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Forecasting Potato Price using Ensemble Artificial Neural Networks

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ABSTRACT

Agricultural price information needs for decision-making at all levels are increasing due to globalization and market integration. Agricultural price forecasting is one of the challenging areas of time series analysis due to its strong dependence on biological processes. In this paper, an empirical mode decomposition based neural network model is employed for potato price forecasting. The daily potato wholesale price series from Delhi market was decomposed into eight independent intrinsic modes (IMFs) and one residue with different frequencies.Then anartificial neural network with single hidden layer was constructed to forecast these IMFs and residue component individually. Finally, the prediction results of all IMFs including residue are aggregated to formulate an ensemble output for the original price series. Empirical results demonstrated that the proposed ensemble model outperforms a single model in terms of root mean square error and directional prediction statistics.

Keywords: Artificial neural network, directional prediction statistics, empirical mode decomposition, intrinsic mode function, price forecasting, root mean square error,

INTRODUCTION

Timely and reliable agricultural price forecasts are useful for farmers, policy planners and agro-based industries. Forecasting of agricultural commodity prices is one of the challenging area of time series forecasting due to its dependence on biological phenomenon. Agricultural commodity prices are often random as they are largely influenced by weather variables and eventualities. This leads to a considerable risk and uncertainty in the process of price modelling and forecasting of agricultural commodities. The main goal of time series forecasting is to predict the future values of variables of interest on the basis of historical data of its own as well as of related variables. The ability to precisely forecast the prices of agricultural commodities depends on understanding or estimation of data generating process. Over the past several decades, researchers have taken keen interest in designing and development of effective and efficient time series forecasting models. The various time series approaches developed for price forecasting can be broadly divided into two categories, *i.e.* statistical models and artificial intelligence (AI) models.

One of the most important and widely used statisticalmodel for forecasting price levels is the autoregressive integrated moving average (ARIMA) model (Box and Jenkins, 1976). The main limitation of ARIMa model is pre-assumed linear relationship of the data series at hand which is generally unknown.The forecasting results and their economic implications are likely to be misleading when the assumed relationship for data generating process is not correct. Further, the formulation of a nonlinear model to a particular data series is a very difficult task since there are too many possible nonlinear patterns and a pre-specified nonlinear model may not be general enough to capture all the important features.

To overcome this limitation, machine learning techniques and more specifically artificial neural networks (ANNs) have emerged as an alternative to traditional statistical models (Darbellay and Slama, 2000). ANNs are non-linear, nonparametric, data driven self-adaptive method with a few a priori assumption about the data series. Hence, it is most suitable for forecasting agricultural price series which is inherently noisy and nonlinear in nature. Moreover, ANNs are universal

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approximators as it can map any nonlinear relationship provided there is an appropriate structure and sufficient data for training is available. It acquires the ability to map nonlinear pattern through hidden layer and nonlinear activation function. A real life complex time series consist nonstationary and nonlinear characteristics. Literature clearly suggest that neural network models are not able to model a nonstationary time series data (Nelson *et al.,* 1999). Huang *et al.* (1998) proposed the empirical mode decomposition (EMD) method for extracting characteristic information from non-linear and non-stationary time series through a divide and conquer concept. The main objective of EMD is to disintegrate a non-stationary and nonlinear time series data into several independent intrinsic mode functions (IMFs) and one residue with different amplitude and frequencies. Hence, EMD combined with neural networks can handle nonstationaryand nonlinear price series. Therefore, in this paper we employed anensemble model (EMD-ANN) for a complex daily potato wholesale price series of Delhi market.

METHODOLOGY

The empirical mode decomposition is a form of adaptive time series decomposition technique for nonlinear and nonstationary time series data like agricultural price series.The prime objective of EMD is to disintegrate a non-stationary and nonlinear time series data into several simple modes (IMFs and residue) those are not visible by human eyes in the original data series.Its decomposition is based on the local characteristic time scale of the price series. Compared with the original series, the decomposed series can be predicted easily with better accuracy.

In machine learning techniques, specifically artificial neural networks (ANNs) have been extensively studied and used for time series forecasting. ANNs are a family of models which are based on the structure of neurons in the brain. Unlike traditional forecasting approaches, ANNs are able to adapt nonlinearity and approximate complex relationships without extensive data or knowledge. Temporal data can be modelled using neural networks in two ways, either with the help of recurrent neural network or by providing buffers on the output of the nodes. In this study, feed-forward artificial neural network (ANN) with single hidden layer has been employed as a multi-scale learning tool for modelling the decomposed IMFs and the residual component. The general expression for a ANN with single hidden layer is given by (Jha and Sinha, 2014)

$$\hat{y}_t = g\,(\alpha_0 + \Sigma_{j=1}^{q} \alpha_j\, f\,(\beta o_j + \Sigma_{i=1}^{p} \beta_{ij}\, y - i)$$

where $\hat{y}_t$ is the predicted value for y_t at time t, $\alpha_j (j = 0,1,2, ..., q)$ and $\beta_{ij} (i = 0,1,2, ..., p; j = 1, 2 ...q)$ are are the model parameters often called the connection weights, p is number of input nodes (tapped delay), q is the number of hidden nodes, f and g denote the activation function at hidden and output layer respectively and C_{t-i} is the i^{th} input (lag) of the model. EMD and ANN are advantageous for nonstationary and nonlinear characteristics of a time series respectively. By combining EMD and ANN, an effort has been made to take account of nonstationary and nonlinear behavior of agricultural price series. An artificialneural network which has been employed in the present study is illustrated in Figure1.

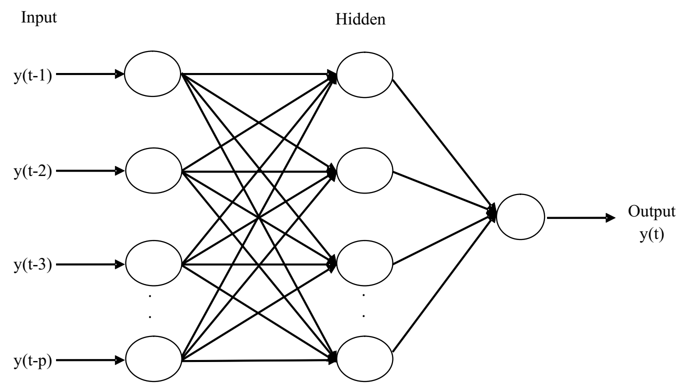

Figure 1. Time-Delay Neural Network (TDNN) with one hidden layer

Clement and smith (1997) suggested that the value of nonlinear model forecast may be represented by the direction of change other than measure of errors like RMSE. Hence, a comprehensive evaluation of each prediction model used in the study has been done in terms of the Root mean squared error (RMSE) and the directional prediction statistics $D_{(stat)}$ for the series. RMSE and $D_{(stat)}$ are explained as-

$$RMSE = \sqrt{\frac{\Sigma_i^n = 1\,(y_t - \hat{y}_t)^2}{n}} \text{ and } D_{Stat} = \frac{1}{n}\Sigma_{i=1}^{n}\, a_t\, X\, 100\%$$

where y_t and y_t are respectively the actual value and predicted value, n is the size of thetesting set and

$$a = \begin{cases} 1, & [\, y_{t+1} - \hat{y}_t]\, [\, \hat{y}_{t+1} - \hat{y}_t] \geq 0 \\ 0, & otherwise \end{cases}$$

RESULTS AND DISCUSSION

For the present study, daily potato wholesale prices (Rupees per quintal, ₹/q) of Delhi market collected from National horticultural research and development foundation (NHRDF) for the period 02 January, 2012 to 23 March, 2018 was used to evaluate each prediction model. Original price series was divided into two sets, namely the training (02 January, 2012 to 09 March, 2018) and the testing set (10 March, 2012 to 23 March, 2018). Here, training set is used for estimation of parameter as well as to measure the generalization ability of the model. Testing set is used to assess the out of the sample performance of the model.

Time plot in Figure 2 clearly indicate the nonlinearity and non-stationarity behaviour of the series. The basic descriptive statistics of the price series used in the study are presented in Table 1 which clearly indicate that wholesale potao price varies from ₹ 310/q to ₹ 2765/qof Delhi market. The value of standard deviation, a crude measure of instability or volatility, clearly points towards volatile nature of daily potato price. The Jarque-Bera statistics suggests non-normal distribution for the series. The series is positively skewed and leptokurtic.

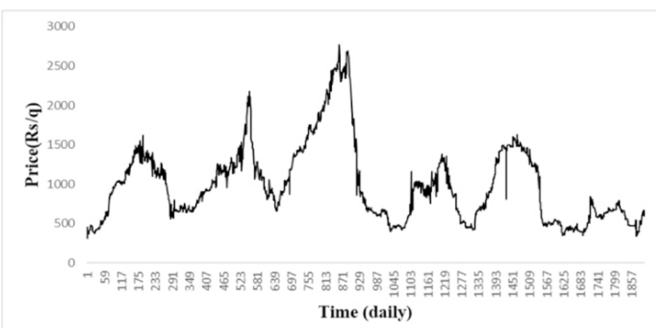

Figure 2: Time plot of daily potato wholesale price series of delhi market

Table 1: Descriptive statistics of daily potato wholesale price of delhi market

Statistics	Value
Observations	1901.00
Mean (₹/q)	996.14
Median	905.00
Maximum	2765.00
Minimum	310.00
Standard deviation	497.52
Skewness	1.10
Kurtosis	4.04
Jarque–Bera	471.06

Before using EMD to decompose a series,the series is tested for stationarity and linearity. To test the stationarity of given data series, we used Augmented – Dickey – Fuller (ADF) which give the presence or absence of unit root in the data set. For ADF test, null hypothesis is unit root is present in the data series which means data is non-stationary and alternative hypothesis is data series is stationary. According to the value of test statistic we decide to accept or reject a particular hypothesis, but in general if statistic is more negative then there is strong evidence for rejection of the hypothesis at some level of significance. The result of the test indicated that the probability value of price series is not less than 25 per cent, indicating that price series are non-stationary at 25 per cent level of significance.

To test the linearity characteristics of price series, we used Brock-Decher-Scheikman (BDS) test. In this test, first data is detrended to remove linear structure by using any linear econometrics model and test whether the remaining residuals are independent or dependent, according to which we have to accept or reject null hypothesis. Forembedding dimensions 2 and 3, probability values were less than 0.001, which indicated that the price series is nonlinear at 1 per cent level of significance.

After testing the prerequisites of EMD *i.e.* nonstationarity and nonlinearity, we found that series is nonstationary and nonlinear. Now EMD is applied to decompose given series into different independent intrinsic mode functions (IMFs) and one residue with different amplitude and frequenciesthrough a sifting process.Accordingly, the potato price series is decomposed into eight IMFs and one residue, as illustrated in Figure 3, which clearly demonstratethat from IMF1 to IMF8 amplitude is increasing whereas frequency is decreasing.

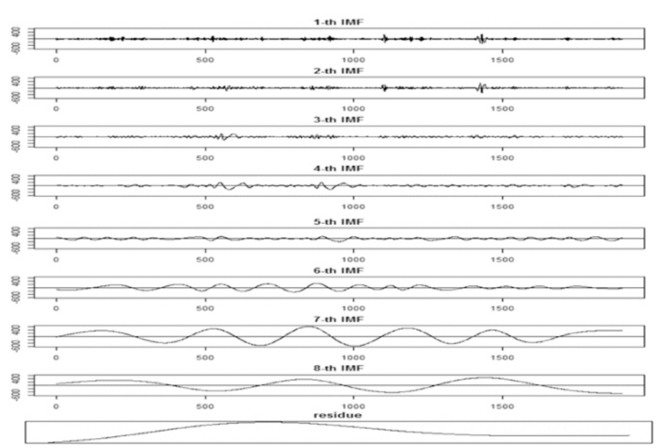

Figure 3: The IMFs and residue for daily potato wholesale price of delhi market

The forecasting results of the EMD-ANN model are compared to artificial neural network (ANN) model. Many studies have used ANN model for commodity price forecasting (Jha and Sinha, 2014). However, inherent nonlinearity and non-stationary properties of commodity prices affect the robustness of the ANN model significantly (Jha and Sinha, 2013). EMD is suitable for agricultural price forecasting as it can decompose a complex data into data into simple independent intrinsic mode functions, which simplifies the forecasting task into several simple forecasting subtasks. Since the decomposition is based on the local characteristic time scale of the data, the decomposed modes become stationary and non-linear in nature. EMD can also reveal the hidden patterns and trends of time series, which can enhance the forecasting ability of ANN. As indicated earlier, using the EMD approach in the data decomposition, the price series has been decomposed into eight independent IMFs and one residue component. Subsequently each IMFs and residue are predicted through ANN.

ANN architecture for a particular time series prediction includes determination of number of layers and total number of nodes in each layer. Neural networks being a universal approximation can map any non-linear function with one hidden layer given sufficient number of nodes at hidden layer and adequate data points for training.

Accordingly, in this study, the ANN with one hidden layer has been used. As mentioned earlier, number of input nodes which are lagged observation of the same variable, is determined with the help of partial autocorrelation function (PACF). One output node is employed and multi-step ahead forecasting is done using the iterative procedure. This involves use of predicted value as an input for forecasting the future value. Further the number of nodes at hidden layer improves the out-of-the sample forecasting ability and also avoids the over-fitting problem. The number of hidden nodes is determined with help of experimentation. We varied the number of hidden nodes from 2 to 20 with basic cross validation method. It can also be observed that a neural network model with 17 hidden nodes performs better than other competing model in respect of out of the sample forecasting accuracy measures.The logistic sigmoied and identify functions have been employed as an activation function for the hidden and output nodes respectively.

In this paper, our focus is on short term forecasting, and hence, we consider forecast horizon of up to twelve days. The prediction ability of EMD based ANN is compared with ANN in terms of RMSE and D_{stat} Table 2 presents the one-step ahead forecasts using the best ANN model for the daily wholesale price of potato of Delhi market for the period of 12 days including some holidays.

Table 2: Forecast of daily wholesale potato price of delhi market (10 Mar, 2018 to 23 Mar, 2018)

Forecast horizon	Actual value (₹/q)	Forecasted value (₹/q)	
		ANN	EMD-ANN
10-Mar-18	527.00	531.06	489.04
12-Mar-18	490.00	531.91	489.43
13-Mar-18	608.00	532.79	570.93
14-Mar-18	608.00	533.66	598.96
15-Mar-18	607.00	534.52	611.71
16-Mar-18	627.00	535.38	621.05
17-Mar-18	635.00	536.24	632.87
19-Mar-18	665.00	537.09	636.18
20-Mar-18	665.00	537.93	639.21
21-Mar-18	665.00	538.77	649.09
22-Mar-18	665.00	539.61	644.46
23-Mar-18	592.00	540.44	633.91

Table 3, clearly demonstrated that the forecasting accuracy of EMD-ANN appears better than the ANN model due to its lower RMSE and high D_{stat} Specifically, compared with theRMSE of ANN (92.72), the RMSE of EMD-ANN is only 23.95. Simillarly D_{stat} of ANN is 66.67 whereas 75.00 in case of EMD-ANN model.In case ofensemble(EMD-ANN)model, non-stationary is handled using EMD while nonlinearity is modelled using ANN.

Table 3: Comparison of RMSE and D_{stat} of each prediction model for daily Potato wholesale price of Delhi market

Model	RMSE	D_{stat}
ANN	92.72	66.67
EMD - ANN	23.95	75.00

CONCLUSION

In this study a hybrid (EMD-ANN) forecasting model has been proposed to predict daily wholesale price of potato for delhi market. The main focus of this study is to present a simple, stable forecasting approach for nonlinear and nonstationary potato price. As we know ANN models only handle non linearity feature of a time series but when a series contains non stationary character also then it is unable to handle such situation. For such series we used EMD as a preprocessor to tackle non stationarity. Firstly, the EMD is used to decompose a series into a set of IMFs and residue those consists simple and smooth structure. Then these modes are forecasted by using ANN. Finally, the forecasted result of each IMFs and residue by using ANN are aggregated into the forecasting value for the series.Empirical results clearly demonstrated the better forecast accuracy of hybrid model (EMD-ANN) as compared to single ANN model across varying hidden nodes for all forecasting horizons because in hybrid model non-stationarity is handled using EMD and nonlinearity is modelled using ANN.Accurate price forecast at pre-sowing and pre-harvest will help farmers to take informed decisions like what to grow, how much to grow as well as whether to store or to market their produce. This will also facilitate advance planning of import and export policy f government.

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