Forecasting the Iranian Tax Revenues: Application of Nonlinear Models

Saeedeh Hamidi Alamdari [1] Hamid Khalizadeh [2] Ayat Zayer[3]

Abstract

Tax is one of the main sources of financing government budget. Therefore, having a clear picture about the attainable amount of taxes are not only necessary for optimal allocation of scarce resources for tax collection, but also helps the government to develop precise tax collection programs .In this article, the structural features of the tax revenues series have first been examined in relation to linearity, chaotic nonlinearity and stochasticity, using Lyapunov Exponent. These series are: total taxes, direct taxes, indirect taxes, corporate taxes, income taxes, salary taxes, real estates taxes, business taxes, wealth taxes, inheritance taxes and goods & services taxes. The results indicated the existence of a chaos in the series of different tax resources with different weakness and severity. Therefore, based on the results it was found that we can do more accurate short-term predictions by applying nonlinear modeling. In the next step, using the data of the period 1963-2006,the tax revenues of different resources were forecasted for the period 2007-2009 by applying both parallel and proposed Multiple-input Multiple-output structures of the ANN's.

Key words: Tax, forecast, chaos, Lyapunov exponent, artificial neural networks, parallel models, multiple-input multiple-output model

1. Introduction

Financing the governmental budget by collecting tax revenues is one the goals of taxation. While the fulfillment of that is the main functions of the INTA. It is considered to be an important indictor for evaluating the INTA's performance by the supervisory bodies. Having a clear picture about the attainable amount of taxes is not only necessary for the optimal allocation of scarce resources for the tax collection, but also helps the government to develop precise tax collection programs. Due to the inherent characteristics of the economic variables and also due to the effects of social, political, psychological and environmental factors on the economic variables, they demonstrate nonlinear behaviors in real world, so a nonlinear method is needed to forecast the economic variables .One of the well-known nonlinear methods developed thanks to the recent advancement in computer science is the artificial neural networks, which in recent years has been applied for the economic forecasting.

---

[1] MA in Economics
[2] Associate Professor of Electrical Engineering , Control Department .Khaje Nasir Aldine Tosi University of technology. h_khaloozadeh@eetd.kntu.ac.ir
[3] MA in Economics

In this article, Neural Networks approach has been applied to forecast tax revenues. In the first part of the article, after a brief review of literature and empirical studies, Lyapunov Exponent Test has been applied to test the forecastibility of the tax revenues. In the second part of the article, using tax revenues series of Iran for the period 1963-2006, tax revenues has been forecasted for the period 2007-2009.

2. Literature Review and Empirical Studies

An interest in the secret of the rapid processing of the information in the human brain, the way through which the information is processed, as well as the performance of memory, learning and retrieving of events all together have pushed the scientists to start and to continue their research on Neural Networks since 1940.The human brain consists of 10^{11} interrelated neurons with 10^{16} connections. The researchers working on Artificial Neural Networks and human brain believe that understanding the way in which neurons are interconnected is the key for understanding the human behavior as an information processing system. The Artificial Neural Networks are able to learn complicated behaviors. It usually consists of several simple interconnected nonlinear processors known as “Nodes” or “Neuron”. The connection of many simple neurons which make altogether the human brain has been the primary idea for developing neural networks models. Neural networks modeling have resulted in good output in function approximation, model diagnosis as well as forecasting nonlinear processes. In fact, using neural networks for function approximation is generalized form of regression analysis and classical statistics. In a regression analysis, a model is fitted for a specific structure, using sets of information by various criteria such as Mean error. The neural networks is called something beyond the regression and the most important advantage of neural networks for model fitting over statistical methods is that the neural networks have more general functional form compared to those methods (Khaloozadeh & Khaki,2003).

The neural networks is widely applied in different fields of economic issues such as oil, share and commodities price forecast, and newly used for tax revenue forecasting. The results of the studies in general show that the performance of this method is much better than the competing approaches.

For instance, Shazly and Hassan (1997), Zhang and HU(1997), Lisi and Schiavo(1999), Leung et al.(2000), Qi and Yangu Wu(2003), Leung and Chen (2004) used Artificial Neural Networks and Time series in their studies for forecasting exchange rate. The results of their studies show that the performance of the artificial neural networks is better than time series models. Thomas and et al (1999), in a study for analyzing sale market response of coffee based on monthly data, compared the accuracy of forward neural network and Multiplicative Competitive Iteration (MCI) model, and showed that the neural networks performs better than MCI in small sample data. Fllareio and Averehenlov (1999) showed in their study that neural networks perform better than ARIMA in forecasting share prices. Palit and Popovic (2000) also showed that artificial neural networks methods have better performance than competing AR, ARIMA forecasting methods. Moshiri and Kameron(2000) reached the same results by comparing the performance of Artificial Neural Networks with traditional Econometric models, time series and structural models; BVAR and VAR in forecasting inflation rate of Canada. Virili and Bernd Freisleben(2000) used Artificial neural networks to examine the effects of non-stationary on demand for house loan in the Netherlands. The results of their study showed that the artificial neural networks perform better than ARIMA.

Ghadimi and Moshiri (2002) have compared the efficiency of an Artificial Neural model with a linear regression model in their study to forecast the economic growth rate of Iran for the period 1936-2001.Chavoshi (2003), in his study, by applying both linear factor model and Artificial Neural Networks forecasted the behavior of Behshahr's Industrial Development Company's share return .Khalozade (2003), in his article, by using data of several corporates in Tehran's Stock Exchange market have forecasted the share prices of them and finally introduced an optimal model for such purpose. Moshiri and Forotan(2004) have compared the results of future oil prices obtained by ARIMA ,GARCH and Artificial Neural Networks model. Hamidi (2005) has forecasted the Iranian Business tax revenues by using forward artificial neural networks , linear regression and ARIMA models .Farjamnia(2007) has compared the oil prices since April 1983 to June 2005 forecasted by ARIMA and Artificial Neural Networks. The results of all above mentioned studies show that the Artificial Neural Networks performs better than other competing methods such as econometrics and time series methods.

3. Chaos in Tax Revenues' Time Series

In order to get a reliable forecast, it is necessary to examine the forecastability of taxes' time series and its type of structure prior to any forecast attempt. To do so,Lyapunov Exponent test is used. If the results of the test confirm the forecastability of the series, then nonlinear modeling can be used to forecast in the short-run. In fact, the forecastability for the period which is in inverse proportion to the Lyapunov Exponent is confirmed if the magnitude of the Lyapunov Exponent is small. Long-run forecast is very difficult or impossible due to the sensitivity of the chaotic systems to initial condition. So, it can be said that forecasting is only a matter of short-run.

3.1 Lyapunov Exponent

Chaos theory provides a new insight into the real world. Chaos is an inherent feature of the nonlinear systems which indicates that even a little change in the initial condition of the model may result in a substantial change in its behavior (Garliauskas, 1999).Among different diagnostic test for chaos in time series, the Lyapunov Exponent is the most important test. It is an indicator of the divergent points in fuzzy space or sensitivity to the initial condition. Positive value of the exponent is a sign for the existence of a chaos in system, and in this case the behavior of system is forecastable in the short-run but not in the long run due to the sensitivity of system to initial condition. In this article the Lyapunov Exponent has been estimated for the period 1963-2006 annually in M dimension (2 to 5) and time span from 1 to 18. Scheinkman and LeBaron nonlinearity test has been employed to confirm the result of the Lyapunov test. Using N data scalar of the series, matrices of m raw and N-m+1 column are constructed to calculate the Lyapunov Exponent and then all of the joint vectors are selected among these matrices so as to be close to each other and …in this relation:

$$r_0 (m; i, j) = \left\| x_i - x_j \right\| < \varepsilon$$

ε is a positive amount. The above calculations are done over the n time spans:

$$r_n \ (m; i, j) = \left\| x_{i+n} - x_{j+n} \right\|$$

Then divergence between the points that are close to each other is calculated. If the close points diverge from each other for any n greater than zero in m space dimension then the $\mathrm{d(m, i, j)}$ will be greater than one.

$$d_n \ (m; i, j) = \frac{r_n}{r_0} = \frac{\left\| x_{i+n} - x_{j+n} \right\|}{\left\| x_i - x_j \right\|}$$

And finally the Lyapunov Exponent is calculated by the following relation:

$$\lambda(m, n) = \frac{1}{N(N-m-1)} \sum \log d_n \ (m; i, j)$$

It is worth mentioning that it is necessary to examine the stationarity of the series for the above analysis. In case of non-stationarity, the series should be become stationary before any attempt to calculate the Lyapunov Exponent.

3.2 Testing the Stationary of the Taxes' Time Series

The results of the unit root test indicate that all of the series are non-stationary. Most of the series are first-difference stationary process while the rest are two-difference stationary processes. The optimal lag has been determined by the Akaike, Schwarz Bayesian and Hanan Quinn information criteria. Table (1) shows the results of the unit root test for the series: total taxes, direct taxes, indirect taxes, corporate tax, income tax, business tax, real estate tax, wealth tax, inheritance tax and goods and services tax for the period 1963-2006

Table 1. Unit Root Test of Tax revenues Series (1963-2006)

Unit Root test		
	With trend	Without trend

	Critical Value	t-Statistics	Critical Value	t-Statistics
Direct Taxes	-2.9446	-3.2646	-3.5348	-4.1511
Indirect Taxes	2.9446	-6.2544	-3.5348	-6.1315
Income Tax	2.9446	-4.2489	-3.5348	-5.2595
Salary Tax	2.9446	-4.2927	-3.5348	-4.6608
Business tax	2.9446	-4.7098	-3.5348	-5.5581
Real Estate Tax	2.9446	-3.5167	-3.5348	-3.5763
Wealth Tax	2.9446	-4.0968	-3.5348	-6.7633
Inheritance tax	2.9446	-3.9228	-3.5348	-4.262
Goods & Services tax	2.9446	-4.4632	-3.5348	-5.947
corporate Tax	2.9446	-4.1729	-3.5348	-4.9616

95% critical value

3.3 Lyapunov Exponent

Figure (1) shows the Lyapunov Exponent estimated for the tax series within the period of 1963-2006. This figure shows the steady state convergence of the estimated values of Lyapunov Exponent. Accordingly, the smaller the positive value of the λ, the weaker the chaos of the system and also the less the sensitivity of system to initial condition. Consequently, past information can be used for forecasting and vice versa. For instance the value of λ for the corporate tax is positive but small for dimensions 2 and 3; therefore, the time series in question has relatively a weak chaos and nonlinear modeling can result in a relatively good short-run forecasts. As it is illustrated in the figures, all of the time series except for wealth and goods & services taxes have relatively weak chaos; therefore, it can be concluded that time series of the Iranian tax revenues are nonlinear and have a specific structure and hence for a short time period, these series may result in an acceptable forecasts using nonlinear modeling methods.

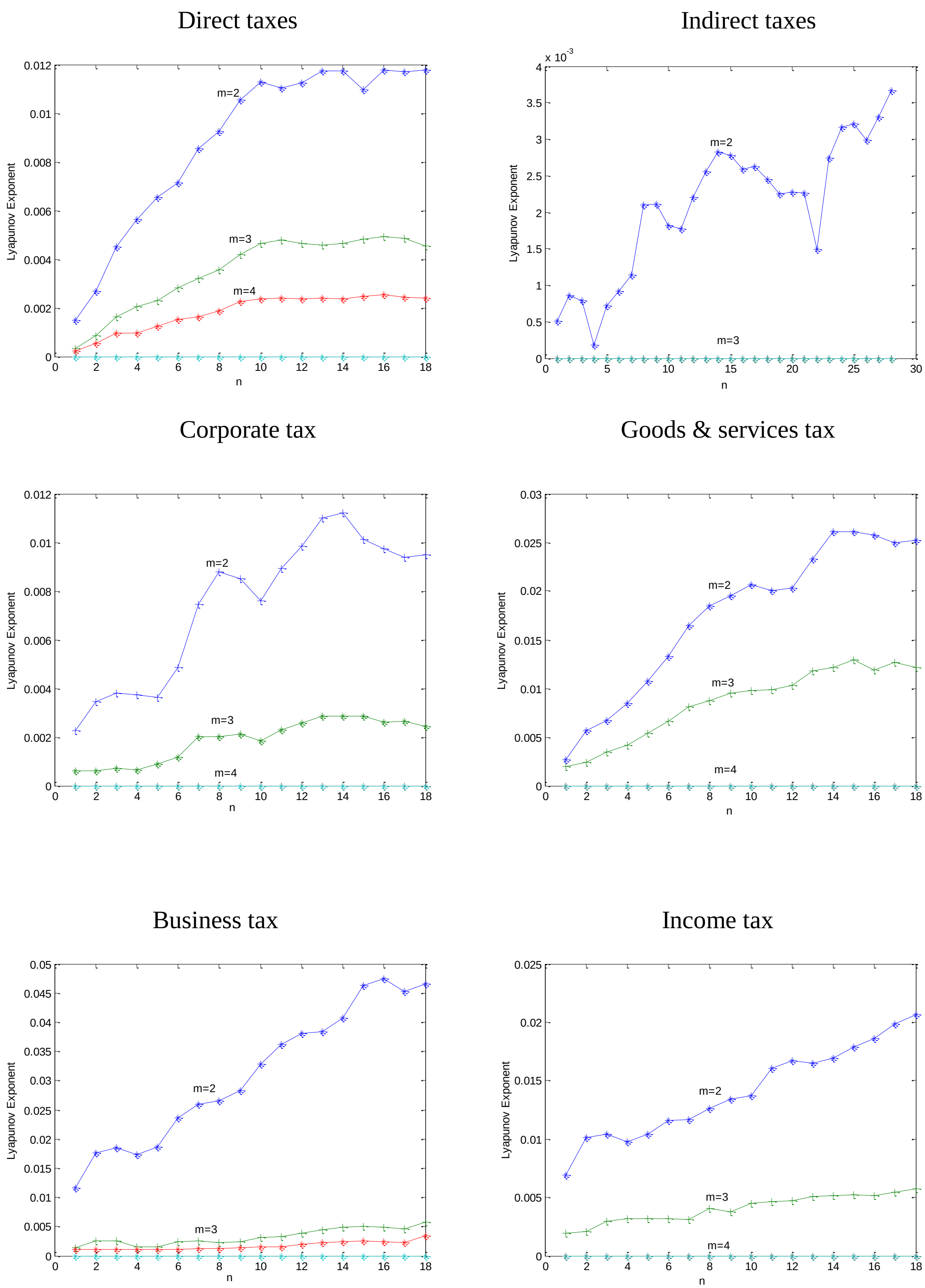


Figure 1. Lyapunov Exponent of taxes time series in different dimensions

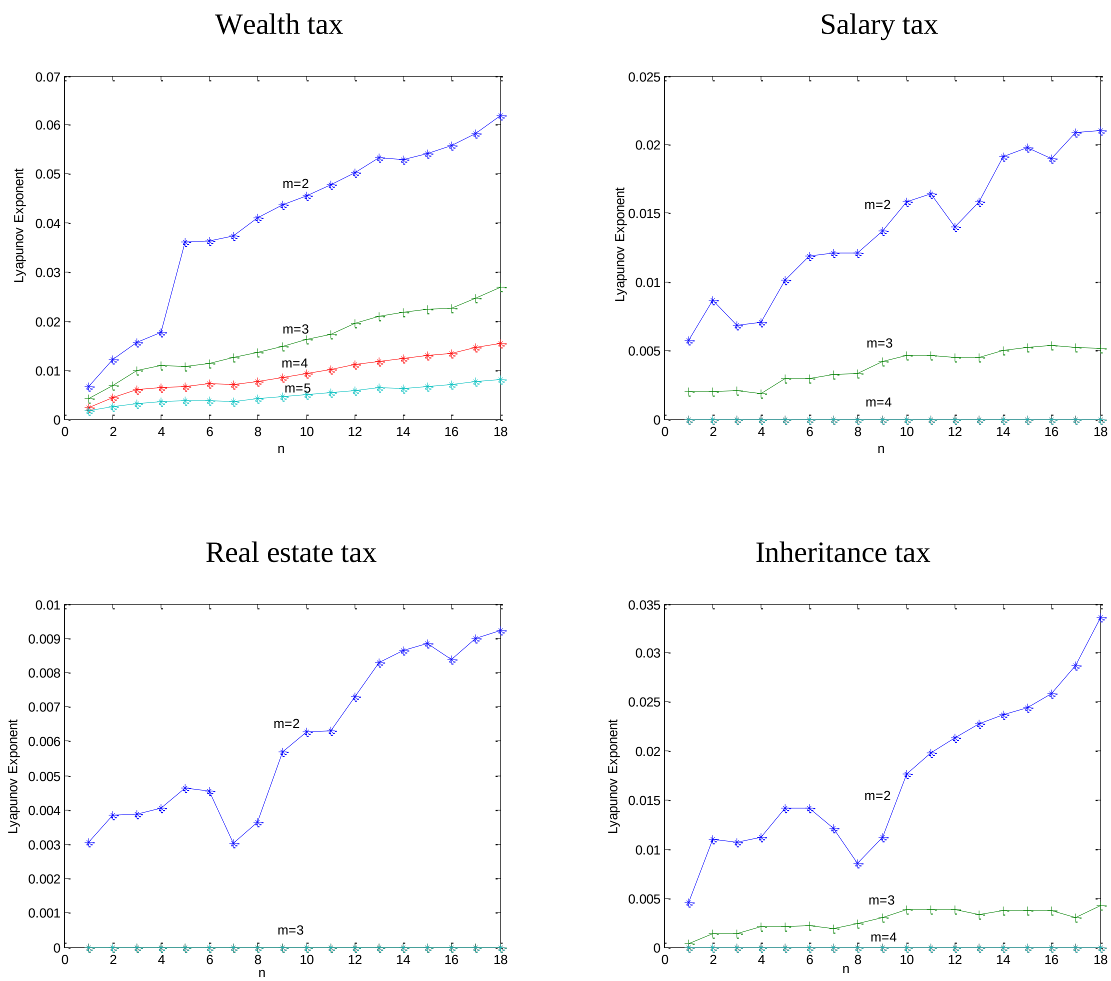


Figure 1. Continued

Finally, Shuffle Test has been used to insure the credibility of the results. As it is shown in table (2), the values of the Lyapunov exponent for the shuffled series, which are lack of any order, are greater than of the original series. This result endorses the non-stochasticity of the series and existence of order in them.

Table 2. Lyapunov exponent and Shuffle tests

dimension λ	2	3	4	5
corporate Tax	0.0104	0.00266	-	-
Shuffled series	0.0155	0.00556	-	-
Direct Taxes	0.0041	-	-	-
Shuffled series	0.013	-	-	-
Income Tax	0.0225	0.006	-	-
Shuffled series	0.0425	0.017	0.006	-
Salary Tax	0.021	0.005	-	-
Shuffled series	0.036	0.006	-	-
Business tax	0.046	0.005	0.004	-
Shuffled series	0.055	0.0083	0.0051	-
Real Estate Tax	0.0092	-	-	-
Shuffled series	0.012	-	-	-
Wealth Tax	0.069	0.03	0.018	0.009
Shuffled series	0.11	0.05	0.03	0.019
Inheritance tax	0.034	0.004	-	-
Shuffled series	0.042	0.006	-	-
Goods & Services tax	0.275	0.01333	-	-
Shuffled series	0.053	0.03	0.015	0.0025

Source: Authors’ Estimations

4. Modeling and Forecasting Tax Revenues: ANN's Approach

The results of Lyapunov exponent test showed a weak chaos in the series of taxes. Therefore, nonlinear modeling approach may result in a robust short-run forecast. The rest of the article is dedicated to forecasting tax revenues by Artificial Neural Networks modeling.

4.1 Forecasting Total Taxes by Using a Multiple Input-output Neural Networks (proposed structure)

As mentioned before, by using a neural network with a hidden layer and a nonlinear impulse function, alongside with sufficient neurons in the hidden layer and a linear impulse function in output layer, any kind of nonlinear function can be approximated. Since the total tax is a combination of several tax bases, to achieve a model with an optimal structure we have applied a multiple input-output structure of ANN (Khalozadeh & Khaki Sedigh, 2001). The Neural Network that is used in this section is comprised of 3 layers (input, hidden and output layers). The number of neurons in input, hidden and output layers is 6, 3 and 6 respectively. A Sigmoid tangent nonlinear function has been used as an impulse function in the hidden layer while the impulse function of the output layer is pure line. In order to derive the output of the ANN model, computation of pre-propagation is done first by applying the inputs of the network and then by applying the error back propagation. The errors between output and computed desired value are distributed among the existing layers, and finally the output vector (several components) is derived by correcting the weight matrices and bias vectors. Each component stands for each year that is to be forecasted. Out of 6 neurons in the output layer, 3 neurons have been employed to forecast total taxes, and the rest 3 neurons for GDP forecast. Almost 85 percent of the time series information related to the period 1963-2000 has been dedicated to the learning process. After the learning process of the network, the learning set is added to the network(those information which has not been used during learning process) and then average error of the network is calculated and those parameters of the network with the least average error is saved for forecasting and finally the step by step forecast is done. By doing so, we first forecasted the total taxes and at same time GDP for the period t+1, t and t+2 (2001-2002-2003) . The outputs of these three years are used as the input for the next 3 period and hence the GDP is forecasted for the periods (t+3 ,t+4, t+5).By doing so, the forecast is done for each 6 periods. In the next step, the performance of the network for the test period is evaluated by using root average of square error and average of absolute deviation criteria. If the performance of the network is confirmed by these criteria, the network can be used for forecasting. Figure (2) shows the forecasted values of the GDP for the 6 periods and the forecasted errors for the period 2001-2006. Figure (3) also shows the forecasted values of the GDP for the period 2007-2009 with the assumption of the past trend continuation.

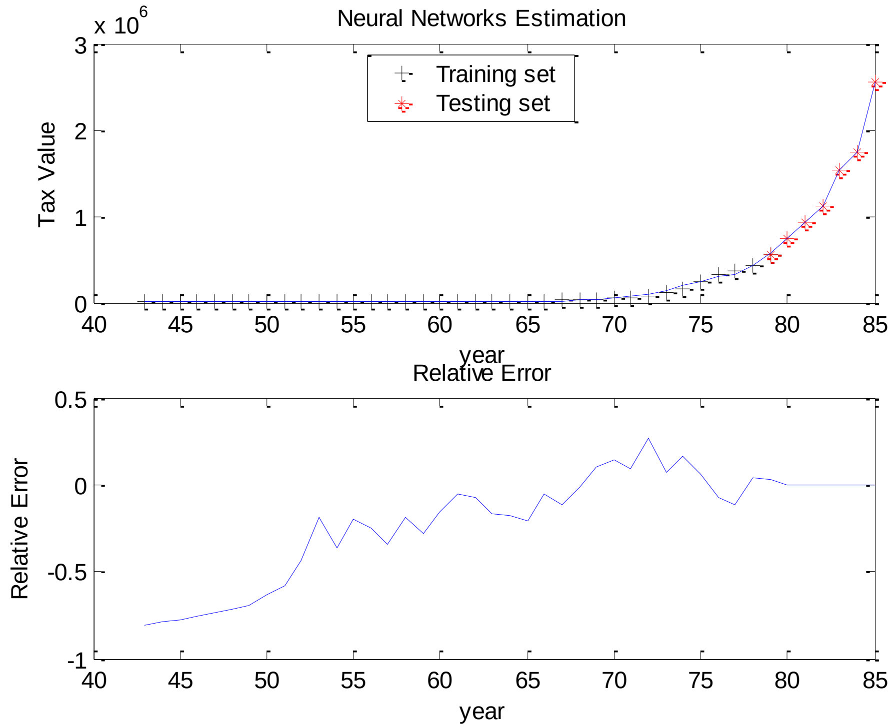


Figure 2. GDP forecasts and values of forecast error for the next 6 periods

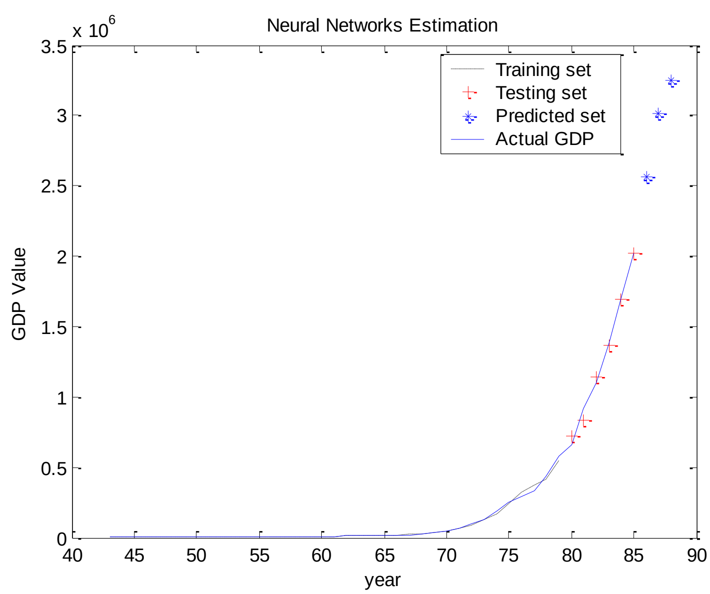


Figure 3. GDP forecasts for the years 1386-88

Finally, these forecasted values are employed to forecast the tax revenues outside the sample. Figure (4) shows the forecasted tax revenues and the forecast errors for 6 periods and figure (5) shows the forecasted tax revenues for the period 2007-2009.

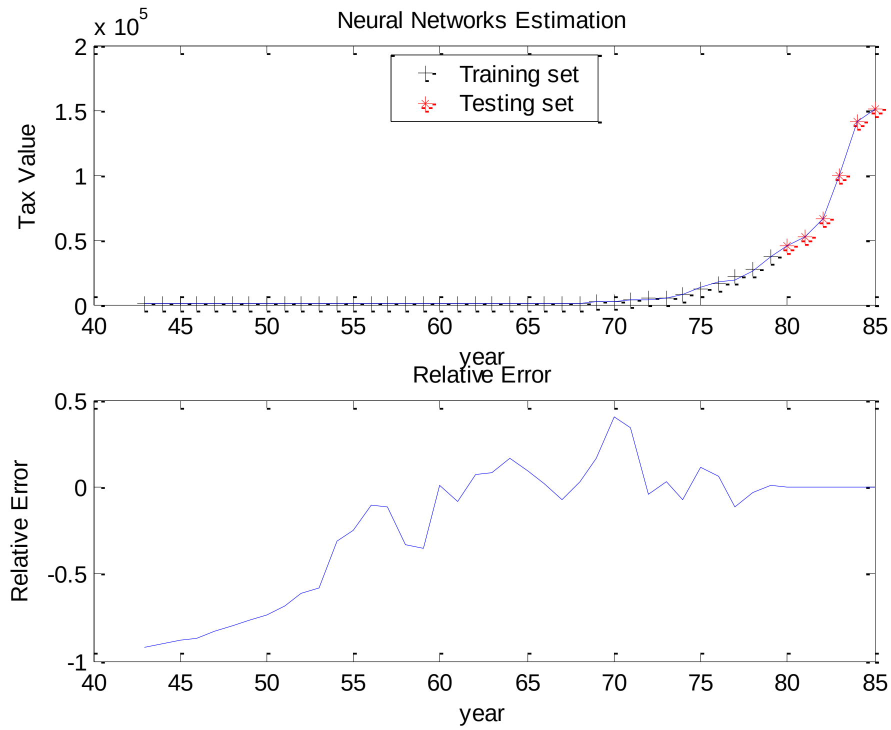


Figure 4. Long-term forecast of total taxes and forecast error for the next 6 periods

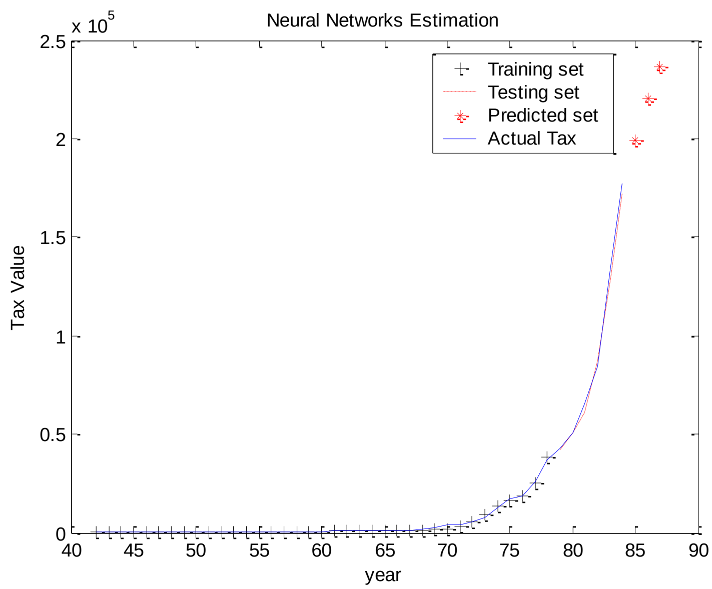


Figure 5. Out-of- sample forecasting of the tax revenues in the period 2007-2009

4.2 Forecasting Direct Tax Based on Multiple Input-output Neural Networks (proposed structure)

The structure of the network for one-step forward forecasting the direct taxes, which is based on the equations of the Iranian third economic, social and cultural development plan, is a function of GDP and as mentioned before it includes a hidden layer and 6, 3, 6 neurons in input, hidden and output layers respectively. The impulse function of the hidden layers is a nonlinear tangent sigmoid function and the impulse function of the output layer is linear function. In this article, error back propagation algorithm has been employed for learning the process of the network. Time series data of the period 1963-2000 has been used for the learning process of the network, while data of the period 2001-2006 has been used for evaluating the performance of the network. It's worth mentioning that in this article we have used those parameters of the network with the least average errors in step by step forecast. In the next step, based on the existing criteria, the performance of the network is evaluated and then an optimal model is selected for forecasting the direct taxes. In figure (6) the results of these forecasts has been shown:

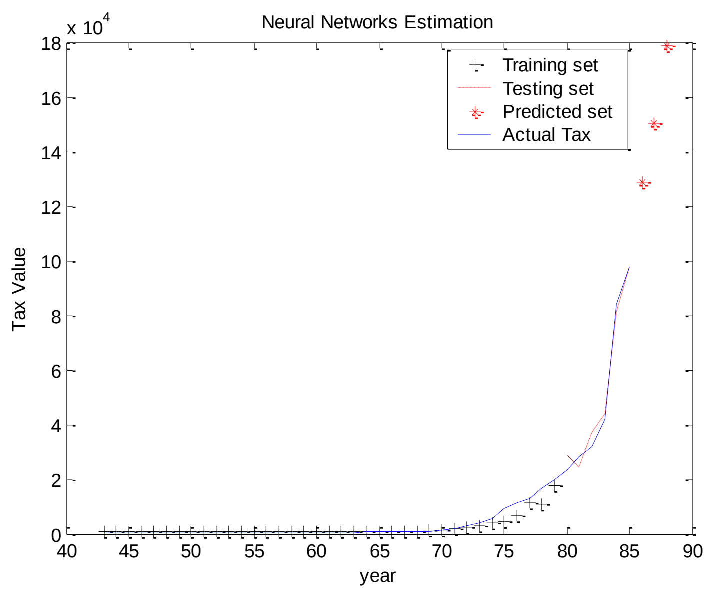


Figure 6. Out-of- sample forecasting of the direct taxes in the period 2007-2009

4.3 Indirect Tax Forecast Based on Multiple Input-output Neural Networks (proposed structure)

The structure of the network for forecasting indirect taxes is based on the equations of the Iranian 3rd economic, social and cultural development plan. Since there is a relatively high chaos in the consumption tax series according to Lyapunov exponent test, the proposed neural network has been employed to forecast the consumption tax. Figure (7) shows indirect taxes forecast for the period 2007-2009:

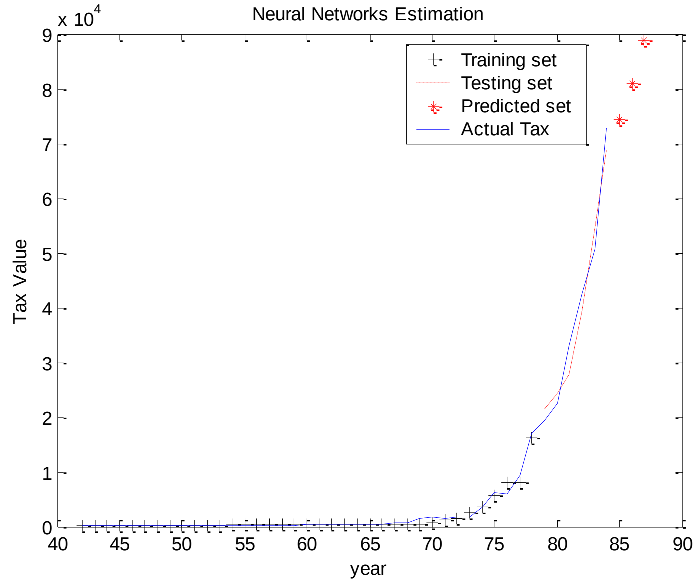


Figure 7. Out-of- sample forecasting of the indirect tax in the period 2007-2009

4.4 Income Tax Forecast Based on Multiple Input-output Neural Networks (proposed structure)

Figure (8) shows the forecasted values of the income tax for the period 2007-2009 based on the proposed model. The input variable is GDP based on the equations of the 3rd development plan. The forecasted value of the GDP has been used for long run forecasting of the income tax:

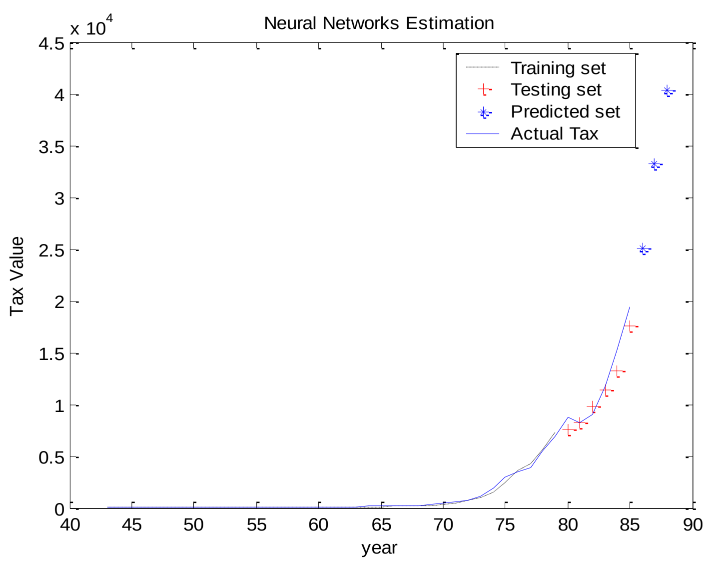


Figure 8. Out-of- sample forecasting of the income tax in the period 2007-2009

4.5 Forecasting Salary Tax Using Artificial Neural Networks (parallel model)

In this section, a backward perceptron of parallel type neural network comprised of 3 layers is used. (The number of neurons in input, intermediate and output layers are 2, 3 and 2 respectively). Impulse function of hidden layer is tangent sigmoid while the impulse function of output layer (purelin) is linear and finally learning process of the network is based on the error back propagation. Using the network, one step forward forecast is first done and then a long run forecast is made by using weights and biases derived in the first step. To do so, outputs of each period were used as an input of the next period, and hence a forecast is done for the last 6 years of the period 2001-2006. By using the generated GDP, a long run forecast has been done for the tax on salary. Figure (9) shows forecasting the tax on salary for the period 2007-2009.

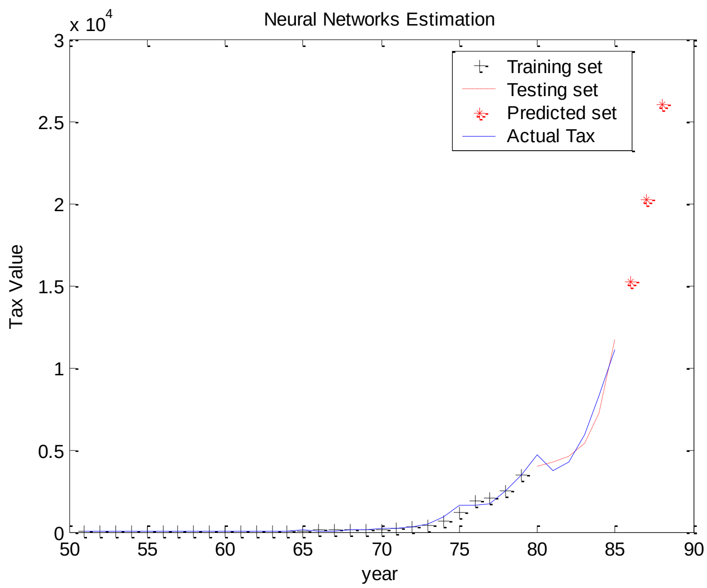


Figure 9. Out-of-sample forecasting of the tax on the salary during the period 2007-2009

4.6 Forecasting Business Income Tax Using Artificial Neural Networks (parallel model)

In this section, business income tax is considered as a function of tax base of business sector[1]. After computing the tax base, out-of-sample forecasting is done for tax on the business income for the period 2007-2009 using the optimal neural structure.

[1] Business tax base=value added of services sector +value added of building in private sector-(public services+ services of monetary and financial institutions+ state transportation+ communication+ services of residential and nonresidential sectors)+ (value added of industry sector- value added of industrial workshops)

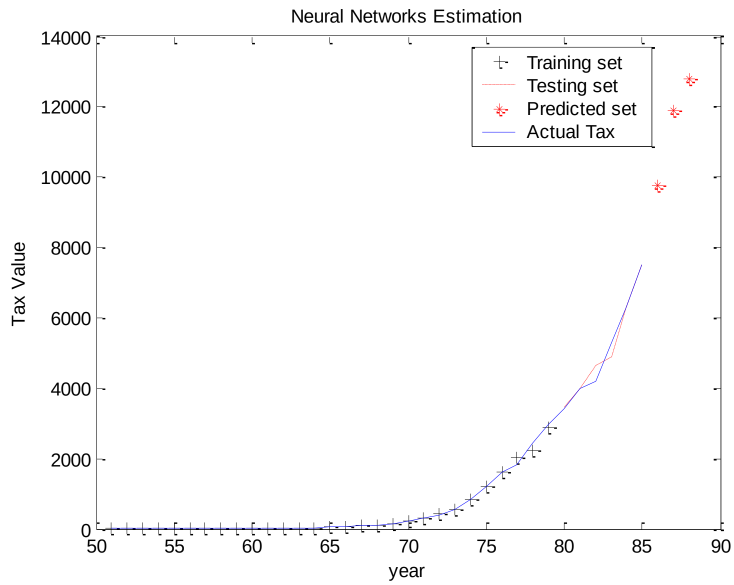
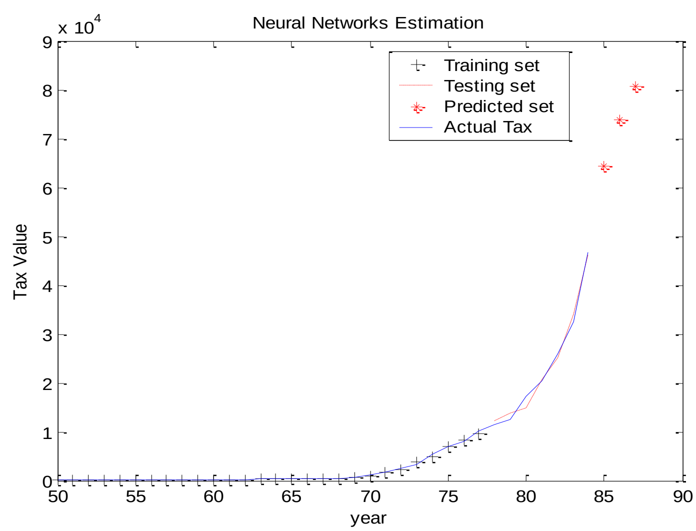


Figure 10. Out-of-sample forecast of the business income tax in the period 2007-2009

4.7 Forecasting Corporate Tax Using Artificial Neural Networks (parallel model)

In this sector, corporate tax base[1] is first forecasted by using a backward perceptron, and finally after selecting the best model, the forecasted values of corporate tax base is used for forecasting corporate tax revenues for the period 2007-2009. Result of the forecast is shown in figure (11).



[1] Corporate tax base= GDP-(value added of business and agricultural sectors)

Figure 11. Out-of-Sample forecasting of the corporate tax in the period 2007-2009

4.8 Forecasting the Real Estate Tax by Using Artificial Neural Networks (parallel model)

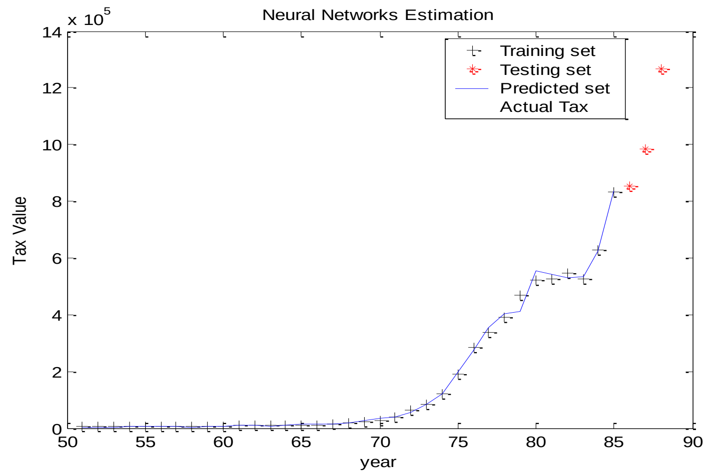


Figure 12. Out-of-sample forecasting of the real estate tax in the period 2007-2009

4.9 Forecasting the Inheritance Tax by Using Artificial Neural Networks (parallel model)

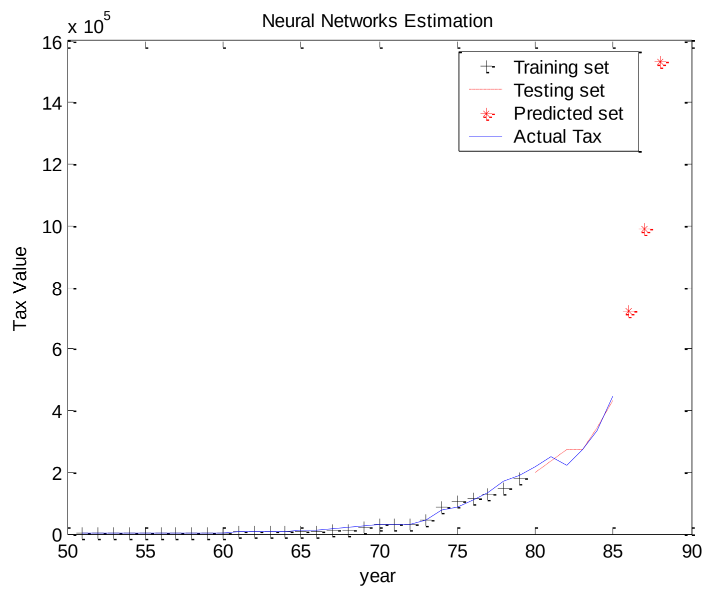


Figure (12)-Out-of- sample forecasting of the real estate tax in the period 2007-2009

4.10 Forecasting the Wealth Tax by Using Multiple Input-output Neural Networks (proposed structure)

The result of Lyapunov exponent test shows a relatively high chaos in the wealth and consumption tax series in comparison to the other taxes; therefore, proposed multiple input-output models is used to get a more accurate forecast of these tax revenues. The result is shown in figure (14):

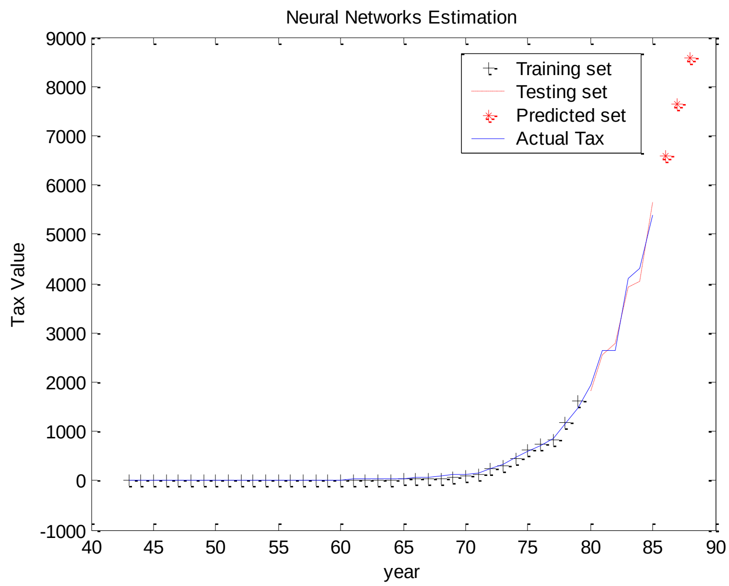


Figure 12. Out-of- sample forecasting of the wealth tax in the period 2007-2009

4.11 Forecasting the Consumption Tax by Using Multiple Input-output Neural Networks (proposed structure)

Structure of the network employed to forecast the consumption tax is a function of the private consumption as a tax base. We have used the proposed neural network to forecast the consumption tax due to the existence of relatively high rate of chaos in the time series of the consumption tax according to Lyapunov exponent test. The network used here to forecast the tax on consumption is comprised of a 3 layer-forward perceptron with 6, 3 and 6 neurons in the input, hidden and output layers respectively. The impulse function of the hidden and output layers is tangent sigmoid and linear respectively and finally the learning process of the network is base on backward transmission law. Figure (15) shows the forecast of consumption tax for the period 2007-2009.

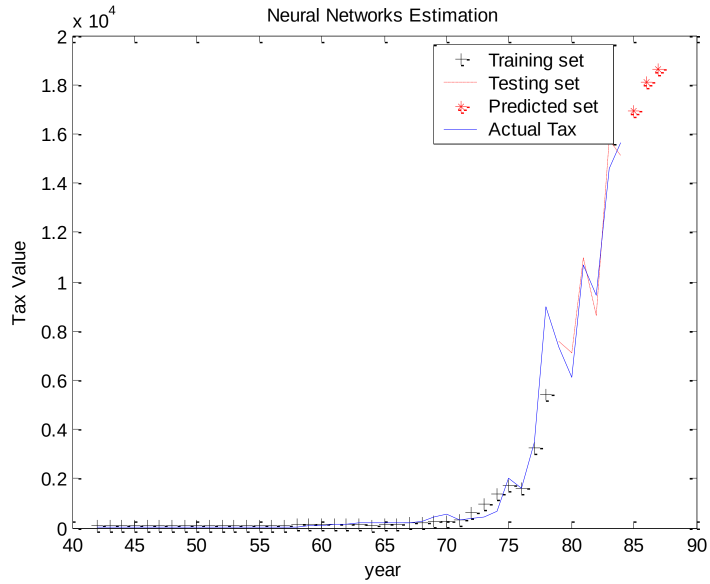


Figure 15. Out-of- sample forecasting of the consumption tax in the period 2007-2009

In general, several performance measures are used to evaluate the process of learning data in neural networks. These measures are often related to the error between the forecast and actual outputs. In table (3), the results of Root Mean Squared Error (RMSE) and Mean Absolute Deviation (MAD) have been shown. The results of the performance measures of the network show that the forecast error of the models is minor and therefore the models are highly reliable.

Table 3. RMSE and MAD of the artificial neural network

Year	RMSE	MAD
Total Tax	0.005298	0.00216
Direct tax	0.0181170	0.007396
Indirect Tax	0.0214669	0.0087638
Income Tax	0.033728	0.013769
Corporate Tax	0.1129808	0.0770312
Business tax	0.0086578	0.0319788
Real estate Tax	0.0935756	0.0498659

Salaries tax	5.66658E-13	7.441528E-13
Wealth tax	0.0299427	0.08179
Inheritance Tax	3.5476E-17	9.89437E-15
Consumption Tax	0.010666	0.0043545

The results of the forecasts of the tax revenues for the period 2006-2009 are shown in tables 4.

Table 4. Forecast of tax revenues by ANN's in the period 2007-2009

Year	Actual 1385	Forecast 1385	Actual 1386	Forecast 1386	1387	1388
Total Tax	177617	178942	197245	198919	220265	236305
Direct tax	97691	97664	126333	128877	150106	178643
Indirect Tax	53929	65473	65473	65608	73677	80988
Income Tax	19451	19498	25960	26669	33288	40276
Corporate Tax	46727	46679	63950	64351	73822	80767
Business tax	7515	7518	9726	9750	11880	12796
Real estate Tax	11061	825	974	971	1176	1266
Salaries tax	11061	11212	15189	15216	20180	26046
Wealth tax	5378	5378	7762	6580.2	7640	8575
Inheritance Tax	448.01	448	719	720	988	1531

Consumption Tax	14123	14156	16662	16952	18016	18599

Source: Authors' estimations

5. Conclusion

In this article, the structure of the tax time series were first studied in relation to linearity, nonlinearity and stochasticity by chaos tests in order to select proper model with more accurate predictability. To do so, the stationarity of the series were investigated by conducting chaos tests. The results of the unit root tests imply that the series under study are non-stationer, where generally are stationer by first-order difference. In order to test the existence of chaos in the series, Lyapunov exponent and Scheinkman and LeBaron shuffle tests were used. The results of the shuffle test indicates that the series are non-stochastic while the series are weakly chaotic according to Lyapunov exponent test; accordingly, a nonlinear modeling can yield an accurate short run forecast results. So, by employing artificial neural network approach and by using the data for the period 1963-2006, total tax revenues as well as direct, indirect, income and consumption taxes were forecasted. The results of the study showed that the general trend of the tax revenues have followed its long term path, except for the years 2001(direct tax reform), 2002(implementation of the Consolidated Tax Act) and 2005 (addition of the tax on crude oil sale to corporate tax). Therefore, error forecasting by ANN's during the test period are minor.

References

Chen, An-S. and Mark T.Leung (2004), "Regression Neural Network for error Correction in Foreign Exchange Forecasting and Trading", Elsevier, pp.1049-1068.

Ellner, S. and P. Turchin (1995), "Chaos in a Noisy World: New Methods and Evidence from Time Series Analysis", American Naturalist, Vol. 145, pp.343-375.

Fallahi, Mohammad ali, Hamid Khalozadeh and Saeideh Hamidy Alamdari(2006), "Nonlinear modeling and forecasting tax on Business incomes in Iran", Journal of economic researches, No 63, pp 143-167

Farjam nia, Iman, Mohsen naseri and Sayed Mohammad Mehdi ahmadi (2007), "Forecasting Oil price by ARIMA and ANN's", Quarterly Journal of Economic Researches of Iran, no 32

Fllareiov, G.F. and E.O. Averehenkov (1999), “Using Netural Nets for Time Series Forecasting”, IEEE, pp. 249-253.

Garliauskas, A. (1999), “Neural Network Chaos and Computational Algorithms of Forecast in Finance” IEEE, pp. 638-643.

Ghadimi, Mohammad Reza, and Saeid Moshiri(2002), “Modeling and forecasting economic growth in Iran by using ANN’s”, Quarterly Journal of Economic Researches of Iran, no 12

Gruca, S. Th., Klemz, R.B. and A. Petersen, (1999), “Mining Sales Data Using a Neural Network Model of Market Response”, ACM SIGDD, Vol. 1, pp.39-43.

Hamidi alamdari, saeideh(2005), “Modeling and forecasting of Business tax in Iran (application of ANN’s and its comparison with Econometric models)”, MA dissertation, Merdosiye Mashhad university

Kendell, E.B. (2001), “Nonlinear Dynamics and Chaos”, Encyclopedia of Life Sciences, Vol. 13, pp.255-262.

Khaki Seddigh and Ali Charlous, Hamid Khaloozadeh(1998), “Is share prices predictable in the Stock market?(A new approach to share price behavior and its predictability in Stock Market”, Journal of economic researches, No 53, pp 87-102

Khalozadeh, hamid and ali khaki(2003), “Evaluating methods of forecasting share price and introducing a nonlinear model based on artificial neural networks”, Journal of economic researches, No 63, pp 43-85

Leung, M. and An-Sing Chen and Hazem Daouk (2000), “Forecasting Exchange Rate Using General Regression Neural Networks”, Pergamon, pp. 1093-1110.

Lisi, F. and Rosa A.Schiavo (1999), “A Comparison Between Neural Networks and Chaotic Models for Exchange Rate Predition”, Elsevier, pp. 87-102.

Mehdi,ahrari(2001), “The Analysis of chaos in the future oil prices”, MA dissertation, Merdosiye Mashhad university

Moshiri, S.,Cameron, N., and Scuse, D. (1999), “Static, Dynamic and Hybrid Neural Networks in Forecasting Inflation”, Computational Economics, 14, pp.219-235.

Moshiri, saeid, and Faezeh forotan(2002),”Chaos test and forecasting future crude oil price, Quarterly Journal of Economic Researches of Iran, no 21

Moshiri, saeid(2002), “Chaos theory and its economic applications”, Essays Published in the first seminar on introduction and application of computational and dynamic nonlinear models in economics”, Iranian Economic Research Center, Allmeh Tabatabaei university, pp11-50

Palit, A. and D. Popovic (2000), “Nonlinear Combination of Forecasts Using Artifical Neural Network, Fuzzy Logic and Neuro Fuzzy Approaches”, IEEE, pp.566-571.

Qi, M. and Yangru, Wu. (2003), “Nonlinear Prediction of Exchange Rates with Monetary Fundamentals”, Elsevier, pp.623-640.

Raei, reza and Kazem Chavooshi(2003),” Forecasting share profits in Tehran stock exchange: ANN’s and Multi-factor models”, Journal of financial Researches, no 15

Scheinkman and B. LeBaron(1989), “Nonlinear Dynamics and Stock Returns,” Journal of Business, No. 62,Vol. 3, pp. 311-338

Serletis, A. and M. Shintani (2003), “No Evidence of Chaos but Some Evidence of Dependence in the US Stock Market”, Chaos, Solitons and Fractals, Vol. 17, pp.449-454.

Shazly, M. and Hassan E.El Shazly (1997), “Comparing the Forecasting Performance of Neural Networks and Forward Exchange Rates”, Elsevier, pp. 345-356.

Virili, F. and B. Freisleben, (2000), “Nonstionarity and Data Preprocessing for Neural Network Predictions of an Economic Time Series”, IEEE, pp. 129-134.

Zhang, G. and Michael, Y.HU. (1998), “Neural Network Forecasting of the British Pound/US Dollar Exchange Rate”, Pergamon, Vol.26, No.4, pp. 495-506.