Long Term Forecasting with Fuzzy Time Series and Neural Network: a comparative study using Sugar production data

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***Abstract*— Forecasting of time series that have seasonal and other variations remains an important problem for forecasters. This paper presents a neural network (NN) approach along with a fuzzy time series methods to forecasting sugar production in India. The agriculture production and productivity is one of the such processes, which is not governed by any deterministic process due to highly non linearity caused by various effective production parameters like weather, rainfall, diseases, disaster ,area of cultivation etc. The study uses the fuzzy set theory and applies different fuzzy time series models to forecast the production of sugar in India. The historical data of sugar production from Food Corporation of India have been taken to investigate the results. The sugar production forecast, obtained through these models has been compared and their performance has been examined**..

Keywords: Fuzzy Time Series, Fuzzy Set, Production, Forecasting, Linguistic Value, high order model

I. INTRODUCTION

Time series forecasting gives future values on the basis of past data measured over time. Forecasting on the basis of past data are carried out by various methods like regression analysis, moving averages ,integrated moving average and autoregressive integrated moving average, but these methods does not support if the historical data are in linguistic terms[6].The sugar production and productivity is one of the such processes, which is not governed by any deterministic process due to highly non linearity caused by various affective production parameters like weather, rainfall, sunshine, diseases, disaster ,area of cultivation etc. As Indian sugar industry is the second largest sector after textile industry in its volume. India is also the largest consumer of sugar in the world. In India, Sugar cane is the source of Sugar, which is cultivated in almost all parts of India as the country's climatic conditions are suitable for the cane cultivation. Apart from sweetening product other by-products that is generated during processing are molasses, baggasse and ethanol. The present work is to apply fuzzy time series models and its implementation testing for forecasting of sugar production and compare the results of various forecasting models. The major objective of present work is to provide practical computational techniques using fuzzy time series with output having higher degree of accuracy and to show the application of fuzzy time series in the field of agriculture management [7].

Fuzzy set theory and fuzzy logic introduced by Zadeh[8] provides a general method for handling uncertainty and vagueness in data in linguistic terms. Various authors given different methods for forecasting using fuzzy time series. The first model was given by Song and Chissom that used fuzzy set theory to develop models for fuzzy time series forecasting and considered the problem of forecasting enrollments on the time series data of University of Alabama. hen proposed a method of fuzzy time series using simple arithmetic operations. The major problem in fuzzy time series forecasting is the accuracy in forecast as many researchers only worked on enrollment forecasting of University of Alabama. Chen [2] considered the forecasting of enrollments with high-order fuzzy time series models. Song [11] considered an average autocorrelation function as a measure of the dependency between fuzzy data for the selection of suitable order for fuzzy time series model of forecasting. Hurang[3] uses the heuristic knowledge and improving Chen[1] first order model. Singh [10] studied the application of fuzzy pattern matching in financial time series forecasting. Our work analysis these models and show its applicability in the field of agriculture production.

The motivation of applying the fuzzy time series forecasting models is to find ways of modeling the prediction of crop yield which is dependent on various factors. The forecasting for a lead year may be applied to help the crop planning and agro based business planning of the area and can be used in economics and business analysis. The historical time series data for sugar production used for present study have been collected from the Food Corporation of India, for the period 1988 to 2010.

II.ARTIFICIAL NEURAL NETWORKS:

Neural networks have been applied to time-series prediction for many years from forecasting stock prices and sunspot activity to predicting the growth of tree rings. In essence all forms of time series prediction are fundamentally the same. Namely given data $\mathbf{X}= \mathbf{X}(\tau)$ which varies as a function of time τ, it should be possible to learn the function that maps $\mathbf{X}\tau+1=\mathbf{X}\tau$. Feed-forward networks can be applied directly to problems of this form provided the data is suitably pre-processed. Consider a single variable x which varies with time, one common approach is to sample x at regular time intervals to yield a series of observations $X\tau$-2, $X\tau$-1,$X\tau$ and so on. We can then take such observations and present them as the input vector to the network and use observation $X\tau$+1 as the target value. By stepping along the time axis one sample at a time we can form the training set for the problem. In other words 'given the last three samples what is the next value?'.Once we have trained the network we should then be able to present a new vector $X'\tau$-2, $X'\tau$-1, $X'\tau$ vector and predict $X'\tau$+1. This is termed *one step ahead* prediction. We could also use the predicted value as part of the next input vector then depending on how many predicted values we allow to be fed back into the network we then have what is termed *multi-step ahead* prediction. Unfortunately the latter approach tends to diverge rapidly from the true pattern due to the accumulation of errors.

1.Neural Network Topologies[12]:

(A). Feedforward neural network: The feedforward neural network was the first and arguably simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network. The data processing can extend over multiple (layers of) units, but no feedback connections are present, that is, connections extending from outputs of units to inputs of units in the same layer or previous layers.

(B). Recurrent network: Recurrent neural networks that do contain feedback connections. Contrary to feedforward networks, recurrent neural networks (RNs) are models with bi-directional data flow. While a feed forward network propagates data linearly from input to output, RNs also propagate data from later processing stages to earlier stages.

2. Training Of Artificial Neural Networks[13]:

A neural network has to be configured such that the application of a set of inputs produces (either 'direct' or via a relaxation process) the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to **'train' the neural network** by feeding it teaching patterns and letting it change its weights according to some learning rule. We can categorize
the learning situations as follows:

(a).*Supervised learning* or Associative learning in which the network is trained by providing it with input and matching output patterns. These input-output pairs can be provided by an external teacher, or by the system which contains the neural network (self-supervised).

(b)*.Unsupervised learning* or Self-organization in which an (output) unit is trained to respond to clusters of pattern within the input. In this paradigm the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified; rather the system must develop its own representation of the input stimuli.

(c). Reinforcement Learning: This type of learning may be considered as an intermediate form of the above two types of learning. Here the learning machine does some action on the environment and gets a feedback response from the environment. The learning system grades its action good (rewarding) or bad (punishable) based on the environmental response and accordingly adjusts its parameters.

III Fuzzy Time Series

1. Fuzzy Set Theory

In the fuzzy set concept, the membership of an individual in a fuzzy set is a matter of degree [8]. A function, called a membership function, assigns to each element a number in the closed unit interval (0, 1) that characterizes the degree of membership of the element. While classical relations describe solely the presence of association between elements of two sets, fuzzy relations are capable of capturing the strength of association.

2. Fuzzy Time Series

In this study, the fuzzy relationship will be employed to model fuzzy time series. In this approach, the values of fuzzy time series are fuzzy sets [8]. And, there is a relationship between the observations at time t and those at previous times. To develop fuzzy relations among the observations at different times of interests. The models tuning and application have been studied in three different cases, in which forecasting have been done for the agricultural production based on time series data.

The time series data used for the study belong to the Food Corporation of India and have been obtained through the annual reports present in their website .The agricultural production database used in the study is the time series data of twenty two years starting from 1988-89 to 2009-10 for the sugarcane crop.

3.Basics of fuzzy time series

Various definitions and properties of fuzzy time series forecasting found in different papers and are summarized and reproduced as [11]:

Definition 1. A fuzzy set is a class of objects with a continuum of grade of membership. Let U be the Universe of discourse with $U= \{u1, u2, u3, . . . un\}$,where ui are possible linguistic values of U, then a fuzzy set of linguistic variables Ai of U is defined by

$$Ai = \mu Ai\ (u1)/u1+ \mu Ai\ (u2)/u2+ \mu Ai\ (u3)/u3 + . . . + \mu Ai\ (un)/un$$

here μAi is the membership function of the fuzzy set Ai, such that $\mu Ai : U = [0, 1]$. If uj is the member of Ai, then $\mu Ai\ (uj)$ is the degree of belonging of uj to Ai.

Definition 2. Let $Y(t)$ (t = . . ., 0, 1, 2, 3, . . .), is a subset of R, be the universe of discourse on which fuzzy sets $fi(t)$ (i=1, 2, 3, . . .) are defined and $F(t)$ is the collection of fi, then $F(t)$ is defined as fuzzy time series on $Y(t)$.

Definition 3(a). Suppose $F(t)$ is caused only by $F(t-1)$ and is denoted by $F(t-1) \rightarrow F(t)$; then there is a fuzzy relationship between $F(t)$ and $F(t-1)$ and can be expressed as the fuzzy relational equation:

$$F(t) = F(t-1) * R(t, t-1)$$

here ‘‘ * ’’ is max–min composition operator. The relation R is called first-order model of $F(t)$.

Further, if fuzzy relation $R(t, t-1)$ of $F(t)$ is independent of time t, that is to say for different times $t1$ and $t2$, $R(t1,t1 -1) = R(t2, t2 -1)$, then $F(t)$ is called a time invariant fuzzy time series.

Definition 3(b). If $F(t)$ is caused by more fuzzy sets, $F(t-n), F(t-n + 1), . . ., F(t-1)$, the fuzzy relationship is represented by

$$Ai1, Ai2, . . . , Ain \rightarrow Aj$$

here $F(t-n) = Ai1$, $F(t-n+1) = Ai2, . . ., F(t-1) = Ain$. This relationship is called nth order fuzzy time series model.

Definition 4. Suppose $F(t)$ is caused by an $F(t-1)$, $F(t-2)$, . . ., and $F(t-m)$ (m> 0) simultaneously and the relations are time variant. The $F(t)$ is said to be time variant fuzzy time series and the relation can be expressed as the fuzzy relational equation:

$F(t) = F(t-1) * Rw(t, t-1)$

here $w > 1$ is a time (number of years) parameter by which the forecast $F(t)$ is being affected. Various complicated computational methods are available to for the computations of the relation $Rw(t, t-1)$.

IV. FORECASTING SUGAR PRODUCTION

1.Computational Procedures by fuzzy time series

The implementation of the above algorithm for the production forecasting of the sugar crop is based on the 22 years (1988-89 to 2009-2010) time series production data of the Food Corporation of India.

Step 1. Define the universe of discourse to accommodate the time series data. It needs the minimum and maximum production and set as Dmin and Dmax[4]. Thus universe of discourse U is defined as [Dmin – D1, Dmax - D2], here D, and D2 are two proper positive numbers. In the present case of production forecasting universe of discourse computed is U = [80 , 290]

Step 2. Partition the universes of discourse into 7 equal length intervals U1, U2,...., U7 such that U1 = [80-110], U2=[110-140], U3=[140-170], U4=[170-200], U5= [200-230], U6=[230-250], U7=[260-290].

Step 3. Define 7 fuzzy sets A1, A2, ..., A7 having some linguistic values on the universe of discourse U . The linguistic values to these fuzzy variables are as follows:

A1: poor production,

A2: below average production

A3: average production

A4: good production

A5: very good production

A6: excellent production

A7: bumper production

These fuzzy sets in terms of its membership to different intervals are expressed as follows:

A1 :[1/u1,.5/u2,0/u3,0/u4,0/u5,0/u6,0/u7]

A2 :[.5/u1,.l/u2,.5/u3,0/u4,0/u5,0/u6,0/u7]

A3 :[0/u1,.5/u2,l/u3,.5/u4,0/u5,0/u6,0/u7]

A4 :[0/u1,0/u2,.5/u3,1/u4,.5/u5,0/u6,0/u7]

A5 :[0/u1,0/u2,0/u3,.5/u4,l/u5,.5/u6,0/u7]

A6 :[0/u1,0/u2,0/u3,0/u4,.5/u5,l/u6,.5/u7]

A7:[0/u1,0/u2,0/u3,0/u4,0/u5,.5/u6, l/u7]

Step 4. Fuzzification of the time series data for the fuzzy input for different models are given in table 1.

Sugar Season	**Production ofsugar (Lakh Tons)**	**Fuzzified Production, Aj**
1988-1989	87.52	A1
1989-1990	109.89	A1
1990-1991	120.47	A2
1991-1992	134.11	A2
1992-1993	106.09	A1
1993-1994	98.24	A1
1994-1995	146.43	A3
1995-1996	164.29	A3
1996-1997	129.05	A2
1997-1998	128.44	A2
1998-1999	154.52	A3
1999-2000	181.93	A4
2000-2001	185.1	A4
2001-2002	184.96	A4
2002-2003	201.32	A5
2003-2004	139.58	A2
2004-2005	130	A2
2005-2006	191	A4
2006-2007	257.54	A6
2007-2008	263	A7
2008-2009	147	A3
2009-2010	188	A4

Table 1 Fuzzification of sugar production data

Step 5. The fuzzy logical relations have obtained for different models.

Fuzzy Relationships

$A_1 \rightarrow A_1$, $A_1 \rightarrow A_2$, $A_1 \rightarrow A_1$, $A_1 \rightarrow A_3$,
$A_2 \rightarrow A_4$,$A_2 \rightarrow A_2$, $A_2 \rightarrow A_2$, $A_2 \rightarrow A_1$, $A_2 \rightarrow A_2$,$A_2 \rightarrow A_3$
A3→A3, A3→A2, A3→A4, A3→A4
A4→A4, A4→A4, A4→A5, A4→A6
A5→A2, A6→A7, A7→A3

Fuzzy logical relationship groups
A1→A1A1A2A3
A2→A1A2A2A2A3A4
A3→A2A3A4A4
A4→A4 A4A5 A6
A5→A2
A6→A7
A7→A3

Second Order FLR group for chen[1] higher model
A1A1→A2
A1A2→A2
A2A2→A1
A2A1→A1
A1A1→A3
A1A3→A3
A3A3→A2
A3A2→A2
A2A2→A3
A2A3→A4
A3A4→A4
A4A4→A4
A4A5→A2
A5A2→A2
A2A2→A4
A2A4→A6
A4A6→A3
A6A7→A3
A7A3→A4

Third Order FLR groups for Chen[1] higher order
#A1A1→A2
A1A1A2→A2
A1A2A2→A1
A2A2A1→A1
A2A1A1→A3
A1A1A3→A3
A1A3A3→A2
A3A3A2→A2
A3A2A2→A3
A2A2A3→A4
A2A3A4→A4
A2A3A4→A4
A3A4A4→A4
A4A4A4→A5
A4A4A5→A2
A4A5A2→A2
A5A2A2→A4
A2A2A4→A6
A2A4A6→A7
A4A6A7→A3
A6A7A3→A4
A7A3A4→#

Forth order FLR group for chen[1] higher order
#A1A1A2→A2
A1A1A2A1→A1
A1A2A2A1→A1
A2A2A1A1→A3
A2A1A1A3→A3
A1A1A3A3→A2
A1A3A3A2→A2
A3A3A2A2→A3
A3A2A2A3→A4
A2A2A3A4→A4
A2A3A4A4→A4
A3A4A4A4→A5
A4A4A4A5→A2
A4A4A5A2→A2
A4A5A2A2→A4
A5A2A2A4→A6
A2A2A4A6→A7
A2A4A6A7→A3
A4A6A7A3→A4
A6A7A3A4→#

Fifth Order FLR group for Chen[1] higher order
#A1A1A2A2→A1
A1A1A2A2A1→A1
A1A2A2A1A1→A3
A2A2A1A1A3→A3
A2A1A1A3A3→A2
A1A1A3A3A2→A2
A1A3A3A2A2→A3
A3A3A2A2A3→A4
A3A2A2A3A4→A4
A2A2A3A4A4→A4
A2A3A4A4A4→A5
A3A4A4A4A5→A2
A4A4A4A5A2→A2
A4A4A5A2A2→A4
A4A5A2A2A4→A6
A5A2A2A4A6→A7
A2A2A4A6A7→A3
A2A4A6A7A3→A4
A4A6A7A3A4→#

Step 6:-Computation of fuzzy forecast of the sugar production have been carried by the four models: Chen[2](Model-1) ,Hurang[3](Model-2),S.R. Singh[6] (Model-3) and Chen higher order[1] (Model-4) .

Step 7. Defuzzification is the process by which fuzzy output of model is transformed to crisp values for getting the forecasted values.

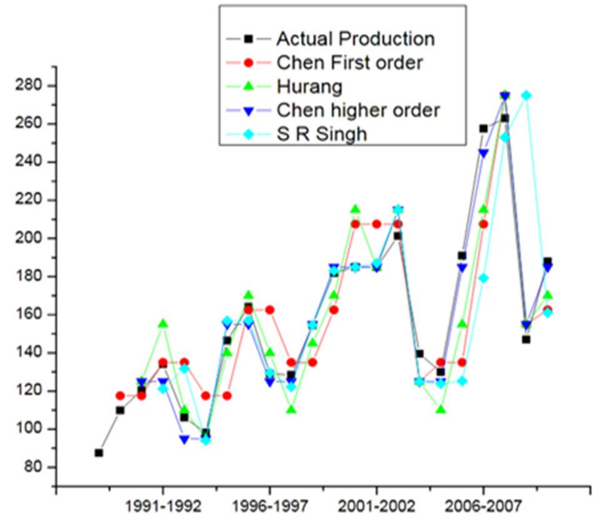

Fig.1 Actual sugar productions vs. forecasted sugar production by different models

In Fig. 1 we can see that there are various up and downs in the sugar production in different intervals of time. In case of sugar production, all the four models provide similar forecast. The forecasted values from model-4 are in close agreement with the actual production, where as other models exhibits some variation with the actual production values and can be visualized in Fig. 1.Forecasting results benefits to know the next session sugar production.

2. Computation Procedure by Artificial Neural Network

In this section, we present the stepwise procedure for neural network forecasting, which is only helpful if we have some more parameters of the data which influence the production.

1. Define the input parameter (viz. those (Z1, Z2, Z3 …., Zn) metrological parameter which directly influencing the crop production like weather, rainfall, diseases, disaster, area of cultivation etc.
2. Collect the production data of year t and previous years (data for the metrological parameters and actual crop production).
3. Normalized the production data so the every value must be in between 0 and 1.
4. Design the Artificial Neural Network (ANN) with the consideration of number of layers in ANN, number of hidden layer and number of neurons in a particular layer.
5. Select the best suited training algorithm for ANN.
6. Define the transfer function for the each layer as suited for the problem, for which we are designing the neural network.
7. Decide the number of epochs and goal for the training of ANN.
8. Select the programming tool to write the simulator for the proposed neural network.
9. Now train the ANN with the collected production data of previous ‘ n’ years for selected parameters (Z1, Z2 , Z3 …., Zn) and(P(t-1), P(t-2), P(t-3),…….., P(t-m)) actual productions .
10. Once the ANN is trained for the set goal then apply the test patterns for the years t + 1, t + 2, t+ 3 ……. t+p ,for which we want to forecast the agricultural products. Output of ANN will be taken as the forecasted values for the corresponding years.
11. Do the Comparative study with fuzzy series forecasting models.
12. Do the error analysis with observed forecasted values and actual production values to validate the model.

This type of approach good for multi-attributed data where we can see that which parameters are influencing the data and which parameter is used for training so this process is time consuming and not applicable for single parameter data. But if we have lots of parameter which influence the production then it will definitely give better results than the fuzzy time series methods. In this paper we explain approach for the forecasting of sugar production by artificial neural network.

V COMPARISION OF FORECASTING RESULTS

In this section, we compare the forecasting results of different methods on historical data of sugar production. A comparison of mean square errors (MSE) of different existing methods is shown on table ,where the mean square error (MSE) is defined as follows:

MSE=$\sum$ (Actual Production –Forecasted Production)^2/n

Where i=1 to n,

	Chen [2]	Hurang[3]	Chen Higher order[1]	S.R.Singh[5]
MSE	562.78	329.05	63.45	1534.12

Table 2 A comparison of mean square error (MSE) of Sugar production forecast

VI CONCLUSION

The motivation of the implementation of fuzzy time series in different crop production forecast is to support the development of decision support system in agricultural production system, one of the real life problems falling in the category having uncertainty in known and unknown parameters. The past experiences reveal that the agricultural production system is a complex process and hard to model by the mathematical formulations, as a matter of fact even all the standard practices of cropping are adapted; the uncertainty lies in the crop production due to some uncontrolled parameters. Further, the sugar production being dealt with the field data, precision of data is always a matter of concern. The historical time series crop production data used in the present study is taken from Food Corporation of India. The other goal was to compare neural network method with various fuzzy time series methods. It is observed that it produces more accurate results in comparison of fuzzy time series methods. The neural network method is objective as compared to subjective fuzzy time series methods, since in case of neural network interpretation is done by only designed artificial neural network model. It can easily handle the inaccuracy and any degree of nonlinearity in the data.

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