Fruit production forecasting by neuro-fuzzy techniques

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Abstract*:* Neuro-fuzzy techniques are finding a practical application in many fields such as in model identification and forecasting of linear and non-linear systems. This paper presents a neuro-fuzzy model for forecasting the fruit production of some agriculture products (olives, lemons, oranges, cherries and pistachios). The model utilizes a time series of yearly data. The fruit forecasting is based on Adaptive Neural Fuzzy Inference System (ANFIS). ANFIS uses a combination of the least-squares method and the backprobagation gradient descent method to estimate the optimal food forecast parameters for each year. The results are compared to those of an Autoregressive (AR) model and an Autoregressive Moving Average model (ARMA)*.*

Keywords: Fruit forecasting, neuro-fuzzy, ANFIS, AR, ARMA, forecasting, fruit production

1. Introduction

Fruit time series are very complex for identification and prediction because their volatile behavior due to the environment conditions. If we consider that fruit production time series has only interior relation, the future production can be forecasted by the follow formula:

$$y_{t+1} = f(y_{t-k}, \ldots\ldots, y_t) \qquad (1)$$

where y_{t+1} is the rate to be predicted and y_{t-k} is the influence factor. Traditional models that have been used to forecast time series fruit production are all based on probability theory and statistical analysis with a certain of distributions assumed in advance. In most cases these assumptions are unreasonable and non-realistic. Also the linear structure of these models doesn’t guaranty accuracy of prediction.

Recent studies have addressed the problem of time series prediction by using different methods including artificial neural network and model based approaches due to the significant properties of handling non-linear data with self learning capabilities (Hornik, 1991; Jain, 1997; Skapura, 1996). The neural networks have been accused by the researches that are ‘black boxes’ and it cannot be known the degree that an input influence the output of the model (Shapiro, 2002; Pao, 1989). Fuzzy logic is an effective rule-based modeling in soft computing, that not only tolerates imprecise information, but also makes a framework of approximate reasoning. The disadvantage of fuzzy logic is the lack of self learning capability. The combination of fuzzy logic and neural network can overcome the disadvantages of the above approaches. In this study, is proposed to use a hybrid intelligent system called ANFIS (Adaptive Neuro Fuzzy Inference System) for predicting the fruit production. In ANFIS, is combined both the learning capabilities of a neural network and reasoning capabilities of fuzzy logic in order to give enhanced prediction capabilities, as compared to using a single methodology alone. ANFIS has been used by many researchers to forecast various time series, (Atsalakis & Valavanis, 2009; Atsalakis et. al., 2008; Atsalakis, 2007; Atsalakis et al., 2007; Atsalakis & Minoudaki, 2007; Atsalakis & Ucenic, 2006; Atsalakis, 2005; Jang et al., 1997; Lucas, 2001, Ucenic & Atsalakis, 2008; Ucenic & Atsalakis, 2006).

.2. ANFIS

A neuro-fuzzy system is defined as a combination of Artificial Neural Networks (ANN) and Fuzzy Inference System (FIS) in such a way that neural network learning algorithm are used to determine the parameters of FIS (Jung, 1993; 1995). Adaptive Neural Fuzzy Inference System (ANFIS) is a system that belongs to neuro-fuzzy category.

Functionally, there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitation of network configuration is that it should be of feedforward type. Due to this minimal restriction, the adaptive network's applications are immediate and immense in various areas.

In this section, we proposed a class of adaptive networks, which are functionally equivalent to fuzzy inference systems.

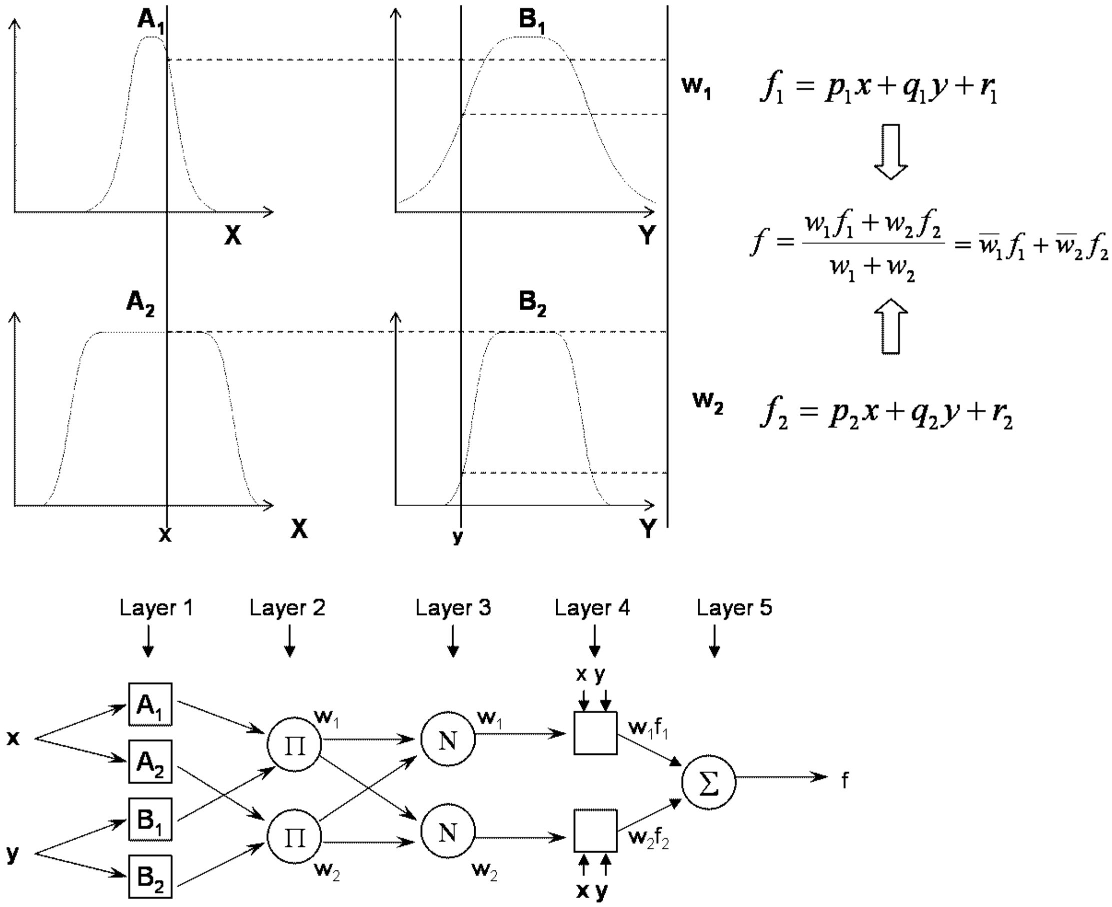

Figure 1: An illustration of the reasoning mechanism for a Sugeno-type model and the corresponding ANFIS architecture (Jang, 1993).

For simplicity, is assumed the fuzzy inference system under consideration has two inputs x and y, and one output f. Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugenos' type:

Rule1: If x is A_1 and y is B_1 then $f_1 = p_1 \cdot x + q_1 \cdot y + r_1$ (2)

Rule2:If x is A_2 and y is B_2 then $f_2 = p_2 \cdot x + q_2 \cdot y + r_2$ (3)

The ANFIS architecture and the reasoning mechanism is depicted in Figure 1. The node functions in the same layer are of the same function family as described below:

Layer 1: Every node i in this layer is a square node with a node function.

$$O_i^1(x) = \mu_{A_i}(x) \qquad (4)$$

where x - the input to node i A_i - the linguistic label (small, large, etc.) associated with this node function. In other words, O_i^1 is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i. Usually is chosen $\mu_{A_i}(x)$ to bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function

$$\mu_{A_i}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \qquad (5)$$

where a_i, b_i, c_i is the parameter set.
As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership function on linguistic label A_i. Parameters in this layer are referred to as *premise parameters*.

Layer 2: Every node in this layer is a circle node labeled π, which multiplies the incoming signal and sends the product out.

$$O_{2,i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(y), \ \ i = 1, 2. \qquad (6)$$

Layer 3: Every node in this layer is a circle node labeled N. The i-th node calculates the ratio of the i-th rules firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \ \ i = 1, 2., \qquad (7)$$

For convenience, output of this layer will be called *normalized firing strengths.*

Layer 4: Every node i in this layer is a square node with a node function

$$O_i^4(x) = \overline{w}_i \cdot f_i = \overline{w}_i (p_1 \cdot x + q_i \cdot y + r_i) \qquad (8)$$

where: $\overline{w}_i$- the output of layer 3$\{p_i, q_i, r_i\}$ - the parameter set. Parameters in this layer will be referred to as *consequent parameters*.

Layer 5: The single node in this layer is a circle node labelled Σ that computes the overall output as the summation of all incoming signals, i.e.

$$O_i^5(x) = overalloutput \qquad O_i^5(x) = \sum_i \overline{w}_i \cdot f_i = \frac{\sum_i w_i \cdot f_i}{\sum_i w_i} \qquad (9)$$

Consider using all possible parameters which the number is function of both, the number of inputs and the number of membership function then can be defined number of all rules as:

$$Rule_n = \prod_{i=1}^{I_{n_n}} M \cdot f_i \qquad (10)$$

and if $premispara_n$ is the number of all parameters which are necessary for membership function then the number of all parameters is defined as

$$para_n = premispara_n \sum_{i=1} I_{n_n} \cdot M \cdot f_i + Rule_n (I_{n_n} + 1) \qquad (11)$$

3. Model presentation

We use an ANFIS model to predict the yearly fruit production. We chose a one step ahead prediction (next year). The parameters of the system are presented in the Table 1. After many tests, two-membership functions of bell shape were chosen. The number of rules is two. The type of ANFIS is Sugeno, the add method is the product, the or method is the max, the defuzzification method is the weight average, the implication method is the product and the aggregation method is the max. The number of nodes is 12, the number of linear parameters is 6, the number of non-linear parameters is 4, and the total parameters are 10. The model uses a hybrid-learning algorithm to identify the parameters for the Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the backpropagation gradient descent method for training the Fuzzy Inference System (FIS) membership function parameters to emulate a given training data set. Also it uses a checking data set for checking the model over fitting. In order to compare the results of ANFIS model, we create an AR model and an ARMA model both of first order.

Table 1: ANFIS parameter types and their values used for training

ANFIS parameter type	**Value**
MF type	Bell function
Number of MFs	2
Output MF	Linear
Number of Nodes	12
Number of linear parameters	4
Number of nonlinear parameters	6
Total number of parameters	10
Number of training data pairs	37
Number of evaluating data pairs	5
Number of fuzzy rules	2

4. Experimentations Setup and Test Results

The input variable consists of the time series data for each year. For training the ANFIS we had one input variable with two bell shape membership functions. The output variable consists of the yearly data of next year in every step. The data concerns the period from 1961 to 2003. The first 85% of data was used for training the model and the 15% for testing the model. The data concerns five deferent time series productions: a) olives production, b) oranges production, c) pistachios production d) cherries production and e) lemons production.

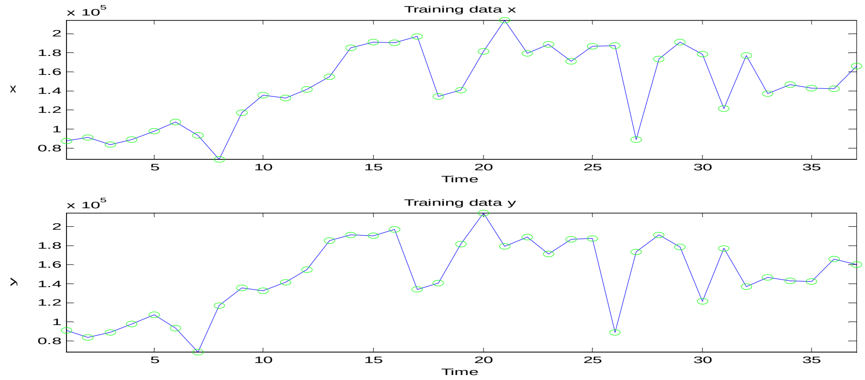

Figure 2**:** An illustration of the row training data

Figure 2 presents the row training data. The initial step size is defined to 0.01. The step size decrease rate is 0.9 and the step size increase rate is 1.1. The training error goal is set to 0. The model was tested many times using different time of epochs. Finally the best results obtained at 500 epochs. Figure 3 presents the initial membership function form before and after the training.

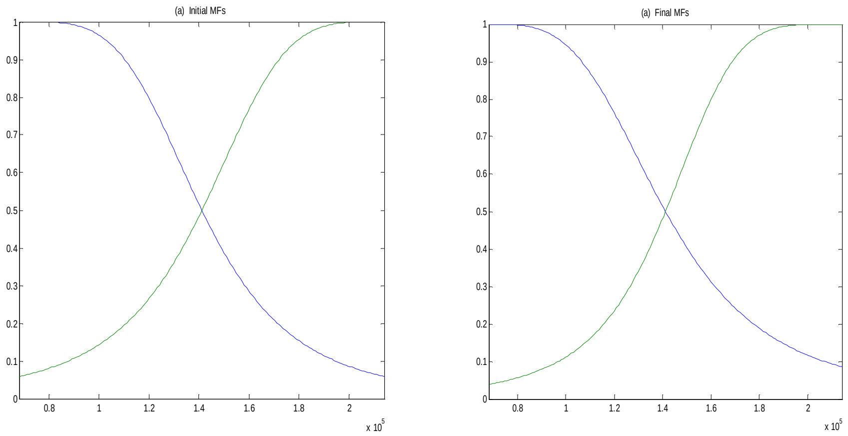

Figure 3**:** Bell shape membership functions before and after training

Figure 4 depicts the RMSE and the step size against the number of training epochs, during the training phase.
A comparison by the main classic error measurements is presented in the next tables.

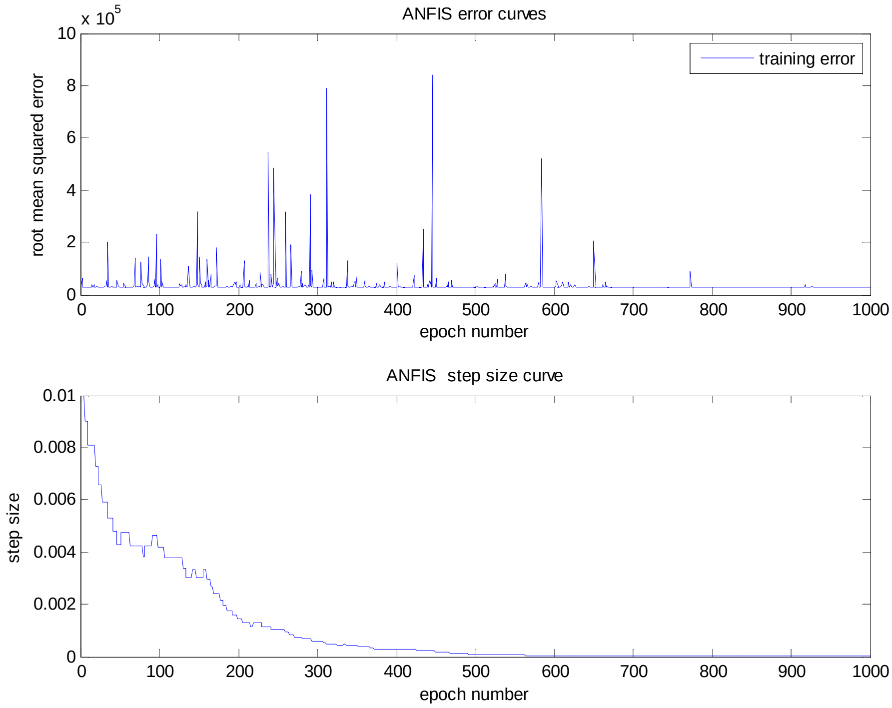

Figure 4**:** RMSE and step size during the training

Table 2 states that the ANFIS olives production forecasting model gives higher forecasting accuracy (the lowest error) compared with the classic forecasting models of AR and ARMA in terms of the well known statistical errors of Mean square error (MSE), Root mean square error (RMSE), Mean absolute error (MAE) and Mean absolute percentage error (MAPE), (Makridakis, 1983).

Table 2: Errors of olives production forecasting (1.0e+009)

	ANFIS	AR	ARMA
MSE	**1.482733459829657**	6.408888222886463	4.526556178092806
RMSE	**0.000038506278187**	0.000080055532119	0.000067279686222
MAE	**0.000034639570489**	0.000075782987185	0.000050915525210
MAPE	**0.000000009400159**	0.000000020420650	0.000000014943671

Table 3: Errors of oranges production forecasting (1.0e+010)

	ANFIS	AR	ARMA
MSE	**0.669734708673041**	1.368606694229773	2.184851773135111
RMSE	**0.000008183732087**	0.000011698746489	0.000014781244106
MAE	**0.000005579336746**	0.000010274909887	0.000011819225876
MAPE	**0.000000000537120**	0.000000001033691	0.000000001161919

Table 4: Errors of pistachios production forecasting (1.0e+006)

	ANFIS	AR	ARMA
MSE	**2.390630238106783**	2.744894704452143	3.462095526186307
RMSE	**0.001546166303509**	0.001656772375570	0.001860670719441
MAE	**0.001483950600326**	0.001542293301336	0.001669728915951
MAPE	**0.000015737822078**	0.000016337812277	0.000018023555181

Table 5: Errors of Cherries production forecasting (1.0e+008)

	ANFIS	AR	ARMA
MSE	**1.027345842154555**	1.935875278722603	7.673814986745047
RMSE	**0.000101358070333**	0.000139135735119	0.000277016515514
MAE	**0.000091259622325**	0.000135888653440	0.000206638253869
MAPE	**0.000000227742730**	0.000000333500116	0.000000527770828

Table 6: Errors of lemons production forecasting (1.0e+009)

	ANFIS	AR	ARMA
MSE	**1.373225033678369**	1.968053968068117	1.906911483082642
RMSE	**0.000037057051066**	0.000044362754289	0.000043668197617
MAE	**0.000028943937443**	0.000034195494971	0.000034222473326
MAPE	**0.000000030034265**	0.000000035779753	0.000000034838812

Tables 3-6 reconfirm the superiority of ANFIS in forecasting four other fruit productions: the oranges, the pistachios, the cherries and the lemons production, respectively. In all cases the ANFIS return the lowest errors (bold column).

5. Conclusion

This paper presents an Adaptive Neural Fuzzy Inference forecasting System (ANFIS) that it depended on previous year fruit production. For comparison purposes an AR and an ARMA model were developed. The results were presented and compared based on four different kinds of error. The system applied in five deferent fruit productions. The ANFIS model gives better results than the AR and the ARMA model in the five fruits production. Based on the above results, the suggested neuro-fuzzy model could be an efficient system of forecasting fruit production time series.

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