GROSS DOMESTIC PRODUCT GROWTH RATE ANALYZING BASED ON PRICE INDEXES, IMPORT AND EXPORT FACTORS

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ABSTRACT

Economic development could be presented by gross domestic product to show how different factors affect the development. Gross domestic product could be affected by different nonlinear factors in positive or negative way. Hence it is suitable to apply artificial intelligence techniques in order to track the gross domestic product variation in depend on the factors. AI techniques require only input and output data pairs in order to catch the output variations based on the input factors. Therefore in this study adaptive neuro fuzzy inference system was applied in order to select the most relevant factors for gross domestic product growth rate. These factors are whole sale price index, consumer price index in urban areas, consumer price index in rural areas, state per capita income, exports, import and industry income. Results shown that the whole sale price index has the highest relevance on the gross domestic product growth rate.

Introduction

Recently artificial techniques became main instrument for modelling and analyzing of complex nonlinear systems. Their application in every area is widely accepted and acknowledged. One of the potential application of artificial techniques is in social problems like economic development (Markovićet.al., 2017; Mladenović et.al., 2016). Economic development could be analyzed based on different indicators but gross domestic product (GDP) is widely accepted and used indicator to track economic

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development. There are many investigations of GDP according to different input factors (Todorović et.al., 2018).

In paper (Jovic, 2019) was investigated the effect of exchange rate pass-through (ERPT) into aggregate import prices and afterwards exchange rate effect on gross domestic product (GDP) was investigated by adaptive neuro fuzzy inference system (ANFIS). GDP per capita is one of the most important indicators of social welfare and all countries try to increase their GDP per capita to contribute to their population's happiness and well-being, as well as strengthen their nation's standing in international relations (Tümer, Akkuş, 2018). Expenditures on health care continue to increase substantially, both absolutely and relative to national income, throughout most of the developed world. In study (Mladenovićet.al., 2016) was analyzed the influence of health care expenditures on the economic growth. Aggregate accounting earnings growth is an incrementally significant leading indicator of growth in nominal GDP (Konchitchki, Patatoukas, 2014). Strong evidence of discontinuities around zero in the distribution of actual minus target GDP growth rates was found in paper (Changjianget. al., 2018). The yield curve – specifically the spread between long term and short term interest rates is a valuable forecasting tool. Results presented in paper (Hvozdenska, 2015) confirmed that 10-year and 3-month yield spread has significant predictive power to real GDP growth after financial crisis. The environment that governs the relationships between carbon dioxide (CO2) emissions and GDP changes over time due to variations in economic growth, regulatory policy and technology. The purpose of research (Marjanovićet.al., 2016) was to develop and apply the Extreme Learning Machine (ELM) to predict GDP based on CO2 emissions.

The main goal of the paper is to present application of adaptive neuro inference system (ANFIS) (Jang, 1993) for GDP analyzing based on input factors influence. The main reason of ANFIS application is strong presence of nonlinear phenomena in the economic problem namely GDP growth rate. There are number of social phenomena like GDP where linearity is exceeded in independent variables (Subic et.al., 2007; Kuzman, Prdić, 2018; Prdic, Kuzman, 2019). Economic aspects have different variables and factors which is challenging to analyzing by conventional approaches (Kuzmanet.al., 2018; Kuzman et.al., 2017; Kuzman et.al., 2016; Kuzman, Prodanović, 2017; Nedelcu et.al, 2015). ANFIS methodology shows good capability to catch and track nonlinearity phenomena since there are multiple parallel operations during training of the ANFIS model. ANFIS technique require only input and output data pairs in order to catch the output variations based on the input factors. In this study ANFIS was applied in order to analyze GDP growth rate based on 7 input factors. These factors are whole sale price index, consumer price index in urban areas, consumer price index in rural areas, state per capita income, exports, import and industry income.

Materials and methods

In order to perform GDP analysing and prediction there is need to collect input and output data pairs for ANFIS training process. Table 1 shows used input factors and output as well. The used input are whole sale price index, consumer price index in urban areas, consumer price index in rural areas, state per capita income, exports, import and industry income. The factors are paired with GDP. After the pairing the ANFIS models are training in order to investigate relationships between inputs and output. All of the data are acquired and arranged based on OECD database for European Union.

Table 1. Input and output factors

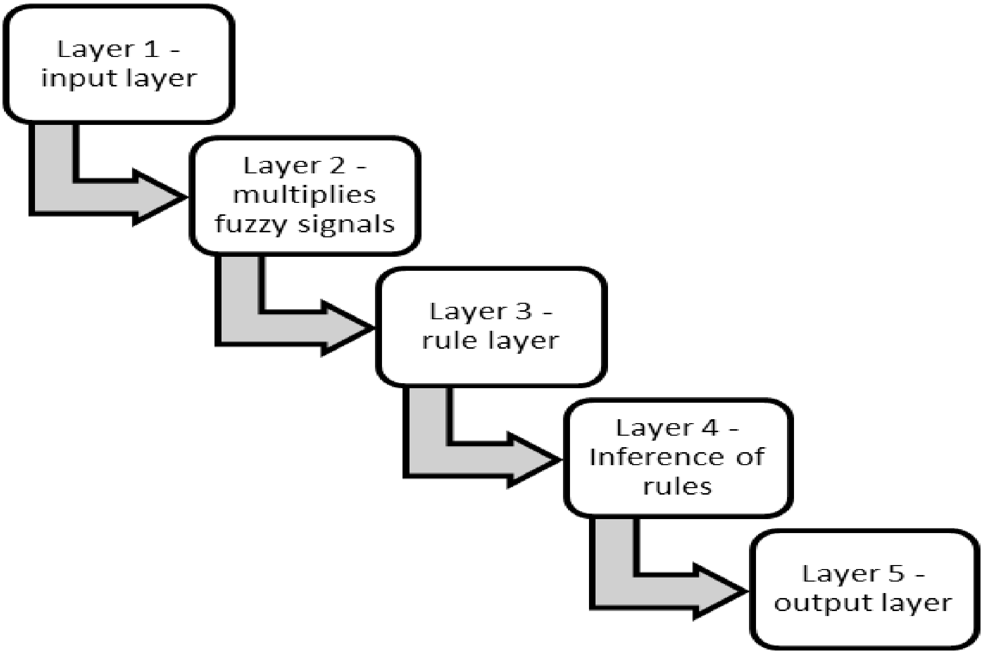
in 1: Whole sale price index	in 2: Consumer price index – Urban	in 3: Consumer price index – Rural	in 4: State Per Capita Income	in 5: Export	in 6: Import	in 7: Industry income	output: Gross Domestic Product
80.02	24.12	30.12	105	4153	62367	50950	286566
85.02	25.35	34.35	133	7128	85156	53550	329567
88.02	42.35	48.35	192	9465	87077	69640	368800
99.02	50.35	59.35	267	12814	87774	81360	405707
105.02	64.35	73.35	338	15849	95101	108520	454014
115.02	76.35	82.35	416	24383	101937	124950	488921
127.02	84.35	92.35	491	32517	106792	127770	532374
137.02	97.35	104.35	548	39963	107921	154930	557097
142.02	108.35	114.35	617	24535	90122	171020	606603
149.02	123.35	129.35	688	26660	94372	182740	645436
154.02	135.35	142.35	744	29635	103076	209900	672222
171.02	143.35	152.35	822	36860	125864	226330	694027
166.37	161.35	167.35	899	39198	127785	229150	720810
178.87	170.35	176.35	967	42547	128482	197910	744859
181.83	179.35	186.35	1022	45581	135809	230670	784955
199.34	193.35	200.35	1074	54166	142646	242230	824655
225.31	210.2	219.2	1151	62300	147500	259640	866113
263.91	251.09	260.09	1350	81500	209400	230930	898394
277.73	256.95	263.95	1269	89700	224075	255065	918879
303.41	302.79	311.79	1373	97900	238750	272645	961097
333.72	314.31	322.31	1376	106100	253425	313385	998466
346.28	330.07	335.07	1827	114300	268100	338030	1031660
381.53	357.26	366.26	2510	141800	290700	342260	1063491
419.16	389.75	399.75	2719	181200	298900	295400	1229030
451.74	416.34	425.34	3141	216900	385100	365800	1449271
493.78	455.34	459.45	3321	317303	465527	486600	1703392
536.16	491.68	498.19	3688	412993	522638	580500	2014567
613.25	572.27	572.04	3966	538988	535921	606500	2156190

in 1: Whole sale price index	in 2: Consumer price index – Urban	in 3: Consumer price index – Rural	in 4: State Per Capita Income	in 5: Export	in 6: Import	in 7: Industry income	output: Gross Domestic Product
693.75	643.91	654.55	4428	688423	731065	767400	2484052
718.76	689.73	695.71	5237	908580	811180	884600	2886822
779.23	751.65	766.28	6935	1246009	1254153	1156200	3522440
851.31	826.35	836.67	7236	1583283	1741672	1320500	4793736
937.9	934.09	935.51	9954	1759627	1496654	1348700	5815175
1046.06	1091.42	1093	11215	1652964	3687789	1036300	6613382
1162.23	1165.5	1164.67	15152	1877128	2348290	1363900	8103589
1199.27	1217.47	1227.47	17525	2698375	2560016	1479500	10525616
1223.26	1270.23	1280.23	18786	1173696	1882137	1653600	11564416
1251.77	1302.34	1310.34	21229	1263124	1862805	1462200	13173056
1270.32	1339.91	1345.91	20975	2503900	3569700	1510000	13091746
1340.84	1308.79	1359.95	21738	3306800	4379800	1910100	13678087
1341	1333.76	1365.73	23476	3478200	7874000	2156700	14965415
1373	1351.12	1370.34	25965	5129800	11298300	2798100	16718287
1377	1358.37	1377.41	31920	6775900	15903500	3778400	20750283
1451	1425.72	1443.49	37635	9176200	19016100	3934100	24626587
1539	1540.25	1540.23	36915	9060300	23098700	3971400	27928746
1640	1661.45	1668.45	49831	11309300	28906600	5914300	29458192
1687	1778.3	1772.38	51097	9176200	19016100	7199300	33921164
1798	2122.67	2134.67	70219	9060300	23098700	7695600	42491835
2026	2368.72	2492.13	72993	11309300	28906600	9136400	54726662
2204	2623.07	2770.16	84496	11309300	28906600	9576510	63902460

Source: Usha and Balamurugan, 1993

ANFIS network has five layers as it shown in Figure 1. The main core of the ANFIS network is fuzzy inference system. Layer 1 receives the inputs and convert them in the fuzzy value by membership functions. In this study bell shaped membership function is used since the function has the highest capability for the regression of the nonlinear data.

Figure 1. ANFIS layers



Source: Jang, 1993

Bell-shaped membership functios is defined as follows:

$$\mu(x) = bell(x; a_i, b_i, c_i) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{1}$$

where $\{a_i, b_i, c_i\}$ is the parameters set and x is input.

Second layer multiplies the fuzzy signals from the first layer and provides the firing strength of as rule. The third layer is the rule layers where all signals from the second layer are normalized. The fourht layer provides the inference of rules and all signals are converted in crisp values. The final layers sumarized the all signals and provied the output crisp value.

Performances of the proposed models are presented as root means square error (RMSE), Coefficient of determination (R^2) and Pearson coefficient (r) as follows:

1) RMSE

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}, \tag{2}$$

2) Pearson correlation coefficient (r)

$$r = \frac{n\left(\sum_{i=1}^{n} O_i \cdot P_i\right) - \left(\sum_{i=1}^{n} O_i\right)\cdot\left(\sum_{i=1}^{n} P_i\right)}{\sqrt{\left(n\sum_{i=1}^{n} O_i^2 - \left(\sum_{i=1}^{n} O_i\right)^2\right)\cdot\left(n\sum_{i=1}^{n} P_i^2 - \left(\sum_{i=1}^{n} P_i\right)^2\right)}} \qquad (3)$$

3) Coefficient of determination (R^2)

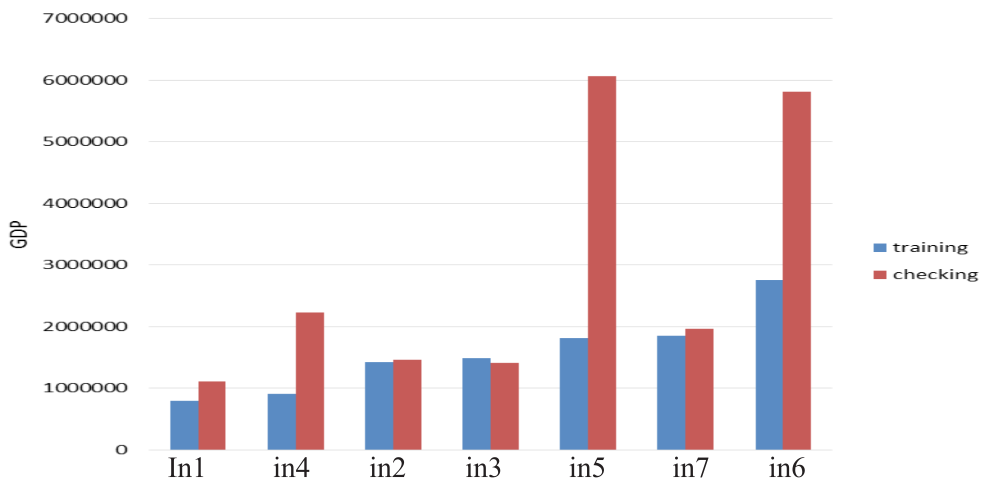
$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\left(P_i - \overline{P_i}\right)\right]^2}{\sum_{i=1}^{n}\left(O_i - \overline{O_i}\right)\cdot\sum_{i=1}^{n}\left(P_i - \overline{P_i}\right)} \qquad (4)$$

where P_i and O_i are known as the experimental and forecast values, respectively, and n is the total number of dataset.

Results

GDP growth rate sensitivity is analysed based on factors influence. The influence is estimated according the RMSE values with ANFIS network. Figure 2 shows GDP sensitivity based on 7 input factors. As can be seen the factors with the smallest RMSE after training process has the highest impact on GDP. In other words the GDP is the most sensitive after input 1(Whole sale price index) variation as can be seen in Figure 2. On the other hand GDP has least sensitivity for input 6 (Import).

Figure 2. Factors influence on GDP



Source: Authors' calculations

Numerical RMSE values after training and checking of ANFIS network is listed in Table 2 for the single factors influence. Furthermore if one combine two factors in same time corresponding results are presented in Table 3. As can be seen factors 1 and 4 forms the most optimal combination for the GDP.

Table 2. Factors influence on GDP

ANFIS model 1: in1 -->trn=792726.2989, chk=1117756.7874
ANFIS model 2: in2 -->trn=1429807.6034, chk=1468704.3377
ANFIS model 3: in3 -->trn=1493654.3340, chk=1408339.6003
ANFIS model 4: in4 -->trn=909715.9459, chk=2230315.8341
ANFIS model 5: in5 -->trn=1822216.2325, chk=6067049.2763
ANFIS model 6: in6 -->trn=2765247.9845, chk=5810924.3048
ANFIS model 7: in7 -->trn=1855191.2124, chk=1967937.0754

Source: Authors' calculations

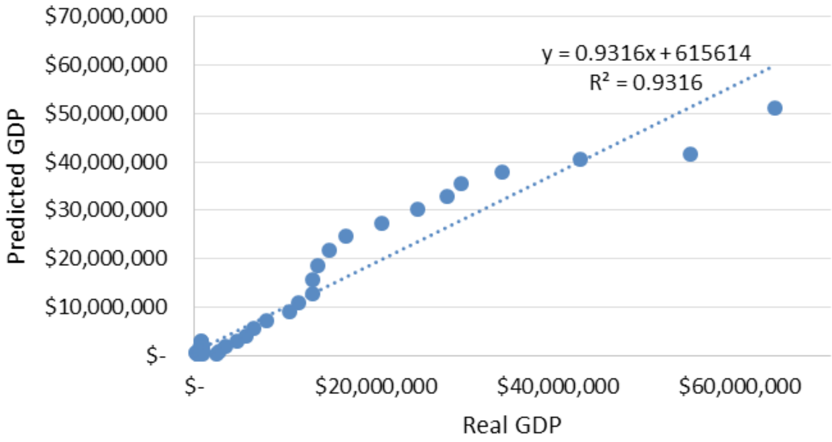
Table 3. Two factors influence on GDP

ANFIS model 1: in1 in2 -->trn=342960.7035, chk=2522862.7201
ANFIS model 2: in1 in3 -->trn=479709.1662, chk=2423824.7198
ANFIS model 3: in1 in4 -->trn=84837.1519, chk=3387077.6216
ANFIS model 4: in1 in5 -->trn=175552.4373, chk=9862009.8207
ANFIS model 5: in1 in6 -->trn=346639.7586, chk=1946191.6651
ANFIS model 6: in1 in7 -->trn=302732.4528, chk=2676305.7847
ANFIS model 7: in2 in3 -->trn=646425.8995, chk=6962905.5315
ANFIS model 8: in2 in4 -->trn=161513.4966, chk=652510.5949
ANFIS model 9: in2 in5 -->trn=182402.3538, chk=15125120.6863
ANFIS model 10: in2 in6 -->trn=218128.6032, chk=23763468.6240
ANFIS model 11: in2 in7 -->trn=143255.5539, chk=1261341.8891
ANFIS model 12: in3 in4 -->trn=164999.7892, chk=382264.7904
ANFIS model 13: in3 in5 -->trn=167085.2171, chk=9023759.5316
ANFIS model 14: in3 in6 -->trn=214559.7395, chk=25735917.0138
ANFIS model 15: in3 in7 -->trn=137387.8742, chk=1906955.9818
ANFIS model 16: in4 in5 -->trn=128090.9853, chk=4416677.0713
ANFIS model 17: in4 in6 -->trn=166177.7496, chk=15333450.6547
ANFIS model 18: in4 in7 -->trn=187533.9938, chk=3404479.0351
ANFIS model 19: in5 in6 -->trn=5265733.0034, chk=13071558.7207
ANFIS model 20: in5 in7 -->trn=1134210.1775, chk=289279828.8118
ANFIS model 21: in6 in7 -->trn=497525.9212, chk=211961264.6433

Source: Authors' calculations

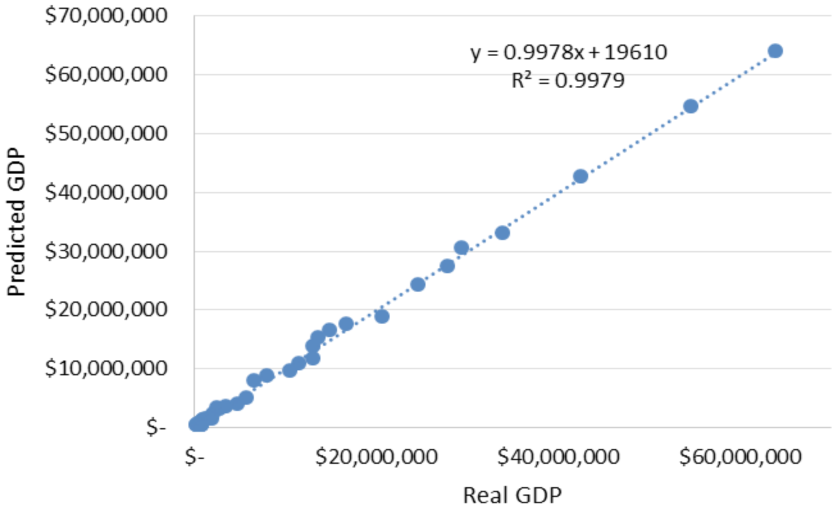
Figure 3 shows scatter plots of GPD prediction by ANFIS based on input 1 while Figure 4 shows scatter plots of GDP prediction by ANFIS based on input 1 and input 4. As can be seen according to the coefficient of determination ANFIS results for two inputs outperforms results for one input. Table 4 shows GDP prediction based on three statistical indicators for ANFIS models. Based on the three indicators one can conclude that the ANFIS with two inputs outperforms ANFIS with one input for the GDP prediction.

Figure 3. ANFIS prediction of GDP based on input 1



Source: Authors' calculations

Figure 4. ANFIS prediction of GDP based on combination of input 1 and input 4



Source: Authors' calculations

Table 4. Statistical indicators for ANFIS prediction of GDP

	One input (1)	Two inputs (1 and 4)
r	0.9652	0.9989
R^2	0.9316	0.9979
RMSE	3728859.321	658353.2683

Source: Authors' calculations

Discussions

The analysis was performed by artificial intelligence model namely adaptive neuro fuzzy inference system (ANFIS) since there are strong nonlinear relationships between input and output factors in the analyzing.Results shown that the whole sale price index has the highest relevance on the GDP growth rate. Moreover combination of whole sale price index and state per capita income forms the most optimal combination for the GDP. The GDP prediction based on the selected inputs has high accuracy based on three statistical indicators. The main feature of the ANFIS model is easy adaptation to any new inputs.

Conclusions

The main goal of the paper was to analyze and to make predictive models for gross domestic product (GDP) growth rate based on 7 factors. These factors are whole sale price index, consumer price index in urban areas, consumer price index in rural areas, state per capita income, exports, import and industry income.In conclusion ANFIS could be used effectively for GDP analyzing and prediction based on given factors or any other inputs.

ANFSI network has feature for training based on its performances. Based on this the network parameters are adjusted in order to make the performance optimal. Main goal of the learning type is based on optimization surfaces where there is need to find the optimal conditions for minimum and maximum of the surface.

There are different training laws in the category of learning performance. These learning laws is based on adjusting of network parameters during training process in order to optimize the network performances.

There are two steps during optimization process. The first step is based on definition of the performance criterion. In other words there is need to find a quantity measure for the network performance which is called performance index, which is small when the network produce good results and vice versa. The second step during the optimization process is based on the finding of parameters space in order to wind the performance index.

Optimization of neural networks represent a complex task since it is need to define the performance index of the artificial neural network for the further optimization process. There are several algorithms for optimization of the performance index of artificial neural networks. One of the most popular algorithm is steepest descent algorithm.

This algorithm require only calculation of function gradient which represent index performance of the network. It is proved that the algorithm will converge up to optimal stationary point if the learning speed is slow. Drawback of the learning algorithm is learning time which is too large. Therefore ANFIS network uses combination of steepest descent algorithm with back propagation in order to increase the learning speed.

ANFIS network has adaptive adjusting feature of the learning parameters with any new additional training. In other words ANFIS network has advantage to save the learned knowledge based on the fuzzy logic system. Once trained ANFIS network has feature to keep the knowledge until new training with new dataset.

Conflict ofinterests

The authors declare no conflict of interest.

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