.

Developing countries, with low values of GDP per capita, are not able to cooperate on an equal footing with countries with high values of GDP per capita, due to the large difference in the level of knowledge. In order to achieve international cooperation of countries in transition economies with developed countries and to achieve an increase in GDP per capita, it is necessary to increase the knowledge and results of science in these countries (Živković and Panić, 2020a).

Mathematical modeling using MLRA and ANNs with significant statistical reliability allows the prediction of outputs to be performed on the basis of known inputs.

The subject of this study is the impact of non-economic parameters of higher education and science (number of published papers, number of citations, number of most cited researchers, number of universities on the ARWU list, and global innovation index) on GDP per capita using MLRA (Hanula et al., 2008; Arsić et al., 2020), and ANNs (Eberhart and Dobbins, 2002; Dreyfus, 2005; Hannula et al., 2008). The aim of this research is to examine the impact of the results of science and higher education on the most important indicator of economic growth of the country – GDP per capita. The subject of the study is the EU countries, the countries of the Western Balkans, Moldova, Ukraine, Belarus, and Russia, as well as Turkey and Israel, as areas with a similar mentality of people and historical tradition.

2. Research Methodology and Discussion of Results

To investigate the impact of non-economic parameters of science and education on the size of GDP per capita as a basic indicator of economic development of a country and quality of life using MLRA and ANNs, the following input parameters (predictors) were used: X_1 – Number of papers in IF journals per million inhabitants (2019); X_2 – Number of papers in IF journals per million inhabitants (1996–2019); X_3 – Number of citations per paper (2019); X_4 – Number of citations per paper (1996–2019) (http://scimagojr.com/countryrank.php); X_5 – Number of the top 500 quoted by areas (a total of 6,167 in the world) per million inhabitants (2019) (http://recognition.webofscience.com./awards/highly-cited/2020/); X_6 – Number of universities on ARWU list in the top 500 (2019) (http://schangairanking.com/ARWU2020.html); and X_7 – Global Innovation Index – GII (Score 0–100) (2019) (WIPO, 2020). GDP (nominal) per capita (10^3\$) is defined as the output parameter (Y) of the prediction model (http://en.wikipedia.org/wiki/List_of_Countries_by_GDP_(nominal)_per_capita). The analysis included available data for 42 countries. SPSS software package v.17.0 was used to process the collected data.

2.1. Modelling the Dependence of GDP per capita on Input Parameters (predictors) Using MLRA

Modelling the dependence of the size of GDP per capita (Y) on the mentioned input predictors (X_1–X_7) was first performed using MLRA. Linear regression (LR) refers to examining the relationship between two or more variables, using the same set of paired scores taken from the same subjects, with a focus on prediction. If two variables are in perfect correlation, then knowing the value of one variable allows predicting the results of another variable, i.e. the result of one variable can be used to predict the result of another variable (Ho, 2006).

In order for an MLRA to be implemented, certain requirements and assumptions must be met (Ho, 2006). The requirements are as follows: (a) for each subject in the study, there must be related pairs of scores, i.e. if a subject has a score on variable X, then the same subject also has a score on variable Y; (b) the variables should be measured at least at the ordinal level. In addition, the following assumptions must be met: linearity (the relationship between the two variables must be linear, ie the relationship can be more accurately represented by a straight line, and homoscedasticity (the variability of scores on the Y variable should remain constant at all values of the X variable).

As a result of the MLRA over the available data set, the following prediction equation was obtained:

$$Y = a + b_1X_1 + b_2X_2 + \cdots + b_nX_n$$

where Y represents the predicted dependent variable, a is the constant, b is the unstandardized regression coefficient, and X is the value of the predictor variable.

Table 1 shows the values of descriptive statistical analysis for all seven input parameters (X_1–X_7), as well as for the output parameter Y.

Table 1.Descriptive statistical analysis of the input and output parameters values of the model

Variable	Range	Minimum	Maximum	Mean	Std. Deviation	N
X_1	5625	143	5768	2284	1528.567	42
X_2	85925	1862	87787	32220.19	23125.806	42
X_3	0.86	0.38	1.24	0.8490	0.22066	42
X_4	24.10	6.82	30.92	16.5695	7.16766	42
X_5	19.52	0	19.52	3.0133	4.17870	42
X_6	2.85	0	2.85	0.5510	0.61297	42
X_7	38.94	27.12	66.06	44.6481	9.63969	42
Y	106.2	3.4	109.6	30.262	24.4385	42

In order to define the correlation dependence of the output parameter of the model (Y) as a function of the input parameters (X_1–X_7), bivariate correlation analysis was performed, and thus Pearson correlation coefficients with the appropriate degree of statistical significance were calculated (Table 2).

In order for the correlation to be considered significant, it is necessary for the Pearson correlation coefficients to be greater than 0.5. It can be seen from Table 2 that the values of this coefficient are very high in all cases, which indicates the existence of a very strong correlation between the observed variables, with a high level of reliability. In all cases, the statistical significance is very high ($p<0.01$), which created the conditions for the application of MLRA as an appropriate tool for modelling the dependence of GDP per capita as a function of the considered predictors (X_1–X_7) using the software package SPSS. Over 97% of randomly selected data from the initial database were used for the model training phase using MLRA, and the rest was used for the testing phase.

Table 2. Correlation matrix for inputs and output of the model

	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Y	1							
X_1	0.816**	1						
X_2	0.771**	0.958**	1					
X_3	0.796**	0.852**	0.820**	1				
X_4	0.755**	0.862**	0.919**	0.872**	1			
X_5	0.773**	0.834**	0.856**	0.740**	0.793**	1		
X_6	0.745**	0.783**	0.769**	0.767**	0.801**	0.617**	1	
X_7	0.796**	0.852**	0.897**	0.791**	0.887**	0.796**	0.656**	1

Note: ** Correlation is significant at the 0.01 level

The calculated linear dependence of the size of GDP per capita (Y) on the input parameters – predictors (X_1–X_7), obtained using MLRA, is shown using the following prediction equation:

$$Y = -47.485 + (0.007 \cdot X_1) - (0.001 \cdot X_2) + (22.14 \cdot X_3) - (1.07 \cdot X_4) + (2.21 \cdot X_5) + (16.52 \cdot X_6) + (1.55 \cdot X_7)$$

(R^2 = 0.818)

A measure of the strength of the computed equation is the coefficient of determination (R^2) which represents the square value of the correlation coefficient (R). The correlation coefficient refers to the linear correlation between the observed and the model predicted values of the dependent variable. Its high value of 0.905 indicates a strong correlation. The value of R^2 is very high and is 0.818, which confirms that 81.8% of the variation in the dependent variable Y is explained by the influence of input variables (X_1–X_7), which also confirms the relationship between Regression and Residual (81.82% : 18.78%), obtained by ANOVA test (Table 3).

Table 3.ANOVA[b] test results in the model training phase

Model	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Regression	20036.263	7	2862.323	21.867	0.000[a]
Residual	4450.516	34	130.898		
Total	24486.779	41			

[a] Predictors: (Constant), X_7, X_6, X_5, X_3, X_1, X_4, X_2
[b] Dependent Variable: Y

The standard error of the estimate allows (at the 95% confidence interval) to predict between which values lie the corresponding value of the predicted Y (GDP) score. By modelling the dependence of Y on the input parameters (X_1–X_7) using MLRA, the standard error of the estimate is 11.44, which is drastically lower compared to the value of the standard deviation for Y of 24.44 (Table 1). Thanks to the parameters obtained in this way, the defined model can be considered adequate for predicting the size of GDP per capita depending on the above predictors (X_1–X_7).

The results of the ANOVA test shown in Table 3 represent the results of testing the null hypothesis that R^2=0. This R^2 value indicates a nonlinear relationship between the predictors and the dependent variable (Landau and Everitt, 2004). The obtained value of F statistics is 21.87, with high statistical significance ($p<0.001$). Therefore, the hypothesis that there is no linear relationship between the predictors and the dependent variable is rejected.

Identifying an independent relationship was performed using the obtained values of standardized Beta coefficients between the predictors (X_1–X_7) and the dependent variable (Y) (Table 4).

Table 4. Standardized Beta coefficients values

Predictors	**Standardized Coefficients**	**t**	**Sig.**
	Beta		
X_1	0.459	1.385	0.175
X_2	-0.735	-1.839	0.075
X_3	0.200	1.074	0.290
X_4	-0.312	-1.112	0.274
X_5	0.378	2.585	0.014
X_6	0.414	2.948	0.006*
X_7	0.611	3.267	0.002**

Note: ** Statistically significant at the 0.005 level
* Statistically significant at the 0.01 level

The Beta coefficients are shown to be positive and statistically significant at the 0.005 level for predictor X_7, and at the 0.01 level for predictor X_6. Therefore, the higher the value of these predictors, the higher the value of GDP per capita is. The value of Beta coefficients is also positive for predictors X_1, X_3 and X_5, but without statistical significance, while the value of Beta coefficients for X_2 and X_4 is negative, also without statistical significance.

In order to confirm collinearity, Table 5 shows the results of the conducted collinearity analysis for the defined prediction model.

After the model training phase, the MLRA testing phase followed, in which the model was validated. Figure 1 shows the linear relationship between the observed and the MLRA model predicted GDP per capita values. Compared to the training phase, the coefficient of determination (R^2) is now lower and amounts to 0.603, which means that greater reliability was achieved in the training phase of the model, which is logical because it included over 97% of data from the initial database.

Table 5. Collinearity analysis results

Predictors	Correlations			Collinearity Statistics	
	Zero-order	*Partial*	*Part*	*Tolerance*	*VIF*
X_1	0.816	0.231	0.101	0.049	20.536
X_2	0.771	-0.300	-1.34	0.033	29.974
X_3	0.796	0.181	0.079	0.154	6.476
X_4	0.755	-1.87	-0.081	0.068	14.769
X_5	0.773	0.405	0.189	0.250	3.998
X_6	0.745	0.451	0.216	0.270	3.697
X_7	0.796	0.489	0.239	0.153	6.536

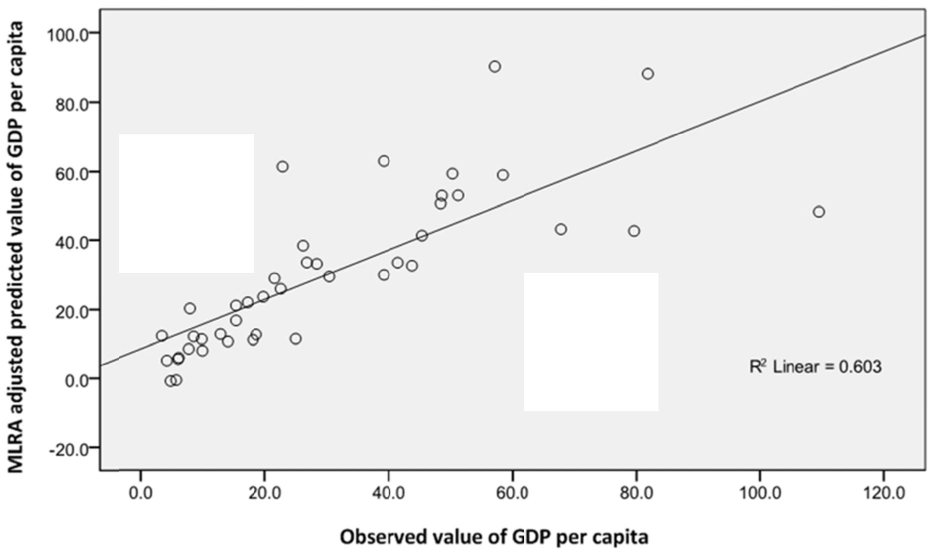

Figure 1. Dependence between observed and predicted values of GDP (nominal) per capita using MLRA

2.2. Modelling the Dependence of GDP per capita on Input Parameters (predictors) Using the ANNs method

ANNs, usually simply called neural networks (NNs), are computing systems vaguely inspired by the biological neural networks that constitute animal brains (Chen et al., 2019). An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called edges. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold.

For more than twenty years, the ANNs methodology has stood out as a reliable tool for nonlinear modelling of the dependence of one or more dependent variables on a number of independent input parameters, especially in situations where conventional regression models become impractical or too complicated. ANNs approach is a computer modelling approach that learns from examples through iterations, without the need for prior knowledge of the relationships between the studied parameters. In this way, ANNs networks can process indeterminate and unordered data, as well as nonlinear dependencies (Dreyfus, 2005). For modelling in this study, a single hidden layer ANNs architecture was used, which is shown in Figure 2 (Meradi et al., 2006).

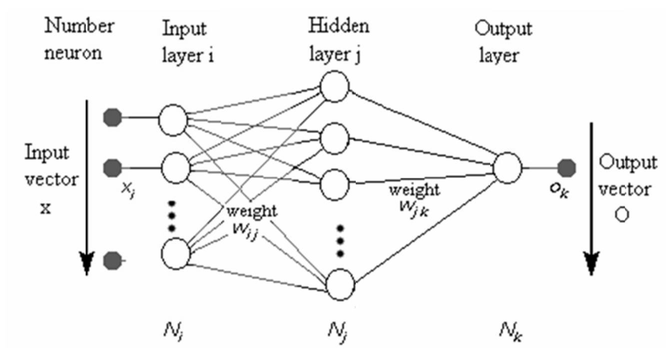

Figure 2. A single hidden layer ANNs architecture (Meradi et al., 2006)

Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), through the one or more hidden layers, to the last layer (the output layer), possibly after traversing the layers multiple times. Each layer comprises one or more neurons, which are interconnected by using weight factors (Arsić et al., 2020).

The input for any neuron (j) in the hidden layer, without the corresponding bias, is given by the expression:

$$I_j = \sum W_{ij} \cdot X_j$$

where Wij represents the weights of the interconnections between neurons i and j, and Xj is the signal at the observed link.

An important component of ANN is its activation function, which appears behind the input layer. Each hidden and output node applies an activation function to its net input. To process the results in this study, a hyperbolic tangent activation function was chosen for the hidden layer. It takes real-valued arguments and transforms them to the range (–1, 1), and has the form:

$$f(x) = \tanh(x) = (e^{x} - e^{-x})/(e^{x} + e^{-x})$$

The identity activation function was used for the output layer. It takes real-valued arguments and returns them unchanged. This function has the form:

$$f(x) = x$$

The general function of neuronal transfer is thus structured as:

$$O_j = A_j = f(\sum W_{ij} X_i)$$

where Oj is the output of the neuron, Aj is its activation, and Xj is the input to the neuron in a hidden layer that is identical to the output of the previous neuron, with the index j of the observed element.

The goal of the ANN network learning process is to reduce overall network error:

$$E = \frac{1}{2} \sum (Y_j - O_j)^2$$

where Yj is the target output value.

During the ANNs application process, a backpropagation algorithm is used to modify the weighting coefficients to minimize the mean square deviation between the network outputs obtained by modeling and the actual outputs of the considered model (Dreyfus, 2005). Backpropagation uses supervised learning that trains the network with a controlled input variable as well as the desired output dependent variable (Eberhart and Dobbins, 2002).

The application of ANN methodology usually consists of three phases: (i) correction of weight parameters through the required number of iterations until the error between the calculated and measured values is brought to a minimum, (ii) testing – "network training" on the remaining 20–30% of the data, when the network uses the calculated weight parameters from the learning phase, and (iii) network validation performed on new data that has already been measured or will be measured and gives an assessment of network success or failure (Dreyfus 2004). Performance evaluation is measured via $R^2_{ANNs} > R^2_{MLRA}$ data.

The initial database is divided into two parts. The first part of 81% of the data was used for the training phase and the second part (19%) for the ANN testing phase. The ANN architecture, for the development of the model of dependence of GDP (Y) on independent parameters (X_1–X_7) used in this study is shown in Figure 3. It consists of three layers: i (input layer), j (hidden layer), and k (output layer) with the number of neurons Ni, Nj and Nk in each layer, respectively. The input quantities (x) in the model are called the input vector, and the output quantities are called the output vector (o). The number of input parameters in this study is 7, and in the output layer, the number of outputs is 1. The number of neurons in the hidden layer was determined by training and testing several different ANNs with an iterative approach, changing the number of neurons (from 2 to 10) in the hidden layer and changing the hidden and output layer activation function, resulting in a minimum of prediction errors. The most optimal results were achieved with the ANN architecture shown in Figure 3, with 2 neurons in the hidden layer and a coefficient of determination (R^2) of 0.877 in the training phase and 0.878 in the network testing phase, indicating that the same reliability was achieved in both phases.

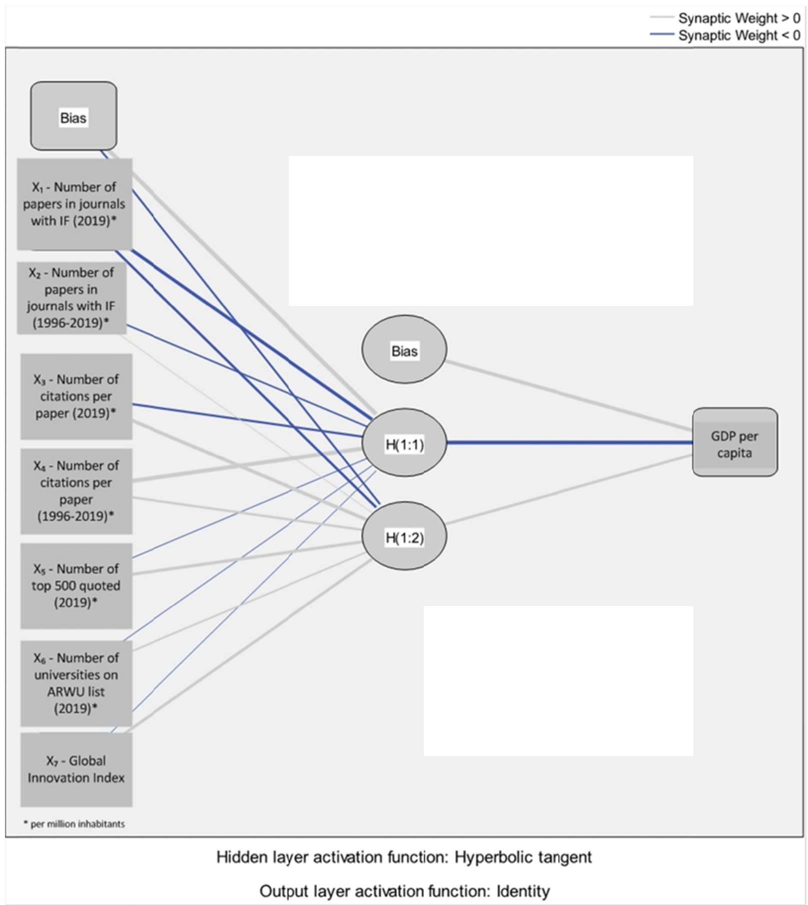

Figure 3. ANN architecture for modeling the dependence of GDP per capita (Y) on input parameters

Each neuron in the input layer is connected to all neurons in the hidden layer, via weight coefficients Wij, and neurons from the hidden layer to neurons in the output layer via Wjk (Meradi et al., 2006). Table 6 shows the calculated weight parameters for the considered ANN architecture shown in Figure 3.

In addition, an independent variable importance analysis was performed, which gives the results of sensitivity analysis, which computes the importance of each predictor in determining the neural network. These values show which variable has a larger and which a smaller role, representing the measure of how much the network model predicted value changes for different values of independent variables. Table 7 displays the importance and normalized importance for each predictor.

Table 6. Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1		Output Layer
		H(1:1)	H(1:2)	Y
Input Layer	(Bias)	1.511	-0.394	
	X_1	-1.016	-0.709	
	X_2	-0.165	0.066	
	X_3	-0.419	1.044	
	X_4	1.384	0.609	
	X_5	-0.028	0.974	
	X_6	-0.061	0.378	
	X_7	-0.153	0.910	
Hidden Layer 1	(Bias)			1.196
	H(1:1)			-1.360
	H(1:2)			0.751

Table 7. Independent Variable Importance

Variable	**Importance**	**Normalized Importance**
X_1	0.239	100%
X_2	0.035	14.8%
X_3	0.204	85.3%
X_4	0.168	70.4%
X_5	0.132	55.4%
X_6	0.072	30.2%
X_7	0.149	62.5%

Obtained importance values for independent variables using ANNs methodology can be compared with the coefficients obtained using MLRA methodology, where a similar significance of the influence of individual predictors (X1–X7) on the value (Y) can be seen.

Figure 4 gives a comparative presentation of observed and predicted values of GDP per capita using the ANNs method.

Comparing the results obtained by the ANNs method with the results obtained by the MLRA method, it can be concluded that better agreement was achieved in the training phase than in the testing phase, which is justified given that the nonlinear ANNs approach is less sensitive to extreme point distribution, unlike the MLRA approach. Thus, the obtained results show that the data on defined predictors (X_1–X_7) may be adequate for predicting the value of GDP per capita.

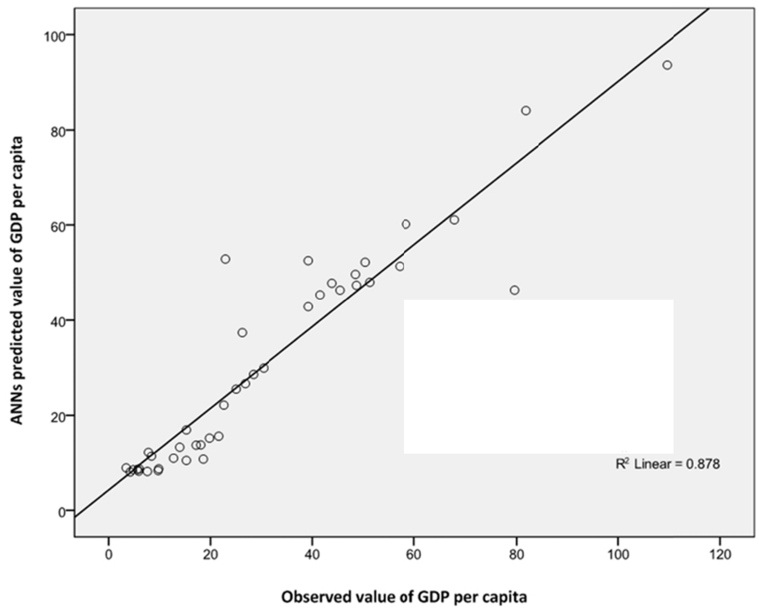

Figure 4. Comparative presentation of observed and predicted values of GDP per capita using the ANNs method

4. Conclusions

The obtained results of modeling the dependence of the influence of non-economic factors (the quality of higher education and science, and GII) on GDP per capita in the considered countries, using MLRA and ANNs indicate that $R^2_{(MLRA)}=0.630 < R^2_{(ANNs)}=0.878$, indicating that the nonlinear ANNs model better describes the defined dependence Y = f (X_1–X_7). The performed statistical analysis of the dependence of GDP per capita (Y) on the predictors (X_1–X_7) indicates that the predictors in descending order have an impact on Y as follows: $X_7 \rightarrow X_6$, while the predictors X_1, X_3 and X_5 with a positive sign, and X_2 and X_4 with a negative sign have no statistical significance on the dependent variable Y.

The obtained results based on a significant correlation Y = f (X_7 X_6) indicate that the greatest influence on the size of GDP per capita has GII, i.e. the degree of transfer of results of science and higher education to industry and society as a whole (X_7). The next in terms of the level of influence is the integral quality of the university, which is measured by several criteria for a position in the top 500 on the ARWU list (X_6). Predictors: number of published papers (X_1), number of citations per paper (X_3), and number of most cited researchers in the previous calendar year who had the greatest impact on the development of science in the world (X_5) for 2019 (Y values were also considered for the same year), have a positive impact, but with little statistical significance, given that the published paper in the same year cannot achieve adequate impact in the same year on the economic effects of the country from which it comes. Finally, the predictors X_2 and X_4 (number of papers and number of citations, respectively, for the period 1996–2019) have a negative impact with low statistical significance, even lower compared to X1, X3, and X5, indicating that the stated values in the longer period back from 20 and more years, cannot be reliably correlated with the values of Y that occurred in 2019, due to the fact that the values of these predictors over a long period of time, have certain dysfunctional changes, cannot provide reliable information on the impact on current Y values.

These results clearly indicate that the quality of higher education and science has a clearly defined positive impact on the size of GDP per capita, and that government investment in the development of higher education and science is one of the most important development potentials of any country.

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