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Abdullah Erdal Tümer, Aytekin Akkuş

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Forecasting Gross Domestic Product Per Capita Using Artificial Neural Networks with Non-Economical Parameters

Abdullah Erdal Tümer [a*], Aytekin AKKUŞ [b]
[a] *Department of Computer Engineering, Necmettin Erbakan University, Software Engineering, Campus of Köyceğiz, Meram, Konya, Turkey*
[b] *Department of Industrial Engineering, Necmettin Erbakan University, Institute Of Science, Campus of Köyceğiz, Meram, Konya, Turkey*

ABSTRACT

Gross Domestic Product per capita is one of the most important indicators of social welfare. All countries try to increase their Gross Domestic Product per capita to contribute to their population's happiness and well-being, as well as strengthen their nation's standing in international relations. Economic growth is affected by economic parameters such as trade, import, and export. However, Gross Domestic Product may also be affected by non-economic factors. Therefore, for a country to increase its Gross Domestic Product per capita, it's important to employ the correct strategy. The aim of this study is to investigate the predictability of Gross Domestic Product per capita based on non-economic data by using artificial neural network with feed forward back-propagation learning algorithm. For this purpose, neural network models have been developed with different architectures. Education level, number of published academic paper per capita, number of researchers per employed, percentage of Research and Development expenditure in the Gross Domestic Product and number of patents per capita are used as input data in the models. The input data has been collected from variety of resources such as Organisation for Economic Co-operation and Development.

A comparison between the model results and actual data give a high correlation coefficient (R^2= 0.96) and show that the model is able to predict the Gross Domestic Product per capita from non-economic parameters.

Keywords: Forecasting, Artificial Neural Networks, GDP per capita, Models, Economic

1. Introduction

Gross Domestic Product (GDP) per capita is one of the most important indicator to compare the level of development within countries. It is widely considered that human welfare and GDP per capita is highly correlated. It is found in the literature that GDP per capita measures happiness of people better than the human capital index [1]. GDP per capita effect in Human Development Index was studied on low and high human development countries. It was found that low human development countries are much more sensitive to changes in GDP per capita [2]. GDP per capita is also used as socioeconomic indicator of health. Correlation between GDP per capita and health has been widely studied in literature [3]. High correlation between GDP per capita and health has been demonstrated with further economic and demographic research [4-10]

Although it is one of the most important indicators for social welfare, GDP per capita estimation was not widely investigated by researchers in economics Instead, much emphasis has been given to GDP Growth estimation [11-13] since GDP is considered as the most important indicator of a country's overall performance. GDP growth rate estimation has been investigated by using machine learning algorithms such as ANN in many studies [14-16].

Another remarkable point is that economic forecasting studies have almost always used economic parameters.

For example, the authors in [14] estimated gross domestic product and Hirschman–Herfindahl Index with four different inputs data. For this purpose, they applied artificial neural network with extreme learning machine and back propagation algorithm. These are gross fixed capital formation (investments) (%), fertility rate and industry value added in GDP (%) and final consumption expenditure of general government (%).

In [15], the authors proposed a forecasting system of economic growth based on ANN. The tertiary industry rates for the years 1971-1997 in China's Zhejiang province were used. It was mentioned that tertiary industry rates are directly related to economic growth in the study. The tertiary industry proportion of the previous first year, previous second year, and previous third year were used as the input data. They found the forecast result of ANN satisfactory and efficiency.

In [16], the authors developed and applied the artificial neural network with extreme learning machine using agriculture, manufacturing, industry and services value were used to estimate economic growth. Based on results, ANN with extreme learning machine (ELM) can be applied effectively in applications of GDP forecasting.

In order to predict GDP growth rate, the authors used ELM method and five input parameters. The input parameters are imports of goods and services, exports of goods and services, trade of services, trade and merchandise trade on the economic growth. They demonstrated that ELM can be utilized effectively in applications of GDP growth rate prediction. [17].

As the examples mentioned above, many studies on economic growth estimates have used economic parameters [18-21].

The major contributions of this paper are follows. The first is the estimate of GDP per capita instead of economic growth. Secondly, estimates are made not only by economic parameters but also by non-economic parameters such as educational level, scientific article number and patent since GDP per capita is much more related to human capital.

The parameters used for GDP per capita estimation in this study are:

i. **Number of papers per capita** indicates how many papers are published in international journals per one million people.
ii. **Number of researchers per employed** indicates that how many researchers are employed per one thousand employed.
iii. **R&D expenditure** indicates the percentage of GDP that is reserved for R&D.
iv. **Number of patents per capita** indicates how many patents are granted per one million people.
v. **Education level** indicates the average education level of all residences within country.

These non- economical parameters are used as input data for ANN model with feed forward back propagation (FFBP) learning. Statistical estimation is widely investigated in many studies by using methods such as moving average, exponential smoothing or regression analysis. In addition to that there are new machine learning methods emerged such as support vector machine, genetic algorithms or neural networks. In this study, artificial neural networks are used as the estimation instrument.

2. Methodology

2.1. Artificial Neural Network

Artificial neural networks (ANN) are systems that mimic the behavior of biological neural networks that make up brains of animal. Artificial neural networks include many simple neural cells [22]. Such systems are being fed with examples, and they learn tasks with these examples, hence there is no need of task-specific programming for ANN systems. They can learn based on experience using the method of pattern recognition [23]. They can process various types of data (fuzzy, nonlinear, and noisy) by employing neuron simulation. There is no formula for what architecture or which learning algorithm to use to find the best solution. Therefore the best solution is obtained by trial and error method.

Generally, neurons are organized in layers as in the case of biological neural networks (Multilayer ANN). Multilayer ANN is the most used model of artificial neural networks since it mimics biological neural networks better [24]. Different layers may perform different kinds of processing on their inputs. Neurons approximate the mapping between input and output through compositions of nonlinear functions [25]. Signals might traverse the layers multiple times. Also ANN is formed in three layers, named the input, hidden, and output layer. Each layer consists of one or more nodes. The architecture of the ANN model is given in Fig. 1.

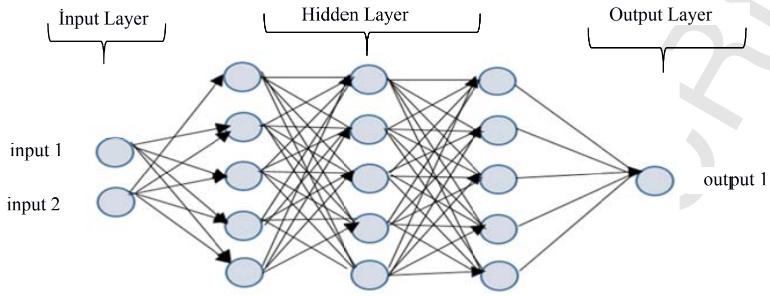

Fig. 1. Architecture of ANN

2.2. Data Collection

GDP per capita estimation is not investigated in literature thus there is a need to build a reliable GDP per capita estimation model. The main aim of this paper is to overcome high nonlinearity of the GDP per capita forecasting by applying the ANN with FBP. To accomplish this, a network structure is built with input parameters education level, number of paper per capita, researcher per employed, research & development expenditure as the percentage of GDP and number of patents per capita. In this study, data from 13 different countries within time period 1996 to 2015 are used. Total number of data is 180. Table 1 shows input and output parameters which are used in this study with detailed statistical. In all, 130 data are used for training and remaining 50 data are used for simulation. All data is distributed randomly for training and simulation to get better results from networks. As it can be seen from Table1, data for each parameter can be approximated with normal distribution.

Table 1. Input parameters and summary statistics.

Input Name	Min	Max	Mean	Std. Dev.
Education level	8,34	52,97	29,95	11,28
Number of paper per capita	73,05	3404,86	1463,81	829,88
Researcher per employed	0,7	13,74	6,91	2,92
R&D Expenditure(% of GDP)	0,35	4,28	1,93	0,92
Number of patents per capita	4,31	3279,25	654,01	915,48

Education level, researcher per employed and R&D Expenditure (% of GDP) data has been taken from OECD open data web site [26]. Number of paper per capita is calculated by using data taken from Scimagorj web site [27]. Number of patents per capita is determined by using data taken from World Bank open data web site [28].

2.3. Software and Performance Criteria

In this study MATLAB software is used to test and simulate network structures. Different networks have been developed with different configurations of number of layers and neurons parameters to find the most optimal architecture.

There are several methods to evaluate the performance of ANN. Root Mean Square Error (RMSE) and Coefficient of Determination (R^2) are most widely used methods to determine performance of ANN [29]. Thus, R^2 and RMSE are used as performance criteria in this study. Also logarithmic transformation variable (e) is used. Formulation of these performance measures are displayed below.

$$RMSE = \sqrt{\frac{1}{n}\sum_1^n (Y_{exp,i} - Y_{prd,i})^2} \quad [1]$$

$$R^2 = 1 - \frac{\sum_1^n (Y_{prd,i} - Y_{exp,i})2}{\sum_{i=1}^n (Y_{prd,i} - Y_m)2} \quad [2]$$

$$e = \sum_i^n \frac{\log Y_i^{prd}}{\log Y_i^{exp}} \quad [3]$$

where Y_{prd} is predicted data, Y_{exp} and Y_m are the measured and average of the batch study data respectively. n is the number of data.

3. Result

In present study, several architectures with more than one hidden layer and more neurons are tested to find the optimum ANN model. Some of the parameters are kept constant while the hidden layer and neuron numbers are changed in the developed models. Table 2. shows that the design parameters belong to the developed ANN models.

Table 2. ANN learning parameters

Network Type	Feed Forward Back-propagation
Number of layers ,Neurons	(1,10),(1,20),(2,10),(2,20),(3,10),(3,20)
Number of iteration	2000
Training function	Levenberg-Marquardt (trainlm)
Adaptive learning function	Gradient Descent (learngdm)
Performance function	MSE
Transfer function	Hyperbolic Tangent (tansig)

Total iteration number was set at 2000 for all learning algorithms. Value of correlation coefficient (R) is considered as the performance criteria for ANN training. Since there is no specific rule for determining layer numbers or neuron numbers, the number of layers and neurons were determined randomly by trial-and-error method. Using very few or many neurons in the hidden layers will be underfitting or overfitting. Table 3 displayed results of the accuracy of the models for the ANN including layers and neurons number. Among the developed architectures, feed-forward back-propagation algorithm with two hidden layers, tansig function and 20 neurons in hidden layer provided the best optimal network based on R indicator.

Table 3. The determination of the number of layers and neurons

Number of layers-Neurons	R
1 layer 10 neurons	0,98731
1 layer 20 neurons	0,95532
2 layer 10 neurons	0,98781
2 layer 20 neurons	**0,99829**
3 layer 10 neurons	0,97587
3 layer 20 neurons	0,98761

Fig.2. depicts regression graph of the most optimal ANN models. If the training results are not compatible with the simulated results, it will not be possible to develop a suitable model for GDP per capita. In this case, the five best models' responses are satisfactory, and simulation can be used for entering new inputs (data that are not shown to the network for testing purposes).

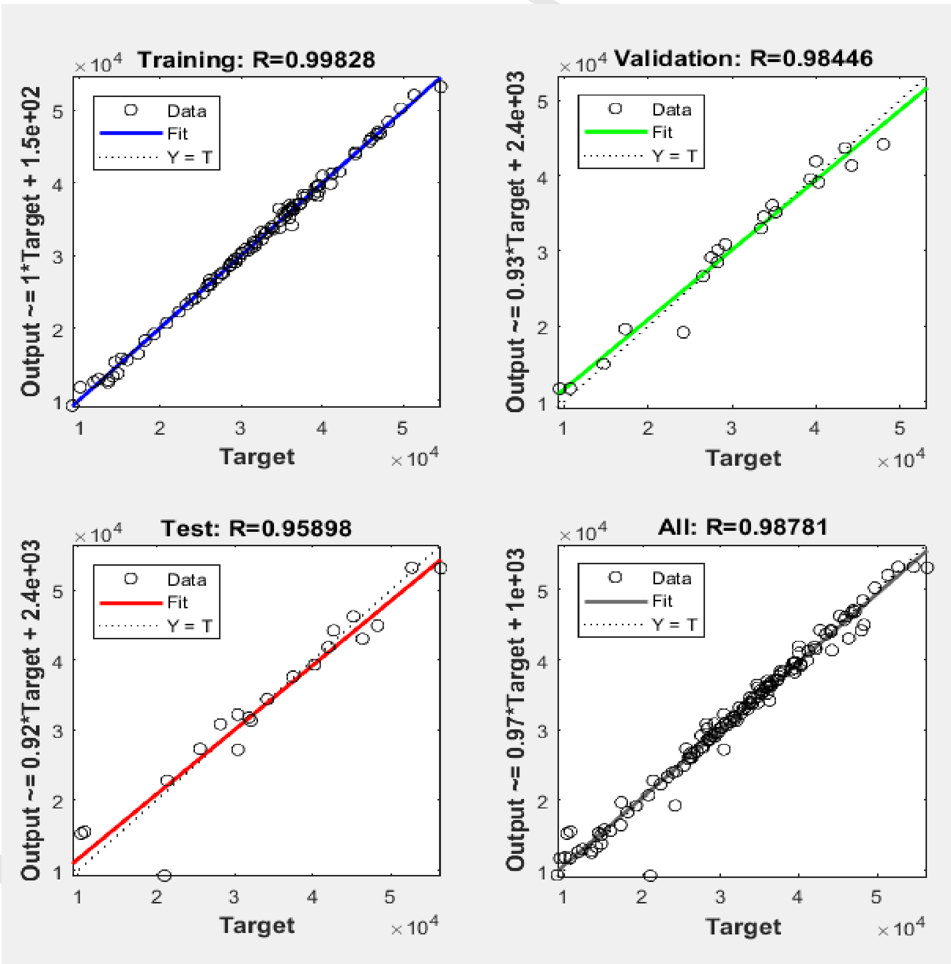

Fig. 2 ANN Regression graph

Each model is simulated with 50 input data for test. Simulated results are then compared with actual values. Table 4. summarizes the estimation results of the five training approaches for the ANN based on the three performance criteria (RMSE, R^2 and e).

Table 4. GDP per capita prediction accuracy with ANN models

Number of layers-Neurons	RMSE	R^2	e
1 layer 10 neurons	2555.,42	0.9372	0.994
1 layer 20 neurons	2911.19	0.9242	0.995
2 layer 10 neurons	3230.01	0.8945	0.994
2 layer 20 neurons	3050.97	0.9160	0.995
3 layer 10 neurons	**1935.67**	**0.9636**	**0.996**
3 layer 20 neurons	3098.78	0.9038	0.995

It is observed that the most optimal network is found -with 3 layer 10 neuron combination and RMSE-value =1935.67, R^2-value = 0.9636, and e-value= 0.996.

The coefficient of determination (R^2) of 0.96 indicates that the model has an estimated power of almost 96 %. In other words, ANN model can estimate with 4 % error.
The logarithmic transformation variable (e) has been found to be 0> e. The developed ANN model, according to the found 0.996, shows that the estimates are slightly above the actual values.
The most suitable ANN model of simulated data and actual data for the GDP per capita is given in Fig. 3.

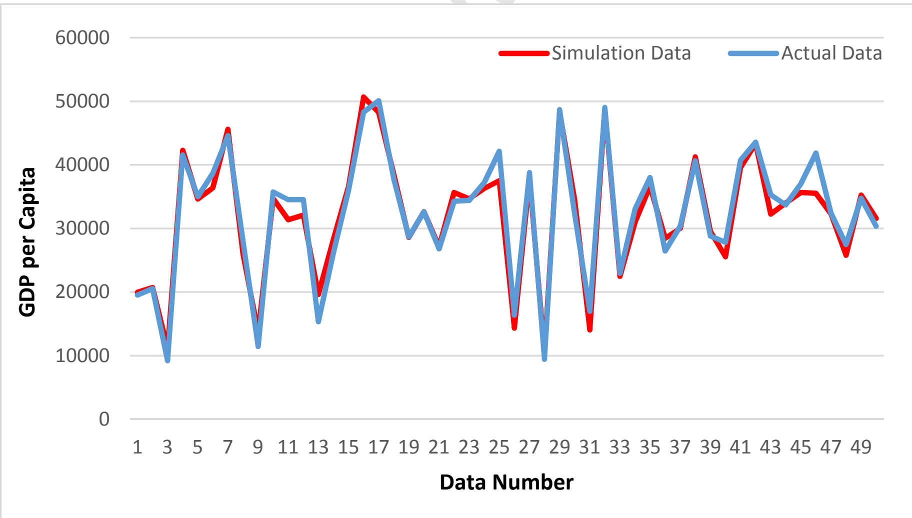

Fig. 3. Simulated data and actual data for GDP per capita

According to the results obtained from models developed, it is observed that ANN can be used as an estimation device for estimating GDP per capita and they give quite good and satısfactory results.

4. Conclusion

In this study, GDP per capita based on non-economical parameters is investigated by using artificial neural networks. Education level, number of paper per capita, number of researchers per employed, percentage of R&D expenditure in GDP and number of patents per capita are used as input parameters for GDP per capita forecasting. Different configurations of artificial neural networks are constructed and results are investigated for each configuration. Each configuration is used with 130 input data for training and 50 input data for simulation. Value of correlation coefficient (R) up to 0,99828 and 0,9636 are achieved from training and simulation respectively. As a result, it can be concluded that artificial neural networks can be used as an effective tool for GDP per capita estimation. As a future investigation, either number of input might be increased or different models of artificial neural networks might be constructed to improve performance of artificial neural networks.

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HIGHLIGHTS

- The prediction of the gross domestic product (GDP) per capita.
- GDP per capita based on combination of non-economic parameters.
- The accuracy of the artificial Neural Network (ANN).