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Full Length Research

Application of NNARX to agriculture sector value added forecasting: A case of Iran's agriculture sector

S. M. Fahimifard[1*], S. A. Mohaddes[2], H. Mohammadi[3] and R. Keshtkar[4]

[1]Department of Agricultural Economics, Marvdasht branch, Islamic Azad University, Marvdasht, Iran.
[2]Member of Agricultural and Natural Resources Research Center of Khorassan Razavi Province, Iran.
[3]Department of Agricultural Economics, University of Zabol, Zabol, Iran.
[4]Department of Accounting, Marvdasht branch, Islamic Azad University, Marvdasht, Iran.

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This study firstly uses the Cobb-Douglas production function and Auto-Regression Distributed Lag (ARDL) approach for estimating the long-run function of Iran's agriculture sector value added and then compares the forecasting performance of specified ARDL model with Neural Network Auto-Regressive model with eXogenous inputs (NNARX) using forecasting performance criteria (R^2, MAD and RMSE). The results of ARDL specification indicated that 1% increase in labor, capital and energy factors will increase Iran's agriculture sector value added 0.36, 0.23 and 0.32%, respectively. Also, the results of forecast performance criteria show that NNARX nonlinear model forecasting performance for Iran's agriculture sector value added is better in contrast with the ARDL linear model because (1) The Root Mean Square Error (RMSE) and Mean Absolute Deviation (MAD) divided are less than 1 and (2) The R2 divided is more than 1. Therefore, according to the importance of the agriculture sector as the main alimentary source for mankind, accurate prediction of agriculture sector value added for its using new NNARX model is strongly recommended to the agriculture sector policy makers.

Key words: Agriculture sector value added, forecasting, auto-regression distributed lag (ARDL), neural network auto-regressive model with eXogenous inputs (NNARX).

INTRODUCTION

In the last few decades, many forecasting models have been developed which among them, the autoregressive integrated moving average (ARIMA) model has been highly popularized, widely used and successfully applied not only in economic time series forecasting (Ho and Xie, 1998). Recently, it is well documented that many economic time series observations are non-linear while, a linear correlation structure is assumed among the time series values therefore, the ARIMA model cannot capture nonlinear patterns and, approximation of linear models to complex real-world problem is not always satisfactory. While nonparametric nonlinear models estimated by various methods such as Artificial Intelligence (AI), can fit a data base much better than linear models and it has been observed that linear models, often forecast poorly which limits their appeal in applied setting (Racine, 2001).

AI systems comprise areas like expert systems, ANN (Artificial Neural Network)s, genetic algorithms, fuzzy logic and various hybrid systems, which combine two or more techniques (Kamwa et al., 1996). Among the mentioned AI systems, according to Haykin 1994, a neural network is a massively parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use (Hykin, 1994). In dynamic networks (such as NNARX Neural Network Auto-Regressive model with eXogenous inputs), the output depends not only on the current input to the network, but also on the current or previous inputs, outputs, or states of the network. Dynamic networks are generally more powerful than static networks (although somewhat more difficult to train). Because dynamic networks have memory, they can be trained to learn sequential or time-varying patterns (Racine, 2001).

On the other hand, the agricultural products represent the main alimentary source for 6.7 billion people. Therefore, agriculture represents a fundamental sector of

*Corresponding author. E-mail: mfahimifard@gmail.com.

the world economy that has to supply food for all mankind. Beside, today a growing population of the world has increased the need for agricultural products and consequently increased the pressure on based resources that is required for those products. In order to feed the growing population, agricultural production is to be increased. Not excepted the other world, agriculture is a very important sector in Iran in order that this sector contributed 11% of the gross domestic product (GDP) in 2004 and employed a third of the labor force. In addition benefiting from 123,580 km^2 of land suitable for agriculture, the agricultural sector is one of the major contributors to Iran's economy. It accounts for almost 13% of Iran's GDP, 20% of the employed population, 23% of non-oil exports, 82% of domestically consumed foodstuffs and 90% of raw materials used in the food processing industry (Iran's Ministry of Agricultural Jihad, 2009). Therefore, according to the key role of the agriculture sector in food security and lack of suited farmland in Iran, studying and forecasting the factors which affect Iran's agriculture sector value added is unavoidable.

Concerning the application of neural nets to time series forecasting, there have been mixed reviews. For instance, Haofei et al. (2007) introduced a Multi-Stage Optimization Approach (MSOA) used in back-propagation algorithm for training neural network to forecast the Chinese food grain price. Their empirical results showed that MSOA overcomes the weakness of conventional BP algorithm to some extent. Furthermore, the neural network based on MSOA can improve the forecasting performance significantly in terms of the error and directional evaluation measurements. Fahimifard (2008) compared the ANFIS (Adaptive Neuro Fuzzy Inference System) and ANN as the nonlinear models with the ARIMA and GARCH as the linear models to Iran's meat, rice, poultry and egg retail price forecasting. His research stated that nonlinear models overcome the linear models strongly. Fahimifard et al. (2009) studied the application of ANFIS in Iran's poultry retail price forecasting in contrast with ARIMA model.

Their findings stated that ANFIS outperforms the ARIMA model in all three 1, 2 and 4 weeks ahead. Imandoust and Fahimifard (2010) studied the application of NNARX as a nonlinear dynamic neural network model which compares with ARIMA, as a linear model to forecast Iran's agricultural economic variables. As a case study the three horizons (1, 2 and 4 weeks ahead) of Iran's rice, poultry and egg retail price are forecasted using the two mentioned models. The results of using the three forecast evaluation criteria (R^2, MAD and RMSE) state that, NNARX model outperforms ARIMA model in all three horizons. This study estimates the function of Iran's agriculture sector value added using Auto-Regressive Distributed Lag Approach (ARDL) and compare its forecast performance with NNARX as a nonlinear dynamic neural network model.

METHODOLOGY

Agriculture sector value added function based on ARDL approach

Harrod-neutral technical change is a condition that must be placed on production to achieve a steady state. The Cobb-Douglas form is the only form that reduces to Harrod neutrality, even when inputs productivity grow over time. So, although Cobb-Douglas is a restrictive form, it allows one to envision a number of flexible mechanisms by which technical progress augments growth, in a model consistent with steady state (Cobb and Douglas, 1928). The relation 1 represents the augmented Cobb-Douglas production function, which consist of labor, capital and energy inputs:

$$Y = \alpha_0 . L^{\alpha_L} . K^{\alpha_K} . E^{\alpha_E} \quad (1)$$

The variables are described as follows:

Y: Value added at current price (milliard Rials).
L: labor in complete employment level (1000 persons).
K: Capital stock at current price (million Rials).
E: Consumed energy including oil products and electricity (million barrels crude oil).
α_L, α_K and α_E: are the production elasticity of labor, capital and energy factor, respectively.

Due to the fact that the current price affects the quantity of value added and capital stock, we consider the *Y* and *K* at the current price. In addition, the logarithmic form of Cobb-Douglas production function is as follows:

$$\ln Y = \ln \alpha_0 + \alpha_L \ln L + \alpha_K \ln K + \alpha_E \ln E \quad (2)$$

In order to study the long-run and short-run relationship between dependent and independent variables of the model, usually the cumulative methods like Engel-Granger and Error correction (ECM) are used. But because these methods have disadvantages -such as: limitation in application, bias in small samples and inability in testing statistical hypothesis- more suitable methods are suggested to analyze the long-run and short-run relationship between variables such as ARDL approach (Pesaran and Pesaran, 1977).

In this method, the equality of variables cumulative degree is not essential while in Engel-Granger method, it is necessary (Yusefi, 2000). Other advantages of ARDL are the simultaneous estimation of long-run and short-run patterns and removing the resulted problems of variables elimination and autocorrelation. Therefore, in this method the estimators are efficient and unbiased because of avoiding some problems like autocorrelation and inter-production (Sidiki, 2000). These priorities encouraged the ARDL method application to this research. The augmented ARDL model is shown as follows:

$$\alpha(L,P) y_t = \alpha_0 + \sum_{i=1}^{k} \beta_i (L, q_i) x_{it} + u_t \ ; \ i = 1,2,...,k \quad (3)$$

So that α_0, y_t and *L* are intercept, dependent variable and lag factor respectively. And *L* is explained as follows:

$$L^j y_t = y_{t-j} \quad (4)$$

Thus,

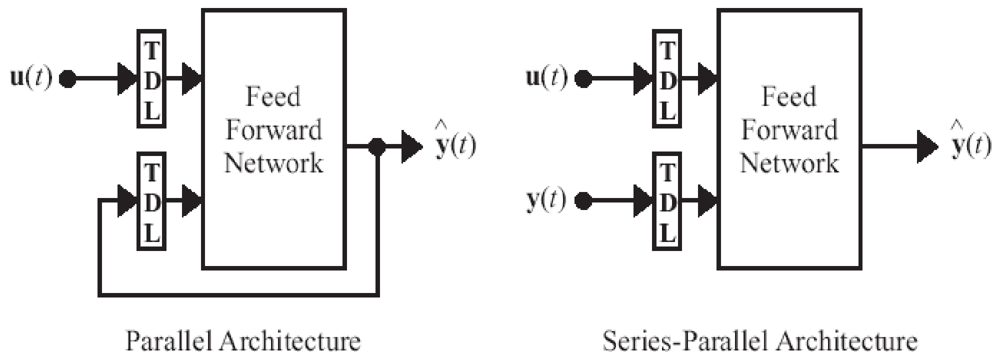


Figure 1. Parallel and series-parallel architectures.

$$\alpha(L,P) = 1 - \alpha_1 L^1 - ... - \alpha_p L^p \quad (5)$$

$$\beta_i(L,q_i) = \beta_{i0} + \beta_{i1}L + \beta_{i2}L^2 + ... + (\beta_{iqi}L_i^q) \quad (6)$$

Therefore, the dynamic ARDL model for agriculture sector value added function will be in this form:

$$\ln Y_t = \alpha_0 + \sum_{i=1}^{m}\beta_i \ln Y_{t-1} + \sum_{i=1}^{n}\gamma_i \ln L_{t-1} + \sum_{i=1}^{o}\lambda_i \ln K_{t-1} + \sum_{i=1}^{p}\omega_i \ln E_{t-1} + \gamma_0 \ln L_t + \lambda_0 \ln K_t + \omega_0 \ln E_t + u_{it} \quad (7)$$

So that *m*, *n*, *o* and *p* are numbers of the best lags for the variables lnY_t, lnL_t, lnK_t, and lnE_t respectively.

Neural network auto-regressive model with exogenous inputs (NNARX)

Neural networks can be classified into dynamic (e.g. NNARX) and static (e.g. ANN) categories. Static networks have no feedback elements and contain no delays; the output is calculated directly from the input through feed-forward connections. In dynamic networks, the output depends not only on the current input to the network, but also on the current or previous inputs, outputs, or states of the network. Dynamic networks are generally more powerful than static networks (although somewhat more difficult to train). Because dynamic networks have memory, they can be trained to learn sequential or time-varying patterns (Medsker and Jain, 2000). This model has a parametric component plus a nonlinear part, where the nonlinear part is approximated by a single hidden layer feed-forward ANN. The neural network is autoregressive with exogenous inputs (NNARX) is the current dynamic network, with feedback connections enclosing several layers of the network. The NNARX model is based on the linear ARX model, which is commonly used in time-series modeling.

Also, this has applications in such disparate areas as prediction in financial markets (Roman and Jameel, 1996), channel equalization in communication systems (Feng et al., 2003), phase detection in power systems (Kamwa et al., 1996), sorting (Jayadeva and Rahman, 2004), fault detection (Chengyu and Danai, 1999), speech recognition (Robinson, 1994), and even the prediction of protein structure in genetics (Gianluca et al., 2002). The defining equation for the NNARX model is as follows:

$$y(t) = f(y(t-1), y(t-2),...y(t-n_y), u(t-1), u(t-2),..., u(t-n_u)) \quad (8)$$

Where, the next value of the dependent output signal *y*(*t*) is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal. The output is fed back to the input of the feed-forward neural network as part of the standard NNARX architecture, as shown in the left (Figure 1). Because the true output is available during the training of the network, a series-parallel architecture can be created (Rosenblatt, 1961), in which the true output is used instead of feeding back the estimated output, as shown in the right (Figure 1). This has two advantages. The first is that the input to the feed-forward network is more accurate. The second is that the resulting network has purely feed-forward architecture, and static back-propagation can be used for training. Dynamic networks are trained in the same gradient-based algorithms that were used in “Back-propagation.” Although they can be trained using the same gradient-based algorithms that are used for static networks, the performance of the algorithms on dynamic networks can be quite different, and the gradient must be computed in a more complex way (De Jesús and Hagan, 2001). A diagram of the resulting network is shown in Figure 2, where a two-layer feed-forward network is used for the approximation.

This type of network's weights has two different effects on the network output. The first is the direct effect, because a change in the weight causes an immediate change in the output at the current time step; (This first effect can be computed using standard back-propagation). The second is an indirect effect, because of some of the inputs to the layer, such as *a*(*t*,1), are also functions of the weights. To account for this indirect effect, the dynamic back-propagation must be used to compute the gradients, which are more computationally intensive (De Jesús and Hagan, 2001). Expect dynamic back-propagation to take more time to train, in part for this reason. In addition, the error surfaces for dynamic networks can be more complex than those for static networks. Training is more likely to be trapped in local minima. This suggests that you might need to train the network several times to achieve an optimal result (De Jesús and Hagan, 2001).

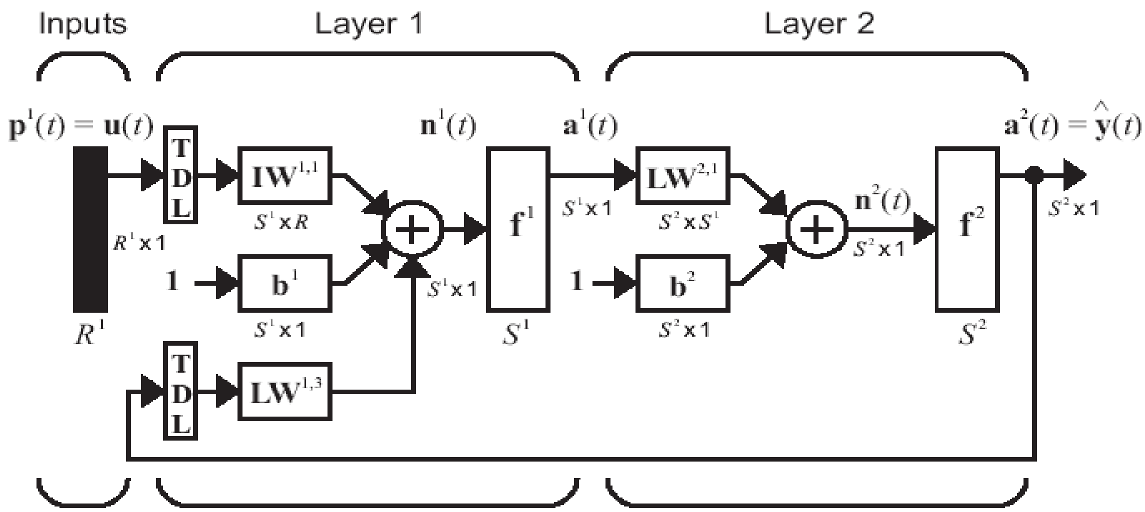


Figure 2. A typical neural network auto-regressive with exogenous inputs (NNARX).

Table 1. Three common types of forecast performance measures.

Measure definition	Formulate
Absolute fraction of variance (R^2)	$R^2 = 1 - \frac{\sum(\hat{y}_t - y_t)^2}{\sum \hat{y}_t^{\,2}}$
Mean absolute deviation (*MAD*)	$MAD = \frac{\sum \lvert \hat{y}_t - y_t \rvert}{n}$
Root Mean square error (*RMSE*)	$RMSE = \sqrt{\frac{\sum(\hat{y}_t - y_t)^2}{n}}$

Where y_t, $\hat{y}_t$ and *n* are the target value, output value and number of observations, respectively. Clearly, the best score for R^2 measure is 1 and for other measures is zero.

Data description and forecast performance measures

For the exercise which is as follows, Iran's agriculture sector value added is modelled as a function of labor, capital and energy factors. The yearly data time series for the period 1960 to 2010 has been obtained from the website of the Central Bank of Iran (www.cbi.ir). Besides, Forecast researchers need measures in order to compare the forecasting performance of various models. Commonly, these measures include R^2, MAD and RMSE as in Table 1 that shows their definition and general formulas.

RESULTS AND DISCUSSION

Specification of Iran's agriculture sector value added function

Usually only the two labors and capital factors are used in production function estimation, and the important energy factor is disregarded. In this research, the effect of energy factor on agriculture sector value added is considered alike the two other factors. Table 2 states the results of dynamic estimated ARDL (1,0,0,0) model of Iran's agriculture sector; Table 2 shows that according to LM version of test statistics, functional form of Iran's agriculture sector value added is acceptable. Also, the existence of serial correlation and heteroscedasticity hypothesizes will be rejected. Indeed, considering the Table 2, the calculated *t* statistics of Iran's agriculture sector are equal to 5.67, which are more than the absolute of offered critical quantity by Banerjee and Dolado 5% significance level (equal to -3.91). Thus, we cannot reject the existence of long-run relationship among the model variables.

Table 2. Results of estimated dynamic ARDL (1,0,0,0).

Variable	Coefficient	S.E	t Ratio
Ln (Y-1)	1.68	0.12	14
Ln L	0.36	0.15	2.4
Ln K	0.23	0.09	2.56
Ln E	0.32	0.15	2.13
Intercept	22.31	10.5	2.12
Test statistics		**LM version**	
Serial correlation		25.94 (0.11)	
Functional form		8.53 (0.18)	
Heteroscedasticity		43.76 (0.09)	

Source: Research findings.

Also, Table 2 shows that, Iran's agriculture sector long-

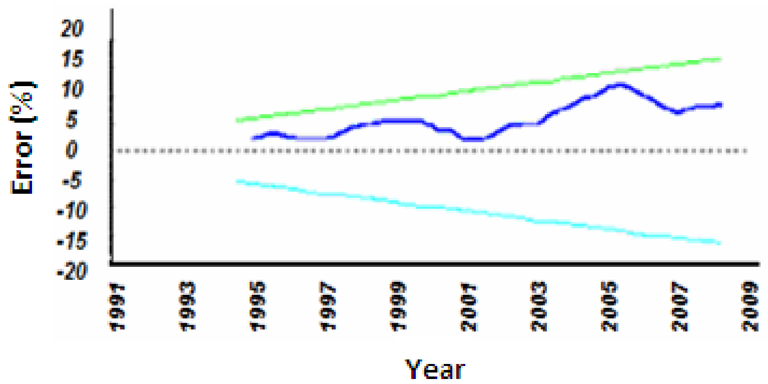


Figure 3. Plot of Cusum of Iran’s agriculture sector.

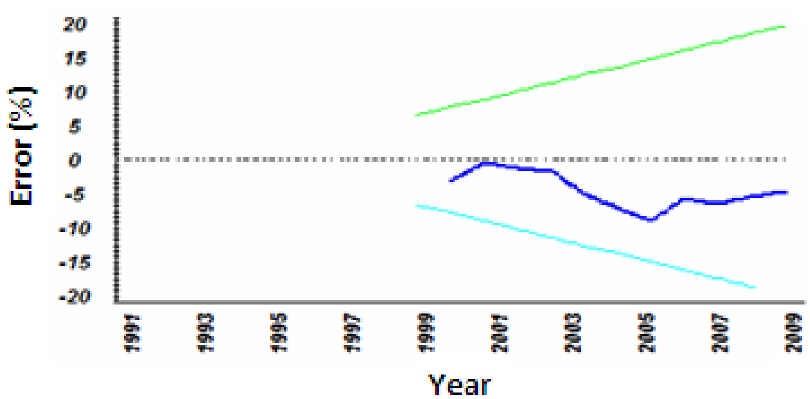


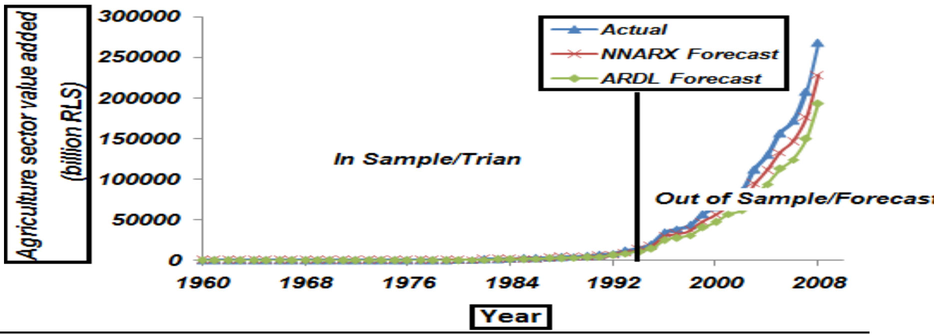
Figure 4. Plot of Cusum Square of Iran’s agriculture sector.

run production elasticities for the labor, capital, and energy variables are respectively, 0.36, 0.23, and 0.32, and there is a positive and meaningful relationship between the current value added and the last year one of Iran’s agriculture sector. Besides, the stability of estimated coefficients during the studied period has been tested by Cumulative sum of recursive residuals (Cusum) and Cumulative sum square of recursive residuals (Cusum Square). Figures 2 to 5 illustrates the results of these two tests. In Figures 3 and 4, the straight lines represent critical bounds at 5% significance level. According to the aforestated figures, the estimated model coefficients of Iran’s agriculture sector are stable; this is because their "Cusum"s and "Cusum Square"s are located between the two up and down straight lines.

Comparison of NNARX and ARDL to agriculture sector value added forecasting

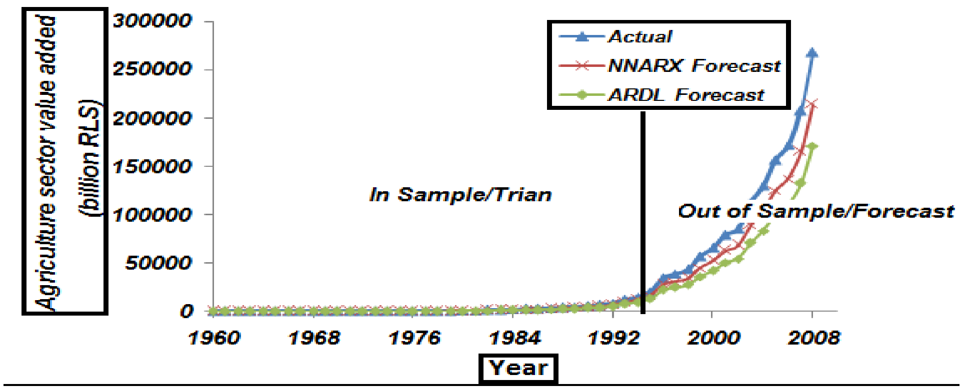
For nonlinear part of NNARX, the various architectures of feed-forward back-propagation networks designed using "logsig" activation function, "Levenberg-Marquardt" learning algorithm, 100 epochs and 0.01 learning rate for 1, 2 and 4 years ahead of Iran's agriculture sector value added. Figure 5 demonstrates the schematic and quantitative forecasting performance of Iran’s agriculture sector, value added obtained by the best structures of NNARX model in comparison with the ARDL approach. The Left side of Figure 5 demonstrates fitness of the best designed structures of ARDL and NNARX models for forecasting 1, 2 and 4 years ahead of Iran’s agriculture sector value added in comparison with the actual observations. And its right side represents the values of evaluation criterions corresponding to the best ARDL and NNARX structures for forecasting the considered horizons.

According to the earlier stated results, the performance of ARDL and NNARX models for Iran's agriculture sector value added forecasting, will decrease with the time horizon increscent. In order to compare the performance of considered linear (ARDL) and nonlinear (NNARX) models for Iran’s agriculture sector value added forecasting, we divided the values of forecast evaluation



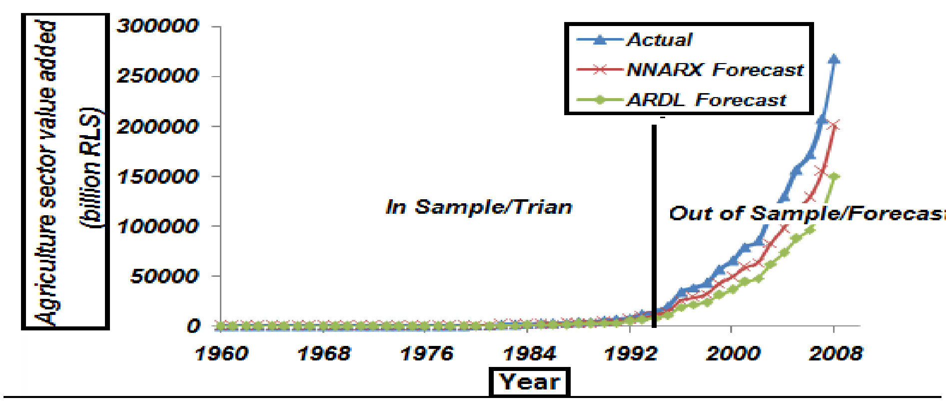
1 Year ahead					
RMSE		MAD		R^2	
ARDL	NNARX	ARDL	NNARX	ARDL	NNARX
0.022	0.017	0.008	0.006	0.975	0.983

(a)



2 Years ahead					
RMSE		MAD		R^2	
ARDL	NNARX	ARDL	NNARX	ARDL	NNARX
0.024	0.019	0.009	0.008	0.973	0.981

(b)



4 Years ahead					
RMSE		MAD		R^2	
ARDL	NNARX	ARDL	NNARX	ARDL	NNARX
0.027	0.021	0.011	0.009	0.972	0.980

(c)

Figure 5. Comparison of NNARX and ARDL for forecasting Iran's agriculture sector value added (Source: Research findings).

Table 3. Comparison of NNARX and ARDL models.

NNARX/ARDL			
Horizon(s)	**R^2**	**MAD**	**RMSE**
1 year ahead	1.008	0.750	0.773
2 years ahead	1.008	0.889	0.792
4 years ahead	1.008	0.818	0.778

Source: Research findings.

criterions of NNARX to ARDL model per each horizon. Table 3 demonstrates the results of these comparisons. According to Table 3, the NNARX nonlinear model forecasting performance is better in contrast with the ARDL linear model because (1) the RMSE and MAD divided are less than 1 and (2) the R^2 divided is more than 1.

SUMMARY AND CONCLUSIONS

Although capital and labor have widely been used as the production factors of many countries agriculture sector value added function, but there is a little body of literature which has used the energy as a production factor in Iran. In this study, the Cobb-Douglas production function and Auto-Regression Distributed Lag (ARDL) approach were used to estimate in the long-run Iran's agriculture sector value added.

Results showed that the elasticities of labor, capital and energy factors of Iran's agriculture sector value added are 0.36, 0.23 and 0.32, respectively. Also, the results of forecast performance criteria indicated that NNARX model outperforms the ARDL model for forecasting 1, 2 and 4 years ahead of Iran's agriculture sector value added.

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