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Forecasting Industrial Production in Iran: A Comparative Study of Artificial Neural Networks and Adaptive Nero-Fuzzy Inference System

Afsaneh Kazemi Mehrabadi*, Vahid Taghinezhad Omran, Mohammad Valipour Khatir, Saeed Rasekhi

Faculty of Economics and Administrative Sciences, University of Mazandaran, Babolsar, Iran.

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Abstract

Forecasting industrial production is essential for efficient planning by managers. Although there are many statistical and mathematical methods for prediction, the use of intelligent algorithms with desirable features has made significant progress in recent years. The current study compared the accuracy of the Artificial Neural Networks (ANN) and Adaptive Nero-Fuzzy Inference System (ANFIS) approaches to assess the current state and predict the future state of industrial production. The seasonal dataset comprised the labor force, capital stock, human capital, trade openness, liquidity and credit financing to the industrial sector as input variables and value added of industrial production as the output variable for the period of 1988 to 2018. The dataset was used to forecast industrial production for Seasons of the year 2019 and 2020. The results showed that, while both are appropriate tools for forecasting industrial production, ANFIS had a lower the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) than ANN. The findings of the research indicate that ANFIS is more effective in forecasting industrial production, which can help policymakers in planning and creating an effective strategy for the future.

1. Introduction

Industrialization is the foundation of developmental stimuli in each country and is one of the most important factors in the structural transformation of the economy, improving welfare, technology transfer and reducing unemployment (Samouel & Aram, 2016). Thus, accurate predictions can have a positive effect on economic decision-making. Predicting plays an important role in effective planning for financial and economic managers.

Researchers tend to improve on existing forecasting models to improve the ability of institutions and individuals to make decisions about the planning and creation of effective strategies for the future (Atsalakis et al., 2011; Ayodele et al., 2014). Precise and dependable forecasts of the level of economic activity are crucial to making efficient economic policy and successful business decisions

* akazemi@modares.ac.ir
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(Acedański, 2013).In prediction models, inefficient use of resources increases prediction error. Of the reasons of inefficient use of resources is the lack of proper parameters in models, the lack of proper modeling techniques, and the lack of use of indicators that has capable of predicting sufficiently in the forecasting process (Günay, 2018). A survey of the GDP in recent years (Fig. 1) shows that the share of the industrial sector has fallen (World Bank). In addition, significant fluctuations have been experienced in the economic environment, which have reduced the predictive power of variables and created uncertainty about the future (Zamanzadeh, 2010). This is why researchers must provide an efficient way to predict industrial production through the planning and managing of the effective parameters to manage of the future trends.

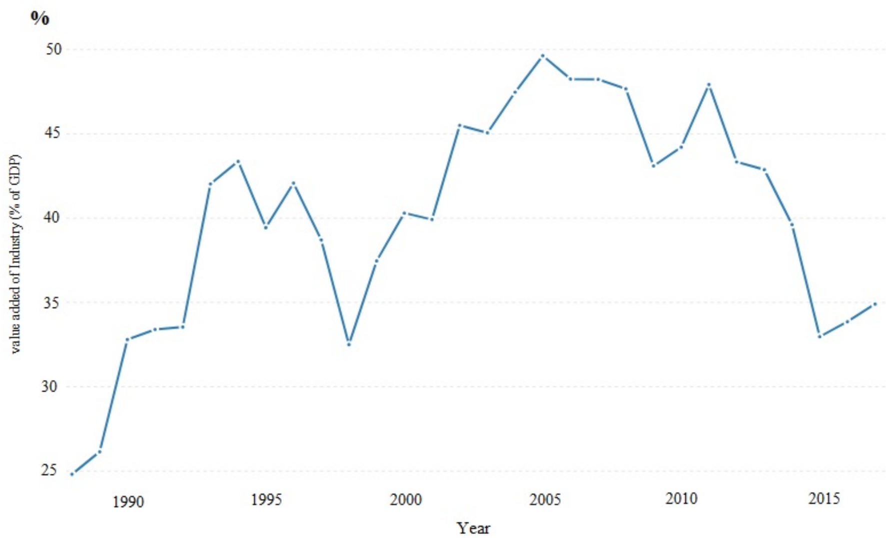

Figure 1. Value added of industrial production (% of GDP)
Source: *World Bank*

The main approach to industrial production forecasting is the use of time series and classic models. These methods are often able to predict with good approximations of the environments with limited changes. If environmental conditions are constantly changing (as in forecasting economic activity), it is not possible to estimate environmental changes with the correct approximations. Modern models and intelligent systems are necessary for prediction in these cases. For this reason, ANN, fuzzy logic, ANFIS and other metaheuristic algorithms have been developed to solve problems in under such conditions. The nonlinear nature, rapid processing and intelligent prediction models using ANN and ANFIS approaches have made them increasingly popular for modeling and prediction (Murat & Ceylan, 2006; Sözen & Arcaklioğlu, 2007).

Because modeling is required to forecast industrial production, the purpose of this study was to determine the ability of ANN and ANFIS to forecast industrial production at lower rates of forecasting error. This study compared the performance of these two methods to obtain the appropriate model for forecasting industrial production.

This paper is structured in five sections. Section 2 reviews related literature. Section 3 describes the methodology and materials. Section 4 provides the empirical results and comparison of the forecasting error of models using the mean square error (MSE) and mean absolute percentage of error (MAPE) indexes. Section 5 presents the conclusions.

2. Literature Review

Heravi et al. (2004) forecasted industrial production of the German, French and UK using linear and neural network models. They considered 24 series of industrial production indicators using seasonally unadjusted monthly data. The results show according to the root mean-square error (RMSE) index the performance of neural network models better than linear models in forecasting the direction of change for these series.

Kavitha Mayilvaganan and Naidu (2011) considered a predicting model using ANN and ANFIS for forecasting monthly groundwater level fluctuations in the Thurinjapuram watershed, Tamilnadu, India. They showed that ANFIS method is good potential for modeling complex, nonlinear and multivariate problems. The results show ANFIS has the lower RMSE than ANN method. The ANFIS method is better than the ANN in the modeling and predicting of groundwater level of a watershed.

Tiwari et al. (2012) attempted using ANN and ANFIS models to forecast Industrial Solid Waste (ISW) of the generated in the Durg-Bhilai Twin city India for the period of 2010 to 2026. They predicted generation of ISW in order to the correct management of the solid waste. Therefore, they first forecasted Waste Generation (WG), then using uncertainty analysis to define the uncertainty of two hybrid models. Results show for approximation of function, the prediction and control of time series ANFIS is more effective than ANN.

Kangarani Farahani and Mehralian (2013) investigated the ability of ANFIS and ANN models for gold price prediction. Used Statistical tools (Mean Tendency Error (MTE), percentage error and Root Mean Squared Error (RMSE)) to evaluate the performance of these methods showed that the ANFIS method had better performance than the ANN method.

Mirsoltani and Niaki (2013) presented a short-term forecasting model for energy price and consumption in Iranian industrial sector using ANN and ANFIS models for the period of 1996 to 2010. They showed while both are suitable tools to forecast price and consumption, often the ANFIS method could forecast better than the ANN method.

Sarmad (2017) constructed three models and compared them using both ANN and ANFIS techniques for forecasting the daily discharge of a river depending on data collected in previous years. Three statistical parameters (root mean square error, efficiency coefficient and coefficient of correlation) are used to evaluate the performance of the three models in each technique. At last, in all models, statistical parameters and graphical results showed that the convergence between observed and predicted data is very good using ANFIS models as compared to ANN models.

3. Methodology and Materials

Economic forecasts use mathematical, statistical and classic models (Chen & Chen, 2015). In these models, it is assumed that expression of a behavioral pattern by the historical data can be achieved by models with high explanatory power (Assaf, 2011; Van Eyden, 1996). Classic models have weaknesses such as the need for extensive historical data, the assumption of a linear relationship between parameters and the normality of the data. While due to numerous factors affecting the complex environment of economic activities and nonlinear relationships between parameters affecting production, require the use of intelligent methods (Chen & Chen, 2015). Intelligent systems are one of the modern technologies, which can be used to design models for predicting industrial production (Heravi et al., 2004). In the models of Artificial Intelligence (AI) and machine learning, it is assumed that the economic markets are not stable and application of complex mathematical models in practice is difficult; thus, by emulation from human biological systems through the learning machine, a pattern can obtained for approximation of the prediction function (Van Eyden, 1996; Assaf, 2011).

3.1 ANN Method

ANN was inspired by biological systems such as the way the brain processes information. This system consists of a large number of super-interconnected processing elements called neurons that coordinate to resolve an issue (Chester, 1993). Neural networks are models of real nervous systems with the goal of solving problems in many areas. The area of application of such a network is wide and includes classification, prediction, estimation, interpolation and detection (Mohamad Alizadeh et al., 2015). Several algorithms have been introduced for network learning. These include the perceptron learning, Hebbian, minimum mean squared and back-propagation algorithms. The multi-layer perceptron (MLP) method has the most applications in financial research (Azar & Karimi, 2010). These networks are located in the group of feed-forward MLP networks. They include a set of sensory units (base neurons) that publish the input signals on the forward path layer-by-layer (Hykin, 1999). Figure 2 shows the two-layer feed-forward network.

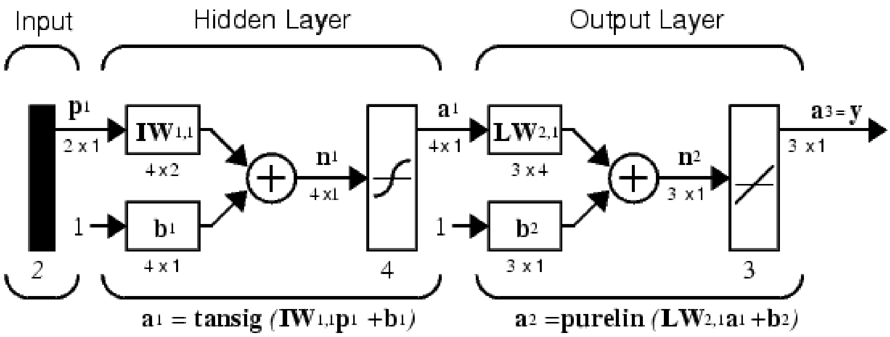

Figure 2. Two-layer feed-forward network
Source: *Hykin (1999)*

3.2 ANFIS Method

One common fuzzy neural system with a learning algorithm, which is similar to compilation learning methods, is ANFIS. Its efficiency for very accurate models has been proven (Kassem et al., 2017). ANFIS can be modified by a combination of the soft-computing methods of ANN and fuzzy logic (Jang, 1993). This model runs a Tacagi-Sugeno fuzzy system in a neural structure and uses either the back-propagation algorithm alone or in combination with a least squares method (hybrid) to process the training data (Kassem et al., 2017). The rules are fixed in ANFIS and the factors of membership functions are optimized. The training trend of a neural network is used to determine the factors (or form) of membership functions. The type of membership function (such as triangular or Gaussian) and the number of membership functions in the inputs and outputs are determined by trial-and-error. It is necessary to specify in the first layer of ANFIS the membership functions and their numbers (Zarra Nejad & Raoofi, 2015).

Suppose that the fuzzy inference system has two inputs(x, y) and one output (f). Then the fuzzy system used has two rules:

Rule 1: If x is A_1 and y is B_1, then $f_1=p_1x+q_1y+r_1$
Rule 2: If x is A_2 and y is B_2, then $f_2=p_2x+q_2y+r_2$

The goal of fuzzy neural system design is to find the best combination of coefficients and estimate the parameters of the above equations. ANFIS architecture is shown in Fig. 3, that it is the combination of the above fuzzy system and 5-layer neural network.

The selected fuzzy neural network model has five layers as described below:

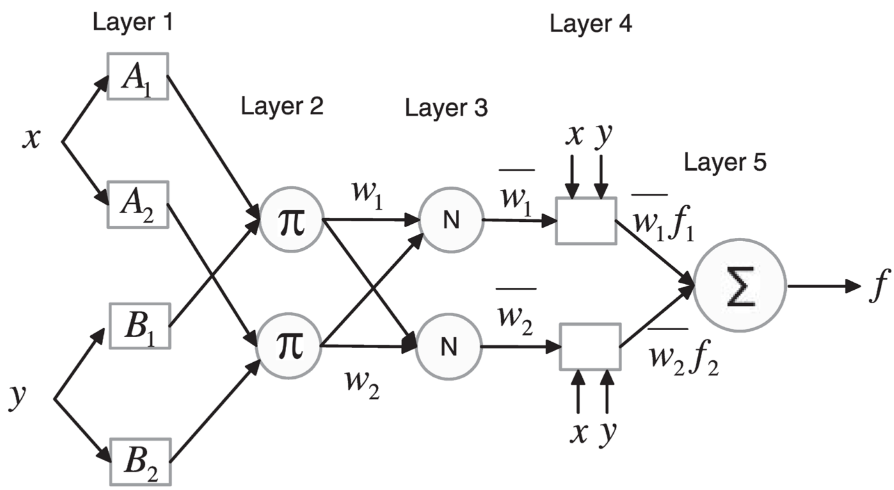

Figure 3. Architecture of an ANFIS network.
Source: *Jang (1993)*

Layer 1: This layer is called the input layer. Each node in this layer corresponds to the node function. The input variables to each node are x and y; O_i is the output of the ith node; A and B are fuzzy rules; and μ is called membership function for A and B.

$$O_{1,i} = \mu_{Ai}(x) \quad , \quad i = 1,2 \tag{1}$$

$$O_{1,i} = \mu_{Bi}(y) \quad , \quad i = 1,2 \tag{2}$$

The membership function for A can be any suitable parametrical membership function like the Gaussian function:

$$\mu_{Ai}(X) = exp\left(\frac{(x-c)^2}{2\sigma^2}\right) \tag{3}$$

where c and σ are the parameter set. By changing these parameters, the Gaussian function also changes.

Layer 2: This layer is called the Fuzzification Layer. The node i in layer 2 is a fixed node, which its output is multiplication of input signals.

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y) \quad , \quad i = 1,2 \tag{4}$$

Layer 2 output is equivalent (if) of rules (the firing strength of a rule).

Layer 3: Layer 3 is called the Rule Base Layer. The layer 3 output is the normalized of the Layer 2. By dividing the output of the node i into the sum of all outputs will be obtained the output of the ith node in Layer 3.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1+w_2} \quad , \quad i = 1,2 \tag{5}$$

Layer 4: Layer 4 is called the Fuzzy Outputs Layer. The nodes in this layer are adaptable

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i X + q_i Y + r_i) \quad , \quad i = 1,2 \tag{6}$$

Each available node function presents a first-order model with the resulting parameters. The parameters are p_i, q_i and r_i.

Layer 5: Layer 5 is called the Outputs Layer that has only one node. This node is specified with mark Σ that calculates the final output as the sum of all inputs (Jang, 1993):

$$O_{5,i} = \Sigma_i \overline{w}_i f_i = \frac{\Sigma_i w_i f_i}{\Sigma_i w_i} \qquad , \qquad i = 1,2 \qquad (7)$$

3.3 Data

In this study, the data was obtained from the World Bank, Statistics Center of Iran and Central Bank of Iran. Because the use of intelligent algorithms with desirable features has been remarkable in recent years, the ANN and ANFIS methods were used to design an industrial production forecasting model in MATLAB version 2016.

Empirical studies show that input variables that guide the industry sector toward rapid economic growth are labor force and capital stock (Pablo-Romero & Sanchez-Braza, 2015; Pablo-Romero et al., 2019).

3.3.1 Human capital

Human beings are new resource of wealth, if human capital is counted. Human resources are important for achieving sustainable competitive advantage and increasing investment in the industry. Human capital development tools include education, education and health care (Samouel & Aram, 2016).

3.3.2 Trade openness

Trade openness leads to the transfer of knowledge and action to product innovation, restructuring by firms, lowering of costs of imports and the entry of domestic firms to competitive markets. As a result, productivity, corporate profits and industrial production will increase (Wacziarg, 2000; Bakhtiari & Salem, 2009; Shahjahan et al., 2016).

3.3.3 Credit financing for industry sector

An efficient financial system for economic activities, especially for the industrial sector, can be effective in its development. Producers and investors need funding for continued production or investment. Due to the high cost of the investment and procuring raw materials for production, need sufficient liquidity to continue manufacturing is important. The banking system can play an active role in providing short-term liquidity requirements for manufacturing firms (Raghuramg & Luigi, 2002; Hadinejad & Mehrabian, 2008; Abbasi, 2009; Samsami & Amirjan, 2011).

3.3.4 Liquidity

The growth of liquidity generated by demand side stimulates the growth of industrial production. Moreover, expansionary monetary policies by facilitating lending to firms provide the necessary resources to increase investment in the productive sector and decrease of the liquidity shortage of firms, as a result, increase the capacity of industrial production (Monjazeb, 2000; Fahim Yahyaee & Falihi, 2003; Samsami et al., 2016).

In this study, the value added of the industrial production (constant 2010 US$) was selected as the output variable.

4. Empirical Results

Models for forecasting industrial production were constructed using both ANN and ANFIS methods. The seasonal data of the variables used was for the period of 1988 to 2017. Both models were trained (80% of the dataset) and tested (20% of the dataset) with the same input combinations to forecast industrial production. The performance of the model was evaluated by using the statistical parameters of the MSE and MAPE.

4.1 ANN Results

The MLP neural network with the Levenberg-Marquardt algorithm was used in this study. The perceptron neural network is a feed-forward multilayer neural network comprising an input, one or more hidden layers and an output layer. Despite the different formulas, the best way to determine the number of hidden layer neurons is trial-and-error. Therefore, in this study for the two-layer networks, all modes of 2 to 7 neurons with a sigmoid function for the first layer and one neuron with a Purelin function for the output layer were trained. In order to provide better training opportunities for each network mode, six runs were made for training in MATLAB.

Fig. 4 shows the optimal structure of the two-layer network with six input variables and an output variable. The result of testing all networks with 2 to 7 neurons for a hidden layer with 6 times retest showed that six tansig neurons was the best number of hidden layer neurons for the two-layer network and the Levenberg Marquardt training algorithm was best for forecasting industrial production.

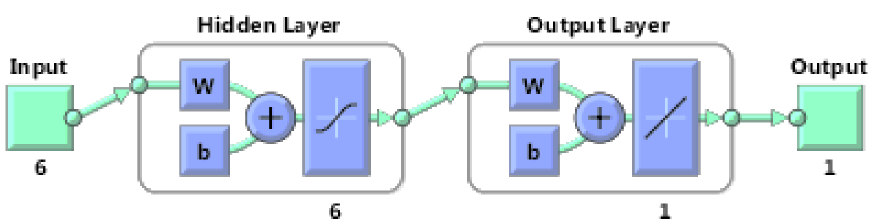

Figure 4. Optimal structure of two-layer network.

Figs. 5 and 6 show the real and forecasted values of industrial production. The red circles represent real industrial production values and the black spots represent the forecasted industrial production values. Fig. 6 is a close-up of Fig. 5 in which the deviation of the forecasted values from real values of industrial production is highlighted.

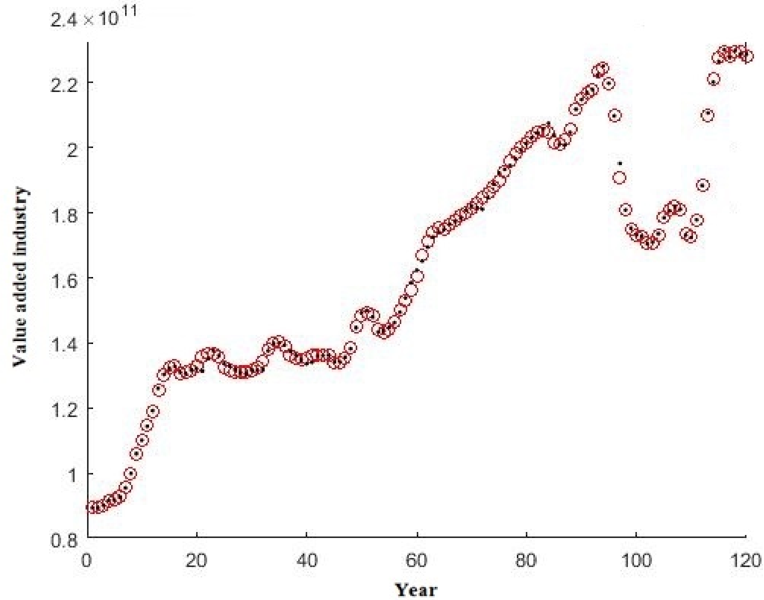

Figure 5. Forecasting of industrial production using ANN method.

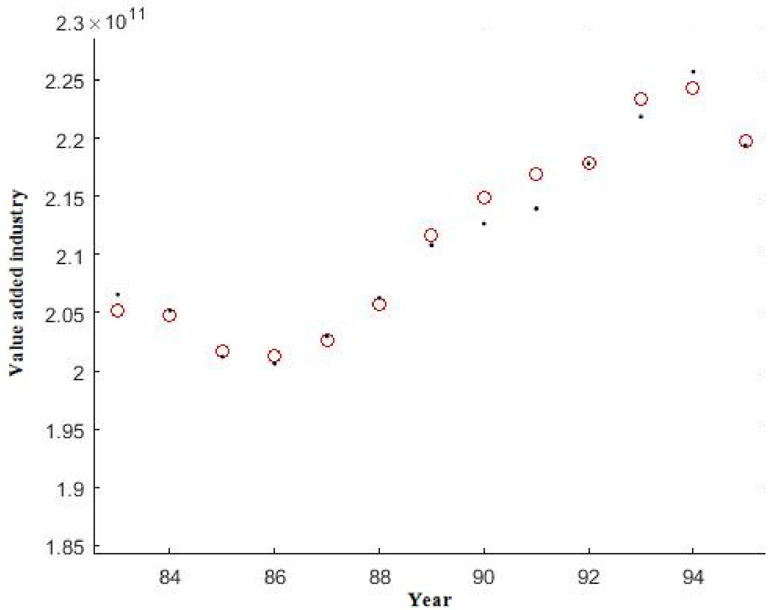

Figure 6. Close-up of forecasting of industrial production using ANN.

Table 1 provides the values of forecasting of industrial production and real industrial production using the ANN method for Seasons of the year 2019 and 2020.

Table 1. Forecasting industrial production using ANN for Seasons of the year 2019 and 2020

Year	Season	Forecasted data (constant 2010 US$)	Year	Season	Forecasted data (constant 2010 US$)
2019	Spring	2.39348E+11	2020	Spring	1.84321E+11
	Summer	2.38893E+11		Summer	1.64293E+11
	Fall	2.31167E+11		Fall	1.57888E+11
	Winter	2.14034E+11		Winter	1.5984E+11

4.2 ANFIS Results

The ANFIS model was tested using the Sugno system and a hybrid method was used for training (back propagation and least squares error). Modeling and training of the network were done by trial-and-error and the continuous change of membership functions, the number of membership functions and the number of interruptions of the variable. A network with 5 membership functions, sigmoid input function, linear output functions and 1,000 interruptions of the variable were made.

Figs. 7 and 8 show the real and forecasted values of industrial production. The red circles represent the real industrial production values and the black spots represent the forecasted values. Fig. 8 is a close-up of Fig. 7 in which the deviation of the forecasted values from the real quantities of industrial production is highlighted.

Table 2 provides the values for forecasting industrial production and real industrial production using the ANFIS method for Seasons of the year 2019 and 2020. The results show that the ANFIS method also effectively forecasts industrial production.

Table 2. Forecasting industrial production using ANFIS for seasons of the year 2019 and 2020

Year	Season	Forecasted data (constant 2010 US$)	Year	Season	Forecasted data (constant 2010 US$)
2019	Spring	2.25875E+11	2020	Spring	2.20047E+11
	Summer	2.25284E+11		Summer	2.01109E+11
	Fall	2.28129E+11		Fall	1.8541E+11
	Winter	2.22482E+11		Winter	1.80119E+11

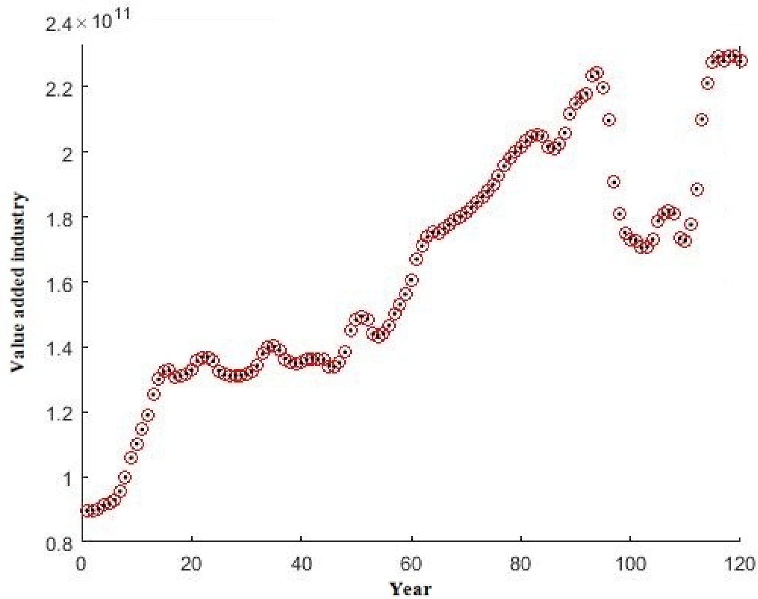

Figure 7. Forecasting of industrial production using ANFIS method.

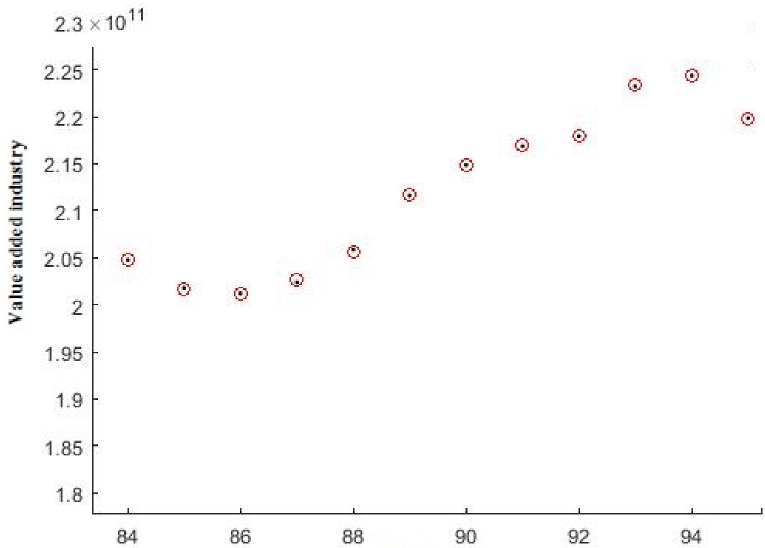

Figure 8. Close-up of forecasting of industrial production using ANFIS.

4.3 ANN and ANFIS Performance Evaluation and Comparison

AI tools having the power of learning improve their performance using samples related to the intended purpose. In this section, MSE and MAPE were used as the performance evaluation indexes to compare ANN and ANFIS. The MSE and MAPE indexes are obtained by:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(ei)^2 \tag{8}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{ei}{Yi}\right| \times 100 \tag{9}$$

where N is the number of observations for the prediction period, e_i is the error residual as defined by the difference between the real and forecast data and Y_i is the real value.

As discussed, high accuracy is desired for the forecasting methods and lower values for MSE and MAPE represent better performance of the procedure (Hykin, 1994). Based on the data available on the labor force, capital stock, human capital, trade openness, liquidity and credit financing for industry sector for the period of 1988 to 2017, the performance evaluation results of the ANN and ANFIS methods obtained using the MSE and MAPE indexes and it is shown in Table 3.

Table 3. MSE and MAPE indexes for ANN and ANFIS Methods

Models	MSE	MAPE
ANN	1.1779E+18	0.0044
ANFIS	7.7449E+15	0.00044

The results in Table 3 show that, while both methods are capable of forecasting industrial production but the lower MSE and MAPE values for ANFIS indicated that it performed better than the ANN method.

5. Concluding Remarks

This research concentrated on forecasting industrial production in Iran using a comparative study of ANN and ANFIS. Because the economic growth and development of many countries is dependent on industrial production, forecasting industrial production plays an important role in efficient planning for managers. Although classic approaches dominate and have been successful in the forecasting of economic variables, their results have not been able to satisfy researchers. The advantages of AI in forecasting have attracted more attention has led economic researchers to use this approach to provide more accurate models for forecasting seasonal industrial production. This was the objective of the current research.

Comparison between of ANN and ANFIS performance for prediction was another objective. The comparison revealed that both methods were capable of forecasting, but that the lower MSE and MAPE values for ANFIS indicate that it performed better than the ANN method. This conclusion is consistent with those of previous research (Kavitha Mayilvaganan & Naidu, 2011; Kangarani Farahani & Mehralian, 2013; Mirsoltani & Niaki, 2013; Sarmad, 2017). Some recommendations for future research are:

- The use of AI to forecast industrial subsectors in many parts of economic activity;
- To undertake similar research in other countries;
- Considering the advantages of AI, the performance of other models, such as metaheuristic algorithms, could be investigated.

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