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A Comparison Between Time Series, Exponential Smoothing, and Neural Network Methods To Forecast GDPof Iran

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Abstract

In general gross domestic product (GDP) is a substantial element in macro-economic analysis. Policy makers of a country use variations of GDP for long run planning. Considering different economic conditions of a country, forecasting is a useful tool to identify the variations of GDP for planning. In this paper, quarterly GDP value during (1998-2003) is used as a base of analysis. The quarterly GDP values of the year (2004 -2005) are forecasted using Time series, Exponential smoothing and Neural network approaches. The results are compared with actual quarterly GDP value and error measurement are computed in each methods. Consequently statistical analyses are accomplished to show the best method of forecasting. We have shown that neural network approach method is the best alternative to forecast the GDP of Iran.

Keyword: Gross Domestic Product, Time Series Method, Exponential Smoothing, Neural Network, Statistical analysis.

1. Introduction

Researchers, policy makers, and participants in the financial markets have paid considerable attention to the empirical relevance of various economic

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leading indicators. The empirical concern of, for example, so-called qualitative Business Tendency Survey (BTS) responses are of large importance since business survey data are very likely to provide significant and early information about the current and future state of the economy. As a consequence, BTS data may have a substantial effect on both financial markets and the policy trends of Central Banks and Treasury Departments. The quarterly business surveys of the National Institute of Economic Research (NIER) in Sweden are an interesting attempt to supply a large dissemination of data and ready availability of high-quality analysis. In these business survey data, the responding manufacturing firms are asked whether they perceive or expect certain variables to increase, decrease, or stay the same over time. For example, these survey data include detailed time-series records on aggregate response percentages of firms whose perceived output in the current quarter has increased, decreased or stayed the same compared to the preceding quarter, and whose expected analogues will increase, decrease or stay the same the next quarter compared to the current quarter. The main reason why survey questionnaires generally require the respondents to provide subjective judgments in terms of directions of change rather than traditional point forecasts is that directions of change are much easier to provide by the respondents than high-precision point forecasts. These business surveys regularly arrive prior to the corresponding official statistics, and hence they are the first reports in every quarter on how the industrial sector in Sweden performs.

It thus follows that these survey data may provide useful leading information about movements in the Swedish industrial sector and aggregate output. A number of surveys are now conducted worldwide on a regular basis. In general, the survey questionnaires are designed to explore individual firms' and/or households' ex post perceptions and ex ante expectations about an array of economic variables. The most recognized survey-based leading indicator today is the U.S. National Association of Purchasing Managers (NAPM) Index. This indicator has been published monthly since the 1930s and is used primarily for predictions of short-term cyclical movements in output. The empirical relevance of business survey data when analyzing industrial production has been recognized by Terasvirta (1986)[1] , who found substantial evidence in Finnish metal and engineering industries that business survey data include useful information about future industrial production. Moreover, Bergstrom (1993)[2] found support for the claim that Swedish business survey data may improve the fit of simple autoregressive models of the change in manufacturing production. Furthermore, Christoffersson et al. (1992)[3] showed that Swedish business tendency survey data are useful when predicting fluctuations in production over the business cycle, and Rahiala and Terasvirta (1992)[4] found evidence in Finnish and Swedish metal and engineering industries on leading information in business survey data. Support for the relevance of survey data when predicting business cycle turning points was found in Oller and Tallbom (1996)[5], and, using Swedish manufacturing survey data, Koskinen and Oller (1998)[6] showed that a Markov regime-shifting model can yield commendable predictions of business cycle turning points. The above-referred body of economic analysis hence confirms the assumption that Swedish (and Finnish) business survey data are closely related to industrial output and that they typically contain useful leading information about movements in the business cycle. In contrast, however, Batchelor (1982) [7] showed that although survey-based growth expectations in Belgium, France, Germany, and Italy produce lower root mean square errors (RMSE) than simple extrapolative predictors, they include no additional information in more complex autoregressive integrated moving average (ARIMA) forecasting models. Moreover, on the basis of survey response data on short-term production expectations from Belgium, France, Germany, Netherlands, and Italy, Hanssens and Vanden Abeele (1987) [8] found that survey expectations do not Granger cause objectively measured production levels. Although, it may seem intuitively plausible that business tendency survey data provide additional information in standard time series models of output growth, empirical studies provide somewhat different results.

2- Problem Methodology

In this research, available data is got from the web site of Iran central bank [9], and used for both training and forecasting. In this way, real gross domestic product during the quarters of the year 1377 and 1382 is used for training area by using three methods that will be discussed below, and quarters of the year 1383 and 1384 are selected for forecasting and testing the results of these three methods in comparison with the actual gross domestic product.

The approach is to select the best method for forecasting among time series method, exponential smoothing and neural network by statistical analysis. Figure 1 illustrates the proposed approach used in this research.

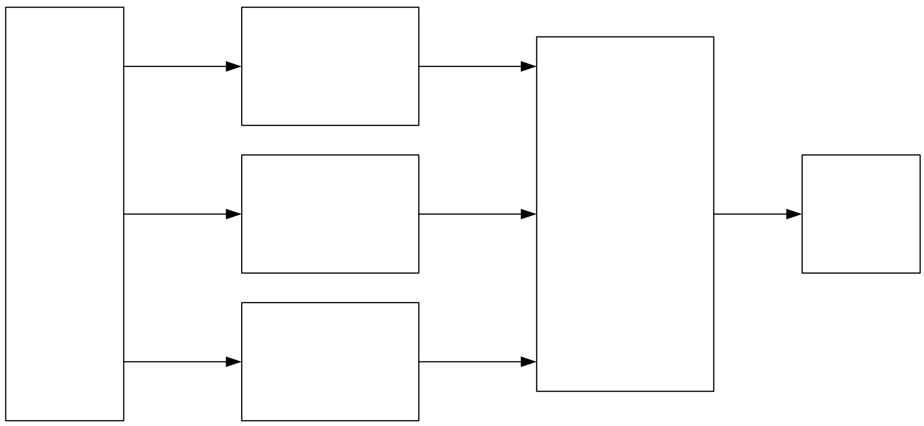

Figure1. The proposed approach

2-1-Time Series (TS)

Time series procedures can be used to analyze data collected over time, commonly called a time series. These procedures include simple forecasting and smoothing methods, correlation analysis methods, and ARIMA modeling. *Simple forecasting and smoothing methods* are based on the idea that reliable forecasts can be achieved by modeling patterns in the data that are usually visible in a time series plot, and then extrapolating those patterns to the future. The choice of method should be based upon whether the patterns are *static* (constant in time) or *dynamic* (changes in time), the nature of the trend and seasonal components, and how far ahead that you wish to forecast. These methods are generally easy and quick to apply. The simple forecasting and smoothing methods model components in a series that are usually easy to see in a time series plot of the data. This approach decomposes the data into its component parts, and then extends the estimates of the components into the future to provide forecasts. There are four different trend models in time series that are: linear, quadratic, exponential growth curve, or S-curve (Pearl-Reed logistic). The short description of each model is as follows:

1. Trend analysis by the *linear trend* model:

$$Y_t = b_0 + (b_1 \times t) + e_t \tag{1}$$

In this model, b_1 represents the average change from one period to the next.

2. The *quadratic trend model* which can account for simple curvature in the data is:

$$Y_t = b_0 + (b_1 \times t) + (b_2 \times t^2) + e_t \tag{2}$$

3. The *exponential growth trend model* accounts for exponential growth or decay. For example, a savings account might exhibit exponential growth. The model is:

$$Y_t = b_0 \times b_1^{\,t} \times e_t \tag{3}$$

4. The *S-curve model* fits the Pearl-Reed logistic trend model. This accounts for the case where the series follows an S-shaped curve. The model is:

$$Y_t = \frac{(10^a)}{(b_0 + b_1 b_2^t)} \tag{4}$$

In this study the first model is used and the following equation is achieved:

$$Y_t = 32944.7 + 1707.05 \times t \tag{5}$$

The preceding equation is being used for forecasting GDP in both training and forecasting periods.

2-2- Exponential Smoothing (ES)

Exponential Smoothing, which is almost like time series, is another kind of data analysis over time. Data smoothing, that is obtained either with some optimal weight generated according to the data estimation or with a specified weight, is achieved. Optimal ARIMA weight is gained by fitting with an ARIMA (0,1,1) model and stores the fits. The smoothed values are the ARIMA model fits, but lagged one time unit. Initial smoothed value (at time one) by back casting is as follows:

Initial smoothed value = [smoothed in period two-α (data in period 1)]/ (1-α) where 1-α estimates the MA parameter.

Specified weight is reached by using the average of the first six (or N, if N< 6) observations for the initial smoothed value (at time one). Subsequent smoothed values are calculated from the formula:

Smoothed value at time t = α(data at *t*) + (1- α) (smoothed value at time *t-1*) where α is the weight.

The fitted value at time t is the smoothed value at time t-1. The forecasts are the fitted value at the forecast origin. If we forecast 10 time units ahead, the forecasted value for each time will be the fitted value at the origin. Data up to the origin are used for the smoothing. In naive forecasting, the forecast for time t is the data value at time t-1.

2-3- Artificial Neural Network

According to McCulloch & Pitts (1943) [10] ANNs are born from approach of developing intelligent systems by simulating the biological structure and the work of the human brain.

Afterwards, the number of studies on ANNs is considerably increased. According to Grossman & Thursby (1995)[11] The theory of ANN is based on neurobiology, mathematics and physics. An ANN is composed of hierarchically organized neural bundles, bound parallel to each other. Unlike the classical systems, the use of ANN is based on their previous experiences. Since information is processed in a parallel fashion by the neurons in ANNs, the system is much faster than the classical systems. Human body consists of trillions of cells. A portion of them is the nerve cells called ‘‘neurons’’. These neurons have different shapes and sizes. The neurons are the cell; made specially for conducting information in an electrochemical way. A biological neuron is composed of a body, which contains the nucleus and two types of extensions called ‘‘dendrite’’ and ‘‘axon’’. The nucleus is located at the center of the neuron and provides energy for cellular activities. A neuron is connected to other neurons via axons and dendrites. The canals which bring impulses to the nerve cells are called as the dendrite; the canals conducting impulses to other cells are called as the axon. Dendrites receive the impulses by contacting with other neurons and conduct these impulses to the nucleus.

The impulse output from nucleus is conducted via axon and this operation is repeated continuously. The touch surfaces between two neurons are called ''synapse''. The impulses conducted by the axon of neuron are conducted to other neuron by synapses.

2-3-1- Generalized Regression Neural Networks (GRNN)

The generalized regression neural network (GRNN) is a special extension of radial basis function network (RBFN). It is a feed forward neural network based on nonlinear regression theory consisting four layers: the input, the pattern (hidden) layer, the summation layer, and the output layer. It can approximate any arbitrary mapping between input and output vectors. Topology of the generalized regression neural network is shown in Figure 2. The basic GRNN was proposed in 1991 by Specht(1991)[12] as an extension of his probabilistic neural network(PNN). It takes advantage of the fact that given a known joint continuous probability density function f(x,y) of a vector input x and a scalar output y, the expected value of y given x can be computed by estimating the joint pdf using the Parzen estimator. The core GRNN equation is:

$$\hat{y}(x) = \frac{\sum_{i=1}^{n} y_i . h\left(\frac{\delta(x, x_i)}{\sigma}\right)}{\sum_{i=1}^{n} h\left(\frac{\delta(x, x_i)}{\sigma}\right)} \qquad (6)$$

Where h is a Parzen kernel estimator, usually Gaussian, and δ is a distance measure, Euclidean in our case. The width of each kernel centered on data x_i is represented by σ, and y_i is the expected output for that data.

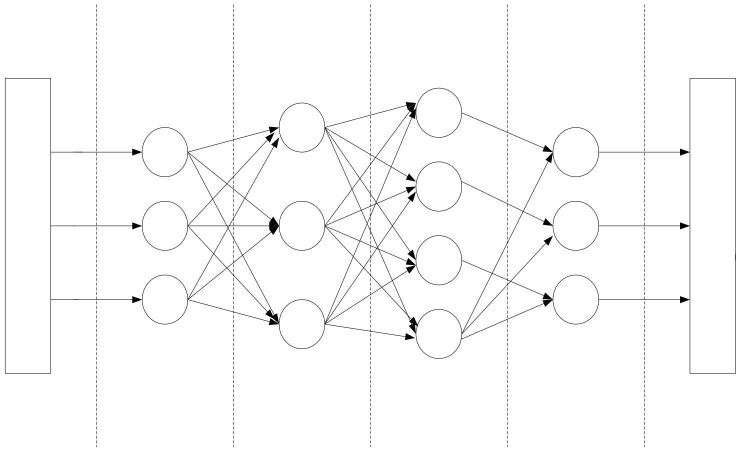

Figure 2.Topology of generalized regression neural networks

3- Comparative Analysis Among Three Methods During Training Period

In this section, a comparative analysis among discussed models during 1377 until 1382, which is considered as training period, is done. The computational results are listed in Table 1. Figure 3 illustrates comparative analysis among results of these three methods.

Table 1: The computational results of three methods in training period

Quarter	ACTUAL	TIME SERIES	EXPONENTIAL SMOOTHING	GRNN
1	47028,36	34651,8	47380	46888,1733
2	45733,88	36358,8	46929	45782,1293
3	45450,46	38065,9	45397	45488,7071
4	45423,23	39772,9	45465	45472,6197
5	46642,96	41480	45411	46854,2451
6	45901,07	43187	46990	45625,2486
7	45546,72	44894,1	45594	45517,354
8	45525,72	46601,1	45533	45699,2974
9	46446,98	48308,2	45524	47965,9233
10	45816,11	50015,2	46707	44098,609
11	45673,77	51722,3	45565	45379,8152

12	45670,82	53429,3	45704	46974,0789
13	51976,6	55136,4	45661	51189,6635
14	38999,69	56843,4	53755	43010,2912
15	44289,43	58550,5	34843	46622,7343
16	50794,6	60257,5	46950	50095,0907
17	51976,6	61964,6	51877	59519,7797
18	39234,1	63671,6	52005	56998,3542
19	46480,73	65378,7	35637	57384,123
20	49166,4	67085,7	49535	58479,3343
21	86805	68792,8	49063	73757,0291
22	111967	70499,8	97436	85723,5057
23	93796	72206,9	116060	76635,844
24	86442	73913,9	87525	73053,4144

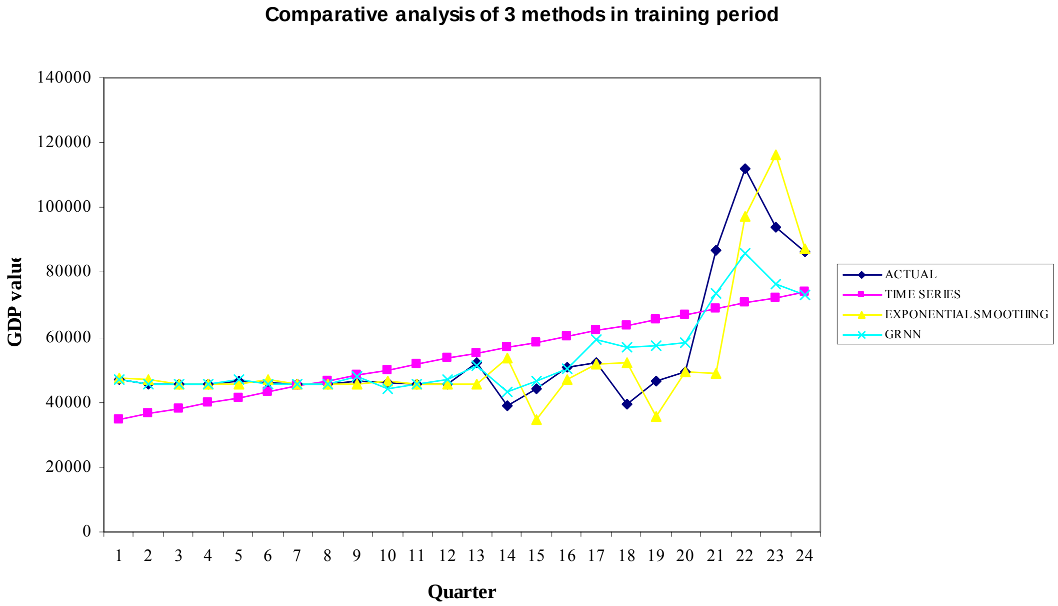

Figure3. Comparative analysis among three methods in training period

3-1- Error Calculation

The following methods are used for measuring reliability and performance of each forecasting methods:

1. MAPE (Mean Absolute Percentage Error)

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|F_t - A_t|}{A_t} \tag{6}$$

2. RMSE (Root of Mean Squared Error)

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(F_t - A_t)^2}{n-1}} \tag{7}$$

3. MAD (Mean Absolute Deviation)

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|F_t - A_t| \tag{8}$$

Where F_t is the expected value for period t, A_t is the actual value for period t, n is the total number of periods.

In this paper MAPE is used for evaluating the performance of various kinds of forecasting models. According to Chang et al (2007)[13] the smaller the value of MAPE, the better the forecasting ability is. The signification of MAPE is presented in Table 2.

Table 2: The signification of MAPE

MAPE	Signification
<10%	Excellent forecasting ability
10-20%	Good forecasting ability
20-50%	Reasonable forecasting ability
>50%	Bad forecasting ability

By using data in Table1, error calculation for each forecasting method is possible. The results of error calculation in training period are presented in Table3.

Table 3: Error calculation in training period

	Time series	Exponential Smoothing	GRNN
MAPE	0.21	0.10	0.086
RMSE	14955.75	10995.77	9185.6
MAD	11409	5835	5374.75

As it is clear from Table 3 the best and more reliable method in training period is GRNN because of the lower value of errors. Also about the performance, according to Table 2, GRNN has excellent forecasting ability with the MAPE value of 8.6%, ES has good forecasting ability with the MAPE value of 10%, and finally TS has reasonable forecasting ability with the MAPE value of 21%.

4- Comparative Analysis For Predicting GDP:

In this part the forecasting is accomplished by the same procedure which is used in the training period. The calculated data is presented in Table 4. A comparative analysis among actual GDP value and forecasting value based on discussed models is shown in Figure 4.

Table 4: The computational results of three methods in forecasting period

Quarter	ACTUAL	TIME SERIES	EXPONENTIAL SMOOTHING	GRNN
1	90489	75621	86137	82662,5949
2	116489	77328	86137	103659,4813
3	98644	79035,1	86137	88384,4791
4	91090	80742,1	86137	82190,2614
5	99703	82449,1	86137	85696,5792
6	121080	84156,2	86137	109746,1945
7	104358	85863,2	86137	92350,8042
8	93780	87570,3	86137	85304,2481

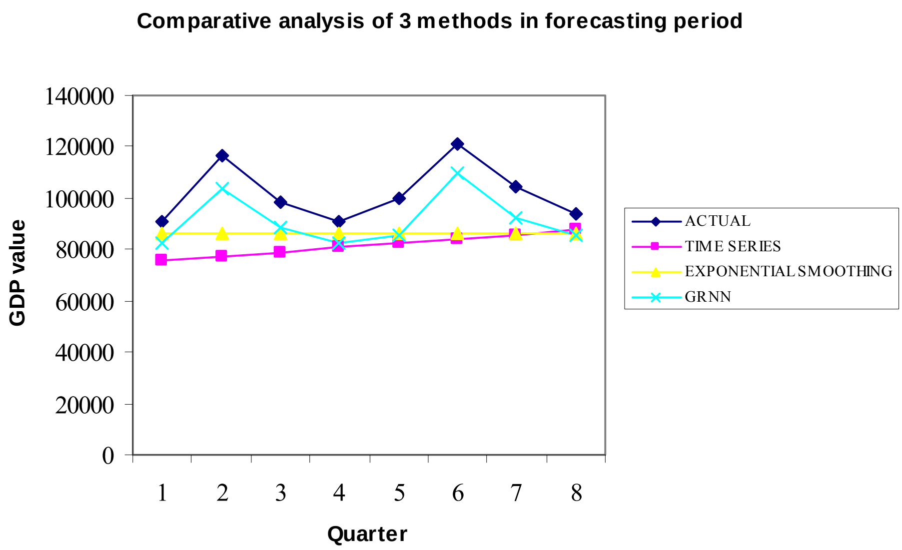

Figure 4. Comparative analysis among three models in forecasting period

According to data in Table 4, error calculation for each forecasting method is done. The results of error calculation in forecasting period are presented in Table 5.

Table 5: Error calculation in forecasting period

	Time series	Exponential Smoothing	GRNN
MAPE	0.064	0.049	0.035
RMSE	13653.97	11260.96	6430.09
MAD	6786.2	5272.4	3568.26

Regarding to Table 5 GRNN method has lower error values in forecasting period. But the contrast with training period is in performance of the 3 methods. According to Table 2, all 3 methods have excellent forecasting ability in forecasting period. Despite the same performance level of 3 methods in forecasting period, still GRNN is the most reliable one because of the lower deviation from the actual value.

5- Statistical Analysis

The purpose of one-way ANOVA is to find out whether data from several groups have a common mean. That is, to determine whether the groups are actually different in the measured characteristic. In table 3 the standard ANOVA table with columns for the sums of squares (SS), degrees of freedom (df), mean squares (SS/df), F statistic, and p-value is shown.

Table 6: ANOVA table

Source of Variation	SS	Df	MS	F	P-value
Between Groups	19385200.92	2	9692600.461	0.044125284	0.956861051
Within Groups	15156603387	69	219660918.7		
Total	15175988588	71			

In this case the p-value is about 1, a very large value. This is a strong indication that the quarterly GDP computed from different approaches are same. In Figure 5 the graphical assurance is shown, indicating that the means are not different by looking at the individual value plots.

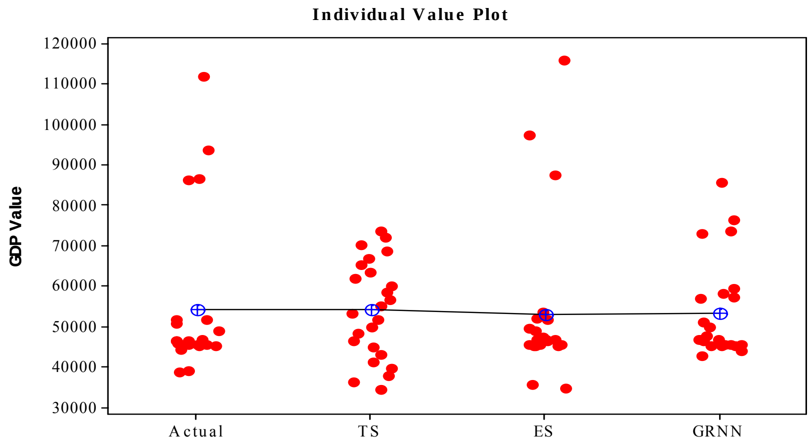

Figure 5. Individual value plot of all groups

In this Figure plot 1 indicates actual GDP and 2, 3, 4 are indicates gained GDP using *TS*, *ES* and *GRNN* methods respectively.

As it is shown in Figure 5 and regarding to MAPE of forecasting period which is represented in Table 5, it is being inferred that all three methods are capable to be used for forecasting of GDP. For more explicit the following hypothesis tests are done to identify the best method of forecasting.

5-1- Hypothesis Testing

The hypothesis tests for discovering the best method in forecasting period are as follows:

$H_0: \mu_{TS} - \mu_{ES} = \delta > 0$
$H_1: \mu_{TS} - \mu_{ES} = \delta \leq 0$

Where H_0 means the mean of *(Actual - TS)* is more than *(Actual - ES)* against H_1 which means the mean of *(Actual - ES)* is more than *(Actual - TS)*. For this hypothesis testing the t-student distribution is used.

Assumption:

$\sigma^2{}_{TS} = \sigma^2{}_{ES}$
$\alpha = 0.05$

Notations:

μ	The mean of the population
$\overline{X}$	The mean of the sample (data)
n	Number of samples
σ	The variance
S	The standard deviation
δ	Difference between the mean of the populations
α	Safety level

$$T = \frac{\overline{x}_{A-TS} - \overline{x}_{A-ES} - \delta}{sp\sqrt{\frac{1}{n_{TS}} + \frac{1}{n_{ES}}}} \tag{9}$$

$$sp^2 = \frac{(n_{TS}-1)s_{A-TS}^{\ 2} + (n_{ES}-1)s_{A-ES}^{\ 2}}{n_{TS} + n_{ES} - 2} \tag{10}$$

$$t_{\alpha, n_{TS}+n_{ES}-2} = t_{0.05,8+8-2} = 1.761 \tag{11}$$

$$T = \frac{20359 - 15817 - 0}{11610.83\sqrt{\frac{1}{8} + \frac{1}{8}}} = 0.782$$

If $T > t_{\alpha, n_{TS}+n_{ES}-٢}$ then H_0 is rejected: *0.782< 1.761*. Therefore the result shows that H_0 is accepted i.e. the mean of calculated GDP by *ES* method is closer to the actual GDP rather than *TS* method.

The next hypothesis test is between *ES* method and *GRNN* as follows:

$H_0: \mu_{ES} - \mu_{GRNN} = \delta > 0$
$H_1: \mu_{ES} - \mu_{GRNN} = \delta \leq 0$

Where H_0 means the mean of *(Actual - ES)* is more than *(Actual - GRNN)* against H_1 which means the mean of *(Actual - ES)* is less than *(Actual - GRNN)*. The whole conditions are like the former test.

$t_{0.05,8+8-2} = 1.761$

T=1.242

T< t

In this test H_0 is also accepted i.e. the mean of calculated GDP by *GRNN* method is closer to actual GDP rather than *ES* method.

The hypothesis-based statistical comparison, the passed procedure that ensued to achieve the best method of forecasting in forecasting period, is shown in Figure 6.

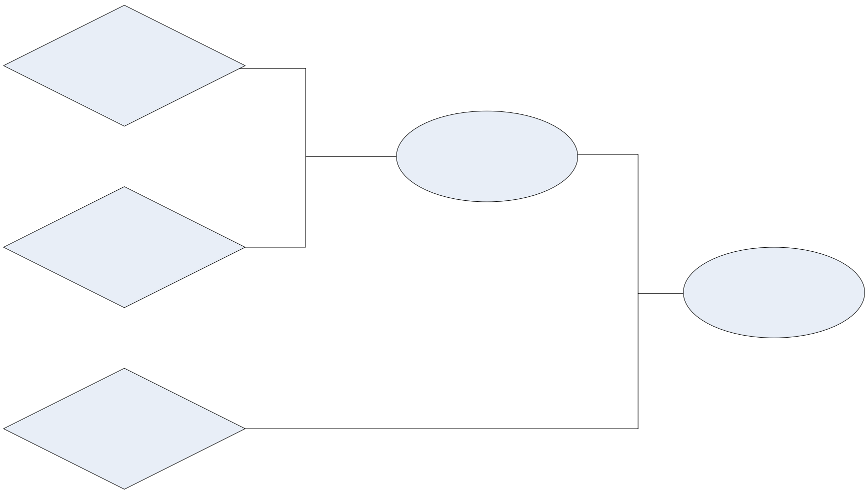

Figure 6. The hypothesis-based statistical comparison

6- Conclusion

In this paper time series, exponential smoothing, and neural network methods were considered to forecast quarterly gross domestic product of Iran. In order to select the best method, the problem was divided into two periods. The first period is considered as the training period during 1377 and 1382, and the second period was defined as forecasting period from 1383 until 1384. One way Analysis of variance method was used to have significant statistical analysis. In the training period *GRNN* method shows minimum *MAPE*, *RMSE*, and *MAD* with the actual GDP value simultaneously.

Although, the statistical results show that no methods have different means significantly from actual GDP in the forecasting period, but hypothesis tests indicate that neural network approach (in comparison with the discussed models) is effective from *MAPE* view point to be used for forecasts. Thus *GRNN* method will be selected as the best alternative to forecast the GDP of Iran.

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