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Development of a new model of gross domestic product forecasting

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Abstract

Economic growth is a result of the increase in real Gross Domestic Product (GDP). Countries or international organizations estimate economic growth to predict the future cycle of the economy. Thus, decision-makers will be able to develop early policies against future situations. In this study, factorial designs, one of the experimental design methods, are used to estimate economic growth. Economic growth and growth estimation studies frequently used time series analysis and econometric methods to determine the factors. In this paper, we analyzed the correlation of the factors such as the inflation rate, unemployment rate, industrial production index, foreign trade volume to GDP ratio, and the ratio of gross external debt stock to GDP by using the correlation analysis. Then, we determined a novel regression model. The output of the regression model is the rate of change in GDP. The novel forecasting model emerges when providing a suitable regression model. In this study, we present a novel 2^k factorial design methodology to solve the GDP forecasting problem. It is different from conventional forecasting models that require complex statistical evaluations. Furthermore, we propose a general framework of the model from the econometrics perspectives and a numerical solution to illustrate this demonstration.

1. Introduction

Economic growth, price stability, and using resources at the employment level are crucial macroeconomic targets. Economic growth is the increase in the number of goods and services produced by the country in a certain period. Economic growth is usually a long-term issue. Using the resources from inadequate employment level to employment level or increasing productivity in production factors impact economic growth. Also, many factors affect the economic growth rate positively or negatively.

Economic growth forecasting is a crucial issue in the management of the economy. In the literature, researchers proposed many approaches to forecasting economic growth. In this study, we present a new economic growth forecasting model using the experimental design methodology. We created experimental combinations of the 2^k fractional factorial design with three replications using the MINITAB package program to obtain results. In the first replication, first quartile data from the year 2005 to 2017 for the five selected factors set. Then, second and third quarter data for years from 2005 to 2017 reflect for the second and third replications, respectively. We examined the data through the MINITAB program using ANOVA analysis for obtaining the regression equation required for economic growth forecasting. The alternative forecasting scenarios can easily facilitate the regression equation. We present three illustrative examples in this study.

The organization of the paper is as follows: Section 2 presents the literature review. Section 3 and 4 present the factorial design application steps. Section 5 illustrates examples. Finally, Section 6 presents the conclusions.

2. Literature Review on Forecasting of Economic Growth

The forecasting studies on economic growth went back to the beginning of the 20th century. Apart from these studies, there are many other studies published in the literature. For example, Sommers and Suits (1971) proposed a cross-sectional model for economic growth. In line with this model, they presented three simple equations for economic growth. They then made a growth forecasting through these equations. Fair and Parke (1980) established a nonlinear estimation model in 1976 and developed it in 1978. In his model, there are 97 coefficients, 29 of which are stochastic. Stock and Watson (2002) estimated the macroeconomic time series variables using several estimators in their study for the United States (US) in 2002. The dynamic factor model established a statistical framework for the prediction of indicators. Their estimation results from the developed model performed better than the univariate autoregression models.

Smets and Wouters (2003) proposed a dynamic stochastic equilibrium model at fixed prices in 2002 and used the prediction study using their multi-variate technique. Adofson et al. (2007) presented a forecasting technique. They developed a dynamic stochastic equilibrium model for open economic conditions. Krkoska and Teksoz (2009) analyzed the performance of Gross Domestic Product (GDP) growth and inflation forecasts for 25 transitional countries between 1994 and 2007 and showed a positive correlation between empirical results. Modis (2013) considered GDP growth as a natural growth process appropriate to the structure of the logistic-growth equation that suggested the S-shaped logistics model would provide good explanations and predictions for the last 80 years in both the nominal and real GDP in the US. Feng and Zhang (2014) used the Artificial Neural Networks (ANN) approach to obtain nonlinear functions to predict GDP growth. This approach offers advantages in self-learning, harmonization, adaptation and fault tolerance, and economic growth forecast applications. They suggested that the ANN method achieves better results in performance and efficiency compared to traditional methods.

Dias, Pinheiro, and Rua (2015) analyzed the multi-factor forecasting model performance of Portugal GDP growth rate using the monthly data set. They concluded that the multi-factor model performs significantly better than the univariate autoregressive model. Ferraini and Scaramozzino (2016) analyzed the effect of production complexity and adaptability on output level and economic growth rate. They confirmed that increasing complexity had an uncertainty effect on the output level. But increase the growth of human capital positively affecting economic growth. In 2016, Maksimovic, Jovic, and Jovanovic (2016) studied the fuzzy logic approach to GDP forecasting. They investigated the effects of agriculture, the manufacturing industry, and the service sector's impact on the GDP growth rate. As a result, they conclude that the service sector is the most effective sector for GDP growth. On the contrary, the manufacturing industry is the minimal effective sector on the GDP growth.

Markovic et al. (2017) developed and implemented the Extreme Learning Machine (ELM) to forecast the GDP growth rate. In the study, they analyzed GDP growth according to ten science and technology-related factors. They compared ELM results with artificial neural networks (ANN) and fuzzy logic results. Based on their simulation results, ELM has better forecasts of the GDP growth rate than the previous studies. Heiberger (2017) proposed a Bayesian approach using probabilistic network criteria to estimate GDP growth rate through networks for the financial markets. He asserted that the model correctly predicted all stagnation and welfare phases of the US economy. Dülger (2016) presented a data mining application by using the ANN technique for GDP forecasting. Feuerriegel and Gordon (2019) proposed a news-based methodology for predicting macroeconomic indicators. They used an experiment-based machine learning model to predict macroeconomic outcomes based on word occurrences and historic lags. Cerqueira et al. (2009) presented Engle–Granger's static equation methodology for estimating the Brazilian GDP quarterly series between the years 1960–1996. Amirat and Zaidi (2020) predicted GDP growth using knowledge-based economy indicators in Saudi Arabia based on time series data collected from 1991 to 2017. They used principal component analysis to choose suitable indicators for their framework, the multiple linear regressions for estimating GDP, and paired t-test to judge the predicted GDP.

Das and Coondoo (2018) examined the relationship between India's quarterly overall GDP, services GDP, manufacturing GDP, and the corresponding monthly data on manufacturing and services Purchasing Managers' Index from January 2006 to July 2014. Dua (2017) discussed the evolution of macroeconomic modeling. Dua's study focused on Bayesian methods and provided some applications for the Bayesian Vector Autoregression methods to the Indian economy. Ndoricimpa (2020) examined the threshold effects of public debt on economic growth in Africa. Kouziokas (2020) proposed a weighted support vector machines-based kernel approach applied in Gross Domestic Product growth forecasting. Yoon (2021) presented a method creating with the machine learning models such as a gradient boosting model and a random forest model to forecast real GDP growth of Japan years from 2001 to 2018. Costa et al. (2020) analyzed the classical time series model efficiency

(Seasonal Autoregressive Integrated Moving Average and a Holt-Winter method) implemented to Brazilian GDP.

The main aim of our study is to present a new GDP forecasting model. In this paper, we proposed a novel 2^k factorial design methodology to solve the GDP forecasting problem. Furthermore, we examine a general framework of the presented model in the econometrics perspectives and a numerical solution to the demonstration. The model proposes a methodology using a relevant macro-economic data set to obtain the regression model. The 2^k factorial design methodology is the concept to determining the regression model. The developed forecasting model should also be expandable, adaptable, easy to use, and flexible for different economic environments.

3. Data Set

There have been attempts to use GDP forecasting issues in econometrics, social sciences, politics, and economics in literature (Arestis et al., 2001; Baldwin, 1995; Choe, 2003; Christopoulos, 2004; Freire-Seren, 2004;Lin and Sosin, 2001; Sylwester, 2001; Koulakiotis et al., 2012) . Generally published studies from the area of social sciences and do not insist on familiar mathematical techniques. They presented to reflect main factors impact on GDP growth rate. As a result of the literature review on the factors affecting economic growth, we selected nine factors for evaluation in this study. These factors are "inflation rate (**A**)," "foreign trade volume /GDP (**B**)," "unemployment rate (**C**)," "industrial production index (**D**)," "external debt/GDP (**E**)," Research and Development (R&D) expenditures/GDP (**F**)," "domestic credit volume of deposit banks/GDP (**G**)," "foreign direct investments/GDP (**H**)," and "yearly energy consumption-billion kWh" (**I**). The freely accessible data years 2005-2017 are collected. Data obtained from The Central Bank of the Republic of Turkey (2017), Turkish Statistical Institute (2017), and World Bank (2017) at various macro-economic measures for the Turkish economy annually or quarterly and made public on their web sites in addition to their collection of information and reports (Table 1).

3. 1. Correlation analysis for data set

Correlation analysis is a statistical method. It obtains the relationship between multiple variables and measures the degree of this relationship. The correlation coefficient (r) usually has a number between -1 and +1. When changes the variables have the same directionality, there is a positive correlation and $0 < r < 1$. There is a negative correlation between the variables in the opposite direction with each other. It has a value between $-1< r <0$ in this case (Yurdakul and İç, 2009). Using the independent factors as much as possible in the experimental design is important to achieve suitable results. We perform correlation analysis using the MINITAB program to obtain an independent factor set. As a result of the analysis, Table 2 shows the correlation coefficient's grades.

In the case of "P-Value <0.05", there was a significant correlation between the two factors. On the other hand, there was no correlation between the factors in the case "P-Value> 0.05". After eliminations, the remaining independent five factors are inflation rate (**A**), trade volume / GDP ratio (**B**), unemployment rate (**C**), industrial production index (**D**), and external debt / GDP ratio (**E**) for experimental design.

4. Experimental Design

In this study, a 2^k factorial design is used. The factor combinations must create with low and high levels for the experiment (Montgomery, 2013; Hinkelmann and Kempthorne, 2008; Antony and Capon, 1998; Chang, 2011). For this purpose, a 2^k fractional factorial design is used that would provide the least number of experimental combinations (1/4 fraction=2(5-2) =8 runs with three replication) according to 5 factors using the MINITAB program.

Table 1. Data set

Year	A	B	C	D	E	F	G	H	I
2005	8.18	37.3	9.7	59.6	33.8	0.57	0.1797	0.0170	162
2006	9.6	40.8	8.9	64.0	37.7	0.56	0.2159	0.0320	176

2007	8.76	40.6	9.2	68.5	36.6	0.69	0.2479	0.0283	192
2008	10.44	42.7	12.0	68.1	35.8	0.69	0.2699	0.0191	198
2009	6.25	37.3	11.9	61.3	41.2	0.81	0.2976	0.0097	195
2010	8.57	38.5	10.0	69.4	37.5	0.80	0.3700	0.0081	211
2011	6.47	44.8	8.5	80.1	36.4	0.80	0.4078	0.0193	229
2012	8.89	44.4	8.8	83.5	39.0	0.83	0.4288	0.0123	239
2013	7.49	42.1	9.1	89.0	41.2	0.82	0.4963	0.0110	240
2014	8.85	42.5	10.2	94.2	43.4	0.86	0.5257	0.0092	252
2015	7.67	40.5	12.0	100.0	46.5	0.88	0.5485	0.0140	262
2016	7.78	39.3	9.0	103.4	46.9	0.94	0.5680	0.0087	274
2017	11.14	45.5	10.0	112.6	48.9	0.96	0.5733	0.0088	296

Table 2. Correlation analysis

	A	B	C	D	E	F	G	H
B	0.207							
	0.519							
C	0.041	-0.283						
	0.899	**0.373**						
D	-0.180	0.342	-0.092					
	0.575	**0.277**	**0.776**					
E	-0.305	-0.089	0.237	0.821				
	0.336	**0.784**	**0.459**	**0.100**				
F	-0.442	0.179	0.103	0.811	0.800			
	0.150	**0.577**	**0.750**	***0.001***	***0.002***			
G	-0.665	-0.266	0.290	0.384	0.642	0.758		
	0.018	**0.404**	**0.360**	**0.218**	***0.024***	***0.004***		
H	0.392	0.153	-0.245	-0.470	-0.522	-0.756	-0.644	
	0.208	**0.634**	**0.442**	**0.123**	***0.082***	***0.004***	***0.024***	
I	-0.255	0.362	-0.042	0.968	0.822	0.921	0.986	-0.586
	0.423	**0.248**	**0.896**	***0.000***	***0.001***	***0.000***	***0.000***	***0.045***

Pearson Correlation Coefficients
P-Value
Positive correlation

Note: Research and publication ethics were followed in this study.

4.1. Application

The inflation rate, unemployment rate, industrial production index, trade volume / GDP ratio, and external debt / GDP ratio are adjusted from 2005 to 2017 for the first eight runs (Table 3). The median values of the data are assigned as threshold values. In the data set, the median values are 8.57 for inflation rate; 40.8 for trade volume / GDP ratio, 9.7 for unemployment, 80.1 for production index, and 38 for external debt/ GDP ratio (Figure 1). The second and third replication values are obtained using the 2nd and 3rd quarter data for the same years with the final experimental design is obtained in the same way (Table 3).

Factors and related yearly GDP values from 2005 to 2017 for the first replication

Year	A	B	C	D	E	GDP
2005	8.18	37.3	9.7	59.6	33.8	9.0
2006	9.6	40.8	8.9	64.0	37.7	7.1
2007	8.76	40.6	9.2	68.5	36.6	5.0
2008	10.44	42.7	12	68.1	35.8	0.8
2009	6.25	37.3	11.9	61.3	41.2	-4.7
2010	8.57	38.5	10	69.4	37.5	8.5
2011	6.47	44.8	8.5	80.1	36.4	11.1
2012	**8.89**	**44.4**	**8.8**	**83.5**	**39.0**	**4.8**
2013	7.49	42.1	9.1	89.0	41.2	8.5
2014	8.85	42.5	10.2	94.2	43.4	5.2
2015	7.67	40.5	12	100.0	46.5	6.1
2016	7.78	39.3	9	103.4	46.9	3.2
2017	11.14	45.5	10	112.6	48.9	7.4

Example

Level Scale

Factor	Low (-1)	High (1)
A	$6.25 \leq A < 8.57$	$\mathbf{8.57 < A \leq 11.14}$
B	$37.3 \leq B < 40.8$	$40.8 < B \leq 45.5$
C	$\mathbf{8.5 \leq C < 9.7}$	$9.7 < C \leq 12$
D	$59.6 \leq D < 80.1$	$80.1 < D \leq 112.6$
E	$33.8 \leq E < 38$	$38 < E \leq 48.9$

Level	A	B	C	D	E
-1	6.25	37.3	8.5	59.6	33.8
	6.47	37.7	8.8	61.3	35.8
	7.49	38.5	8.9	64.0	36.4
	7.67	39.2	9	68.1	36.6
	7.78	40.5	9.1	68.5	37.5
	8.18	40.6	9.2	69.4	37.7
Median	8.57	40.8	9.7	80.1	38
1	8.76	42.1	10	83.5	39.0
	8.85	42.5	10	89.0	41.2
	8.89	42.7	10.2	94.2	42.1
	9.6	44.4	11.9	100.0	43.4
	10.44	44.8	12	103.4	46.9
	11.14	45.5	12	112.6	48.9

Score Card for determination of the coded factor levels

A	B	C	D	E	GDP
1	1	-1	1	1	4.8
1	1	1	1	1	9.7
1	-1	1	-1	1	9.5
1	1	-1	1	-1	3.9
-1	1	-1	-1	1	11.1
-1	-1	-1	1	1	8.5
-1	1	1	-1	-1	9.0
1	-1	1	-1	1	-4.7

Experimental design and corresponding GDP values for the first replication

Figure 1. Determination of experimental design for the replication 1

4.2. 2^k Factorial Design Analysis

The empirical outcomes are examined by the Analysis of Variance (ANOVA) analysis. The ANOVA results give a summary of the factor effects (Table 4). Hence, the regression model (Eq. 1) is a generalization of the GDP forecasting:

$$y = 5.229 - 0.146A + 2.196B - 2.321C - 1.146D + 1.558E + 1.912B * C \quad (1)$$

Table 3. Final experimental design and corresponding GDP values for all 3 replications

A	B	C	D	E	GDP
1	1	-1	1	-1	4.8
1	1	1	1	1	9.7
1	-1	1	-1	1	9.5
1	1	-1	1	-1	3.9
-1	1	-1	-1	1	11.1
-1	-1	-1	1	1	8.5
-1	1	1	-1	-1	9
1	-1	1	-1	1	-4.7
-1	1	-1	-1	1	11.7
-1	-1	1	1	-1	-4.7
1	1	1	1	1	5.2
-1	1	-1	-1	1	7.9
1	-1	1	-1	1	0.8
1	-1	-1	-1	-1	5
-1	1	1	-1	-1	3.6
1	1	-1	1	-1	7.6
-1	-1	1	1	-1	-3.4
1	1	1	1	1	5.6
1	-1	-1	-1	-1	6.5
-1	1	1	-1	-1	9
-1	-1	1	1	-1	-4.7
-1	-1	-1	1	1	8
1	-1	-1	-1	-1	7.1
-1	-1	-1	1	1	8.5

Table 4. Factors and their effects

	Effect	Coefficint	SE Coef	T	P
Term		5.229	0.6329	8.26	0.000
A	-0.292	-0.146	0.6329	-0.23	0.821
[a]**B**	4.392	2.196	0.6329	3.47	**0.003**
[a]**C**	-4.642	-2.321	0.6329	-3.67	**0.002**
D	-2.292	-1.146	0.6329	-1.81	0.089
[a]**E**	3.175	1.588	0.6329	2.51	**0.023**
[†]**B*C**	3.825	1.912	0.6329	3.02	**0.008**
B*E	-0.958	-0.479	0.6329	-0.76	0.460
S = 3,10040		R-Sq = 73,69%		R-Sq(adj) = 62,18%	

[a] **Main factors B, C, and E are statistically significant ($p < 0.05$), A and D is not.**
[†] **Two-way interaction is statistically significant ($p< 0.05$)**

4.3. Model Validation

Model verification measures are used to determine "how accurately the model obtained by the analysis can represent the actual system". The Absolute Relative Error (ARE) method is used to validation process (Kleijnen and Sargent, 2000; Dengiz et al., 2016):

$$ARE(R, F) = \frac{|R-F|}{R} \quad (2)$$

where; R is realized growth values, F is the value estimated from the developed model.

The equation is tested against scenarios at seven selected design points-other than the 2^3 design- within their possible ranges to provide the validity of the developed regression equation in this paper (Table 5). Then, the outputs determined from the regression equation (F) are compared with the results obtained from the realized growth values (R) using the same combination of variables (see Table 5).

Table 5. Validation test results

A	B	C	D	E	Y (GDP)	
					R	F
1	1	-1	1	-1	4.8	5.05
1	1	1	1	1	9.7	7.41
1	1	-1	1	-1	3.9	5.05
-1	1	-1	-1	1	11.1	10.81
-1	-1	-1	1	1	8.5	7.75
-1	1	1	-1	-1	9	6.82
1	-1	-1	-1	1	7.1	6.59
Average						0.14

When the first test point of this design is applied to the regression model, the result will be obtained as follows:

$$y = 5.229 - 0.146 * (1) + 2.196 * (1) - 2.321 * (-1) - 1.146 * (1) + 1.558 * (-1) \\ +1.912 * (1) * (-1) = 5.05 \quad (2)$$

When the same process is applied to other experimental points, model results and ARE values are obtained in Table 5. In this case, the average ARE value was calculated as 14%. Therefore, it is concluded that the regression equation can be used as the GDP forecasting model since it is computationally efficient enough to explore all possible combinations among five economic factors.

5. Empirical Tests of the Developed Model

5.1. Test 1

We proposed a retrospective test study for the regression model using the fourth-quarter data for 2005-2017 (Table 6).

Table 6. Empirical test result for the developed model

Q4	Factor values					*GDP*	Coded values calculated by interpolation approach					*Forecast*	*ARE*
	A	B	C	D	E		A	B	C	D	E		
2005	7.62	37.36	9.87	64.89	34.16	*10.5*	-0.275	0.318	-0.165	-0.777	-0.163	***6.87***	*0.3457*
2006	9.83	40.76	8.9	67.49	37.97	*6.3*	0.424	0.550	-0.538	-0.680	0.077	*7.91*	*0.2556*
2007	8.16	39.17	9.53	71.22	36.89	*5.5*	-0.104	0.442	-0.296	-0.541	0.009	*7.26*	*0.3200*
2008	10.93	38.61	11.53	62.55	36.16	*-5.9*	0.772	0.403	0.473	-0.864	-0.037	*6.20*	*2.0511*
2009	5.71	37.4	12.33	67.73	41.55	*3.1*	-0.880	0.321	0.781	-0.671	0.303	*6.04*	*0.9484*
2010	7.43	39.48	10.43	77.48	37.77	*9.7*	-0.335	0.463	0.050	-0.308	0.064	*6.68*	*0.3113*
2011	9.2	44.89	8.6	87.36	36.71	*9.9*	0.225	0.831	-0.654	0.060	-0.003	*7.37*	*0.2556*
2012	6.77	41.28	8.73	89.3	39.25	*4.2*	-0.544	0.585	-0.604	0.132	0.158	*7.36*	*0.7524*
2013	7.48	42.77	9.33	96.35	41.29	*6.9*	-0.320	0.687	-0.373	0.395	0.286	*7.12*	*0.0319*
2014	8.76	41.19	10.67	100.32	43.32	*5.9*	0.085	0.579	0.142	0.543	0.415	*6.35*	*0.0763*
2015	8.16	39.41	10.6	111.04	46.35	*7.5*	-0.104	0.458	0.115	0.942	0.606	*5.96*	*0.2053*
2016	7.57	39.82	12.2	114.77	47.31	*4.2*	-0.291	0.486	0.731	1.000	0.666	*5.28*	*0.2571*
2017	12.27	45.64	10.33	126.84	53.25	*7.3*	1.000	0.882	0.012	1.000	1.000	*7.43*	*0.0178*
												Average	*0.4483*

For 2005: $\boldsymbol{y = 5.229 - 0.146 * (-0.28) + 2.196 * (0.32) - 2.321 * (-0.17) - 1.146 * (-0.78) + 1.558 * (-0.16) + 1.912 * (0.32) * (-0.17) = 6.87}$

The factor values are converted to coded values between -1 and +1 by interpolation. Predicted GDP values and ARE comparisons results are given in Table 6. In this example, the regression equation is applied to historical data, and the average ARE value is calculated as 44.8%.

5.2. Test 2

This test proposes a new forecasting study for model testing using data for the 2018 year (Table 7). The factor values are converted to coded values between -1 and +1 by interpolation. Forecasted GDP values and current GDP values comparison results are given in Table 7. It is seen that the results obtained for the proposed model are very close to each other.

Table 7. Empirical test result for the developed model

	2018-I		2018-II		2018-III		**2018-IV**	
	Real-Uncoded	Coded	Real-Uncoded	Coded	Real-Uncoded	Coded	Real-Uncoded	Coded
A	10.23	0.645	15.39	1	24.52	1	20.3	1
B	31.64	-1	30.38	-1	28.96	-1	25.63	-1
C	10.5	0.347	9.6	-0.083	11.1	0.608	12.3	1
D	120.7	1	107.2	0.83	114.8	1	117.2	1
E	52.4	1	51.5	1	53	1	55	1
GDP-Forecast		1.88		3.85		0.73		**-0.934**
GDP-Forecast-Moving Average	4.943		5.003		-0.669		4.431	
GDP	7.5		5.8		2.46		-2.68	

For 2018-IV: $\boldsymbol{y = 5.229 - 0.146 * (1) + 2.196 * (-1) - 2.321 * (1) - 1.146 * (1) + 1.558 * (1) + 1.912 * (-1) * (1) = -0.934}$

Figure 2 shows the graphical illustration of the proposed model for the Turkish GDP data concerning the fourth quarter of 2005-2017. The graphic also shows the forecasting results from 2018-Q1 to 2018-Q4 between the periods. Furthermore, we proposed another prediction results from the moving average method (Figure 3).

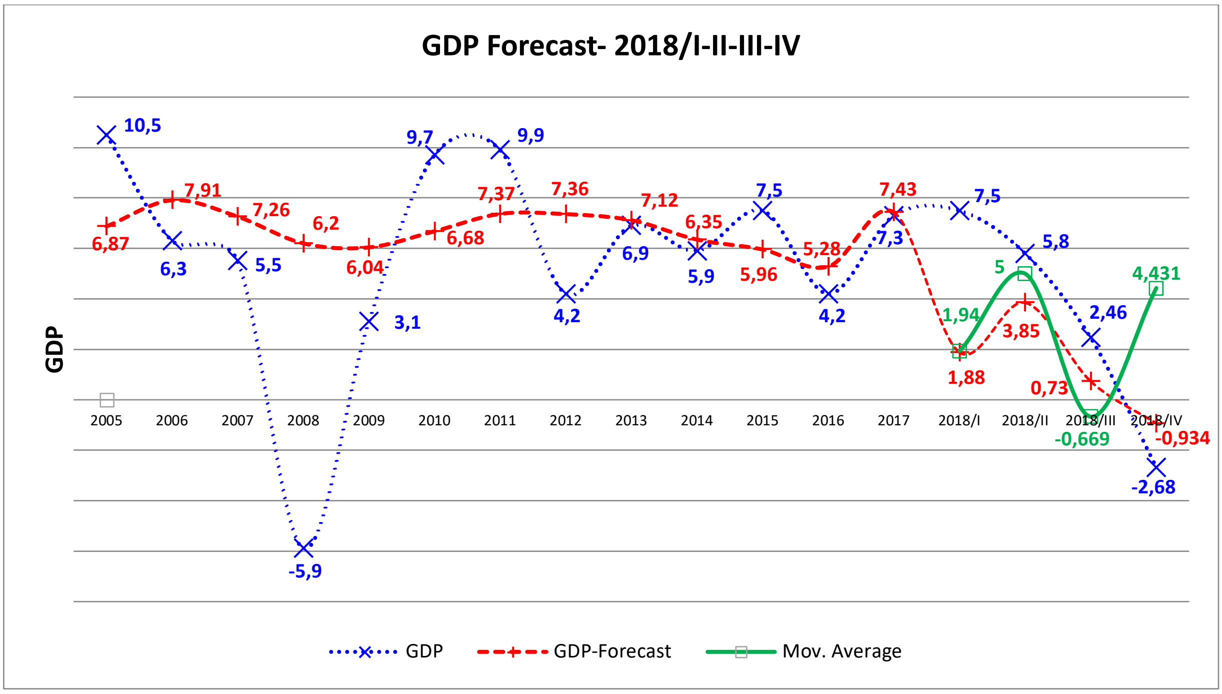
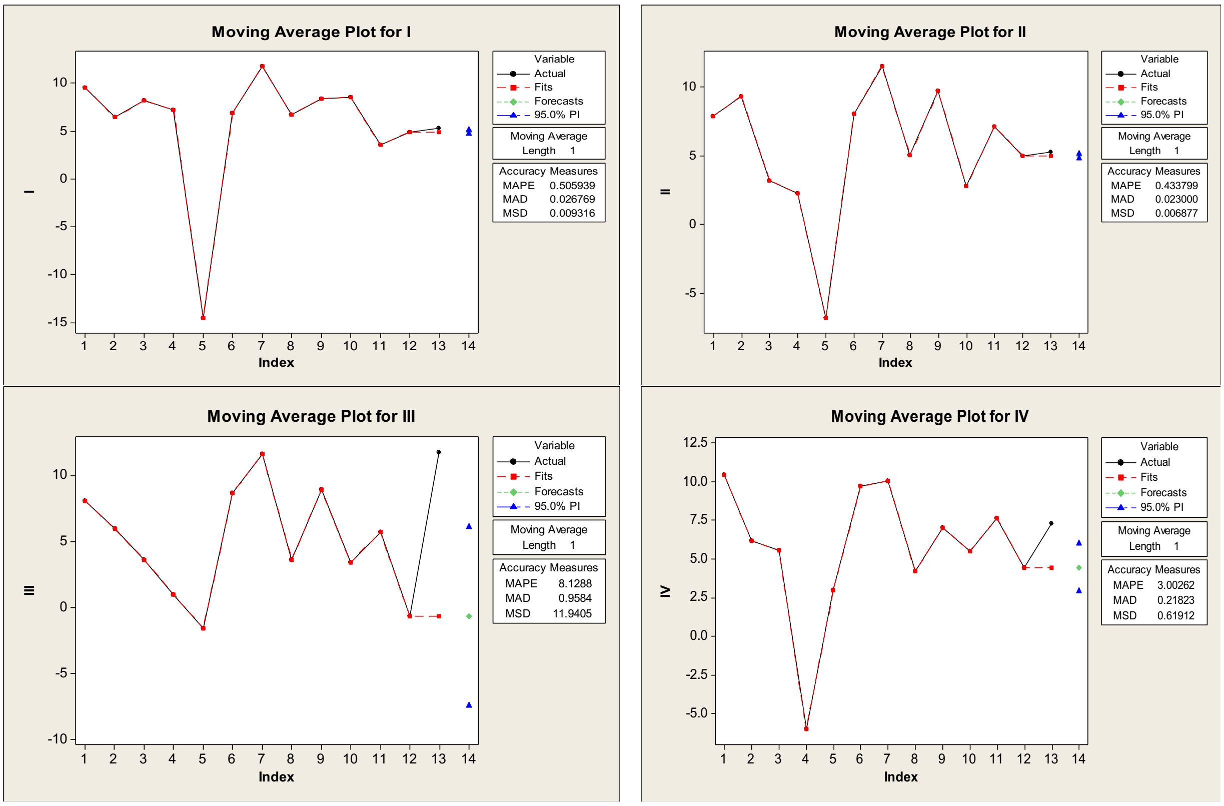


Figure 2. 2^k experimental design model fitted to the observed Turkish quarterly GDP ("x") period from 2005 to 2017. Forecast (red line) for the horizon of 2018 (green line), superimposed on the values observed in this period

It is shown that the proposed 2^k experimental design model is capable of predicting the GDP reasonably. The prediction also occurred significantly in periods after the strong recession, such as the international financial crisis of 2008.



Period	Forecast	Lower	Upper
I	4.943	4.75383	5.13217
II	5.003	4.84046	5.16554
III	-0.669	-7.44167	6.10367
IV	4.431	2.88882	5.97318

Figure 3. GDP forecasting results for 2018 periods using the moving average method

5.3. Test 3

In this test, we form a mathematical model using the obtained regression equation as the objective function. On the other hand, the factors used in the regression equation represent decision variables. We can determine the factor levels to set a growth rate equal to “7.0” using the non-linear mathematical model:

$$Z = 5.229 - 0.146x_1 + 2.196x_2 - 2.321x_3 - 1.146x_4 + 1.558x_5 + 1.912x_2x_3 \quad (3)$$

Subject to:

$-1 \leq x_1 \leq 1$ (4)
$-1 \leq x_2 \leq 1$ (5)
$-1 \leq x_3 \leq 1$ (6)
$-1 \leq x_4 \leq 1$ (7)
$-1 \leq x_5 \leq 1$ (8)

When the mathematical model is solved with MS Excel Solver so that the objective function is equal to 7.0, and the following solution results are obtained: $x_1 = -0.0253$, $x_2 = 0.310947$, $x_3 = -0.31292$, $x_4 = -0.18332$, $x_5 = 0.232539$.

Results obtained with MS Excel Solver consist of coded values between -1 and 1. Interpolation is applied to convert these values to actual values. When these results are converted to encoded data, the following results are obtained: $A = 8.63$, $B = 42.67$, $C = 9.7$, $D = 81.24$, $E = 43.11$. It can be said that the values of the factors should be close to the above results for a level of 7.0 growths for the Turkish Economy. It is seen that the results obtained for the proposed model are very close to each other.

6. Conclusion

This study proposes a GDP forecasting model to estimate economic growth targets. The aim is to create a regression function obtained by taking into account the principles of experiment design. The obtained regression function represents the objective function of the mathematical model. It provides an idea with the macroeconomic indicators for the targeted growth figures using the factors and their lower/upper limits as constraints. The model, of course, has a prediction error. However, the fact that it depends on the model based on historical data. But it can provide a significant reference for the objective of the forecasting process.

The major disadvantage of the prediction model is its usefulness for estimating the next 1-2 years. Apart from this, it's an appropriate model for estimating especially quarterly periods. Of course, it is significant to have a balanced economic period and environment for the prediction process. Balancing the economic conditions is considerable for the forecasting process. Because the Turkish economy balanced between the 2005-2017 periods (except for 2008) in comparison to other years, our forecasts were successful. The new regression model development process is simple by updating with new data in specific periods. On the other hand, for future work, modeling stages can be programmed in a computer environment.

Contribution of Researchers

Hakan Civelek contributed to establishing the Introduction and Literature Review sections and collection of the data. Yusuf Tansel İç contributed to developing the model, obtaining the model solution, and writing the paper.

Conflict of Interest

The authors declared that there is no conflict of interest.

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