Agricultural Economics Research Review 2022, 35 (2), 119-134
DOI: 10.5958/0974-0279.2022.00035.0

Performance comparison of ARIMA and Time Delay Neural Network for forecasting of potato prices in India

Sunny Kumar[1], Kashish Arora[1], Pardeep Singh[2]*, Akhilesh Kumar Gupta[3], Isha Sharma[4] and Kamal Vatta[1]

[1]Department of Economics and Sociology, Punjab Agricultural University, Ludhiana, Punjab, India
[2]ICAR-National Institute of Agricultural Economics and Policy Research, New Delhi, India
[2,3]Department of Agricultural Statistics, Odisha University of Agriculture and Technology, Bhubaneswar, Odisha, India
[4]Symbiosis Institute of Operations Management, Nashik, Maharashtra, India
Symbiosis International (Deemed University), Pune, Maharashtra, India

Corresponding author's email: pardeepmahal1994@gmail.com

Abstract Accurate, timely and adequate forecasting of perishable crops have significant impact on the farmers' well-being in Indian agriculture. The time series data of these perishable commodities usually violate the assumptions of time-series datasets i.e., linearity and stationarity. In such conditions, the development and selection of the appropriate forecasting models for agricultural commodities plays an imperative role for various policy decisions. In this study, we are focused on comparison of ARIMA (linear) and TDNN (non-linear) models to accurately model the potato price. The inclusion of these non-linear model in this study handles nonstationary, nonlinear, and non-normal features of datasets simultaneously. The findings revealed that TDNN outperformed ARIMA, and it is regarded as the best fit model in terms of minimal RMSE and MAPE value. The identification of the best forecasting model and accurate forecasting of market prices would help all the stakeholders to take appropriate decisions.

Keywords Potato, Price, Forecasting, ARIMA, TDNN

JEL codes C53, Q02, Q11, Q12

Agricultural commodity prices are often volatile as these are heavily impacted by factors which are unpredictable (Kumar et al. 2022). Price volatility plays a crucial role in promulgating policies with dynamic political and economic contexts (Kalkuhl, Von, and Torero 2016). Price volatility is widely recognized to destabilize farm revenue and impede farmers from making optimal investments and resource utilization (Schnepf 1999). Higher volatility reduces overall welfare of the economy in the long term (Chavas, Hummels, and Wright 2014). Policymakers, as well as other stakeholders in agricultural commodity marketing chain require price modelling and forecasting (Lama et al. 2015). From a financial perspective, forecasting volatility of agriculture commodity futures helps to assess and hedge risks associated with the contracts and provides the policy makers with tools to evaluate different scenarios (Sharma 2015). A short-term market price forecasting has been a challenge for many decades because of too many factors which cannot be accurately predicted. (Li, Xu and Li 2010). Time series investigation has unavoidable application particularly in agriculture. One of the most important and widely used time series models is the autoregressive integrated moving average (ARIMA) model (Gupta, Patra, and Singh 2019). Lots of application of ARIMA model can be found in the literature (Paul, Alam, and Paul 2014; Paul, Gurung, and Paul 2015; Gupta, Rao, and Singh 2018; Gupta, Patra, and Singh 2019; Paul, Paul, and Bhar 2020). ARIMA model has gained much popularity in modeling linear dynamics but it fails to capture the nonlinearity present in the series. The real-world price data of agro-products and its underlying market changes are often nonlinear in nature, and therefore, linear models may not be suitable when market changes frequently. To overcome the restriction of the linear models and to account for certain nonlinear patterns observed in real problems, several classes of nonlinear models have been proposed in the literature (Paul and Garai 2021; Jha and Sinha 2013). Recently, the use of neural network models in forecasting agriculture phenomenon is getting more attention (Jha, Thulasiraman, and Thulasiram 2009; Paul and Sinha 2016; Zhang et al. 2020). Numerous comparative studies of traditional models and artificial neural networks (ANNs) have been conducted, for example, Hill, O'Connor, and Remus (1996), Chin and Arthur (1996), Elkateb, Solaiman, and Turki (1998) and Paul and Garai (2021) which proved artificial neural networks to be a superior method for forecasting.

The conspicuous element of numerous time series of different horticultural items, primarily the transitory ones, is the nearness of nonlinearity, non-normality and nonstationarity. Among those, potato exhibits high degree of price volatility (Singh, Pynbianglang, and Pandey 2017). Potato price in India is determined by free market conditions that depend on the supply which is highly affected by changes in area under cultivation, unexpected weather conditions, demand of the potato from the major cities etc. (Sreepriya and Sidhu 2020). In the current study, an attempt has been made to assess the forecasting performance of two methods, the ARIMA model, the TDNN model for forecasting the Potato price in the selected Indian markets.

Material and methods

The monthly wholesale price (INR per qtl) of potato in India traded in Azadpur (Delhi), Burdwan (West Bengal), Agra (Uttar Pradesh), Ahmadabad (Gujarat), Jalandhar (Punjab), Bangalore (Karnataka), and Mumbai (Maharashtra) markets was utilized in this study. These markets were chosen based on their percentage share of total potato market arrival. The data for each market was gathered from the AGMARKNET portal. The price series spanned a total of 120 months, from January 2012 to December 2021, with 80% (96 months) utilized as a training set and 20% (24 months) used as a testing set. For data analyses purpose R-statistical package was used.

Test for normality: Skewness, Kurtosis, and density plots were used to determine data normality. The *Shapiro–Wilk test* given by Shapiro and Wilk (1965) was used to provide evidence of normality or non-normality of the datasets.

Test for stationarity: The first stage in price series analysis is to look at the stationarity of each price series individually. A series is considered stationary if its statistical properties, such as mean and autocorrelation structures, remain constant over time. To determine the presence of a non-seasonal unit root in the price series, the Augmented Dickey Fuller (Dickey and Fuller, 1979) and Phillips-Perron (Phillips and Perron 1988) tests were used.

ARIMA model: Introduced by Box and Jenkins (1976), the ARIMA model has been one of the most popular approaches for forecasting. In an Auto-Regressive Integrated Moving Average (ARIMA) model, time series variable is assumed to be a linear function of previous actual values and random shocks. Since seasonal time series data is taken for this study. ARIMA model can be extended easily to handle seasonal aspects denoted as ARIMA(p,d,q)(P,D,Q)$_{[s]}$, where the small letter parentheses part (p,d,q) indicates the non-seasonal part of model while the capital letter part (P,D,Q)$_{[s]}$ indicates the seasonal part of model, s being the number of periods per season (Barathi et al. 2011; Gupta et al. 2019). The general seasonal autoregressive integrated moving average (SARIMA)is given in equation 1:

$$\Phi_P(B^s)\phi_p(B)\,{}_s^{D}{}^{d}\,Y_t = \theta_q(B)\Theta_Q(B^s)_t \qquad \ldots(1)$$

where,

$\Phi_P(B^s) = (1 - \Phi_1 B^s - \ldots - \Phi_P B^{sP})$ is the seasonal AR operator of order P;

$\phi_p(B) = (1 - \phi_1 B - \ldots - \phi_p B^p)$ is the regular AR operator of order p;

${}_s^D = (1 - B^s)^D$ represents the seasonal differences and ${}_s^D = (1 - B)^d$ the regular differences;

$\Theta_Q(B^s) = (1 - \Theta_1 B^s - \ldots - \Theta_Q B^{sQ})$ is the seasonal moving average operator of order Q;

$\theta_q(B) = (1 - \theta_1 B - \ldots - \theta_q B^q)$ is the regular moving average operator of order q;

τ is a white noise process.

In an ARIMA model, the estimated value of a variable is supposed to be a linear combination of the past values and the past errors. The agricultural commodities price data are inherently noisy in nature and are volatile too therefore ARIMA model will not be enough to deal with such series, as it is limited by assumptions of linearity and homoscedastic error variance.

Brock- Dechert-Scheinkman (BDS) test: The BDS test is a non-parametric technique of testing for nonlinear patterns in time series and developed in Brocket al. 1996. The null hypothesis states that data in a time series is distributed independently and identically. The test is unique in its ability to discover nonlinearities in data that are not dependent on linear relationships. The residuals of the best-fitting ARIMA model were used to test for nonlinearity in the data.

Time Delay Neural Networks (TDNN): This has been developed as a viable alternative to classic statistical models in order to overcome the constraint of non-linearity (Darbellay and Slama, 2000). TDNNs are a data-driven, non-linear, nonparametric self-adaptive approach with a few a priori assumptions about the data series (Zhang, Patuwo, and Hu 1998). It can be treated as one of the multivariate nonlinear nonparametric statistical methods (White, 1989; Cheng and Titterington, 1994). As a result, it's best for forecasting agricultural price series, which are typically noisy and nonlinear. Furthermore, ANNs are universal approximators since they can map any nonlinear connection as long as the structure is acceptable and sufficient training data is available.

The number of layers and total number of nodes in each layer of an ANN for a specific issue in time series prediction must be determined. Because there is no theoretical foundation for establishing these characteristics, it is normally discovered by experimentation. Given a sufficient number of nodes in the hidden layer and sufficient data points for training, neural networks with one hidden layer may approximate any non-linear function. We employed a neural network with one hidden layer in this research. The number of input nodes that are lagged observations of the same variable plays an important role in time series analysis since it aids in modelling the autocorrelation structure of the data. It is usually preferable to use a hidden layer model with fewer nodes, since this improves out-of-sample prediction accuracy and minimizes the issue of over-fitting. The general expression for the final output value y_{t-1} in a multi-layer feed forward time delay neural network is given by equation (2)

$$y_{t+1} = g[\textstyle\sum_{j=0}^{q} \alpha_j f(\sum_{i=1}^{p} \beta_{ij}\, y_{t-1})] \qquad ...(2)$$

where, f and g denote the activation function at the hidden and output layers, respectively; p is the number of input nodes (tapped delay); q is the number of hidden nodes; β_{ij} is the weight attached to the connection between i^{th} input node to the j^{th} node of hidden layer; α_j is the weight attached to the connection from the j^{th} hidden node to the output node; and y_{t-i} is the i^{th} input (lag) of the model. Each node in the hidden layer gets the weighted sum of all inputs, including a bias term whose value of the input variable is always one. Each hidden node then transforms the weighted sum of input variables using the activation function f, which is often a non-linear sigmoid function. Similarly, the output node gets the weighted total of all hidden node outputs and creates an output by converting the weighted sum with its activation function g. In time series analysis, the Logistic Sigmoid function (f) and the Identity function (g) are frequently used. The logarithmic function is written as an equation (3)

$$f(y) = \frac{1}{1+e^{-y}} \qquad ...(3)$$

For p tapped delay nodes, q hidden nodes, one output node and biases at both hidden and output layers, the total number of parameters (weights) in a three layer feed forward neural network is q(p + 2) + 1. For a univariate time series forecasting problem, the past observations of a given variable serves as input variables. The ANN model attempts to map the following function

$$y_{t+1} = f(y_t, y_{t-1,\ldots} y_{t-p+1}, w) + \varepsilon_{t+1} \qquad ...(4)$$

where, y_{t-1} pertains to the observation at time t+1, p is the number of lagged observation, w is the vector of network weights, and y_{t-1} is the error-term at time t+1.

Diebold–Mariano (DM) test: In order to assess whether the observed differences in forecasting power across models are statistically significant, the Diebold–Mariano (DM) test for predictive accuracy was performed among the models which present best forecasting power inside each class (Diebold and

Table 1 Descriptive statistics for the potato prices of major markets in India

Particulars	Agra	Ahmedabad	Bangalore	Burdwan	Jalandhar	Mumbai	Azadpur
Mean	938.35	1163.07	1463.65	1106.35	584.44	1336.00	1064.34
Median	872.06	1048.69	1375.24	1011.58	525.88	1228.33	947.67
Min	333.48	464.71	763.24	317.14	151.67	609.09	399.68
Max	2858.75	2847.06	3242.05	3625.24	2078.26	3254.00	2944.76
Range	2525.27	2382.35	2478.81	3308.10	1926.59	2644.91	2545.08
SE	43.31	43.61	38.37	51.45	32.39	39.98	48.50
SD	474.39	477.77	420.29	563.58	354.87	437.98	531.30
Skewness	1.34	1.00	1.19	1.44	1.52	1.31	1.26
Kurtosis	2.30	0.58	2.20	3.11	2.98	2.77	1.67
CV	50.56	41.08	28.72	50.94	60.72	32.78	49.92
CDVI	1.81	0.42	2.87	5.97	0.89	2.47	0.39

Mariano 1995). The DM test approach aims to test the null hypothesis of equality of accuracy against the alternative of significantly different accuracy. The best model was selected on the basis of significance of DM test.

Results and discussion

In Table 1, we compute the summary statistics of prices of potato in major markets of India. The descriptive statistics of potato prices in different wholesale markets indicated a clear-cut difference among different wholesale markets in India . The wholesale average prices of potato were the highest (INR 1464 per quintal) in the case of Bangalore market in Karnataka state with minimum of INR 763 per quintal and maximum of INR 3242 per quintal, indicating the lack of production in the market despite growing consumption demand for potato-based products in the state. Jalandhar market in Punjab received the lowest average prices (INR 584 per quintal) of Potato with minimum of INR 151.67 per quintal and maximum of INR 2078 per quintal. The average wholesale price varied between in range of INR 584 to 1463 per quintal in all the markets of India. The selected price series were positively skewed ranging from 1.01 to 1.52, indicating the distribution was long on the right side as compared to the left. Estimates of kurtosis showed that the pattern of prices among all the selected markets of the different states were non-stationary with upto-kurtic distribution, which implying a relatively peak curve than a normal distribution. The standard deviation in wholesale prices was more than 400 in unit among all the markets however, it was the highest in market Burdwan of the West Bengal state. Further, the skewness and kurtosis estimates imply that the monthly prices in the respective markets are widely spread around its mean.

In time series analysis, the first and foremost step is to plot the data. We have plotted all the price series of all the selected markets (Figure 3). From the time plot of the price series, almost a similar pattern has been observed for all the markets. However, we have replaced the outliers by using standard practices such as interpolation as these price spikes has been seen during month of November of the year 2012 and 2019. Another important property of the time series analysis is checking whether the price series is normally distributed or not. We have used the Shapiro-Wilk test (Shapiro and Wilk, 1965). The null hypothesis for this test is the price series of all the selected markets are normally distributed and results are depicted in Table 2, wherein our null hypothesis was rejected (alternative

Table 2 Shapiro-Wilk test to check the normality for the potato prices of major markets in India

Particulars	Agra	Ahmedabad	Bangalore	Burdwan	Jalandhar	Mumbai	Azadpur
Test-Statistics	0.895	0.921	0.928	0.895	0.869	0.916	0.892
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

hypothesis accepted). It depicts that the datasets of all the selected markets are non-normally distributed. This argument can be supported by the Kernel densities given in Figure 1, which shows highly positive skewness in all the selected markets.

Before proceeding to the subsequent step, it is pertinent to see the price series of the selected markets must be stationary. If not, then further statistical practices such as differencing has to be applied to make the price stationary because ARMA methodology can only be applied for the stationary series.

The "SEAS" test, a measure of seasonal growth strength was used to test the presence of seasonal unit root, where seasonal differencing is suggested if the seasonal strength exceeds 0.64 (Wang, Smith and Hyndman, 2006). The data were seasonally adjusted if the seasonal unit root were present. Augmented Dickey-Fuller test (Dickey and Fuller, 1979) and Phillips-Perron test (Phillips and Perron, 1992) have been applied to see the presence of non-seasonal unit root in the seasonally adjusted series. The results of ADF and PP test are illustrated in Table 3. Non-rejection of null hypothesis (presence of unit-root) of ADF and PP test at 5% level of significance indicates that differencing is required to make the price series stationary for the selected markets otherwise the data is stationary.

ARIMA

In this study, we exercised many ARIMA models while

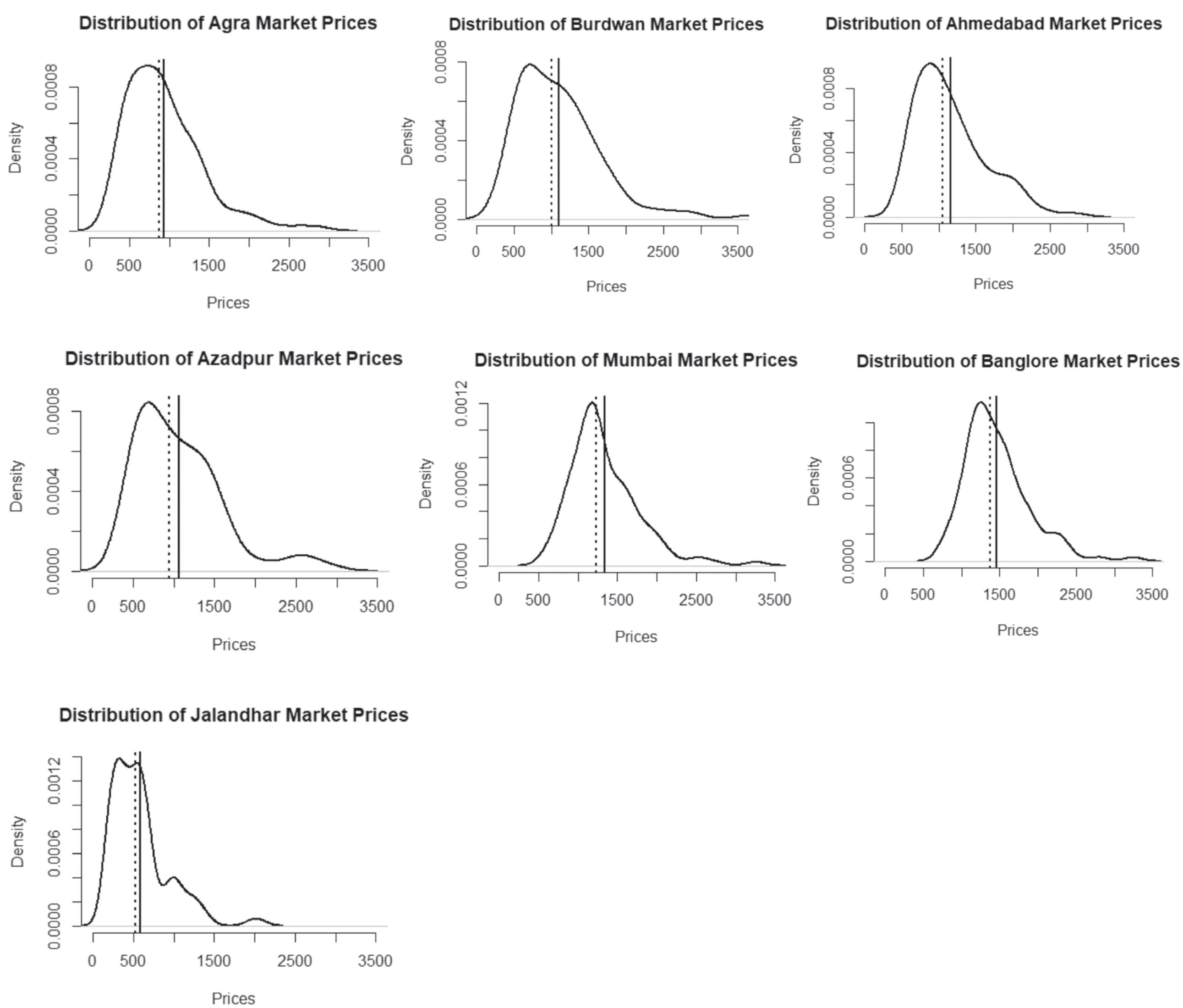


Figure 1 Kernel Density Plot for the potato prices of major markets in India

Table 3 Stationarity test for the potato prices of major markets in India

Particulars	Agra	Ahmedabad	Bangalore	Burdwan	Jalandhar	Mumbai	Azadpur
ADF	-3.998	-3.299	-3.354	-4.227	-3.279	-2.996	-3.916
	(0.012)	(0.075)	(0.065)	(0.010)	(0.072)	(0.163)	(0.016)
PP	-23.781	-22.710	-21.195	-28.980	-18.05	-21.025	-26.779
	(0.025)	(0.033)	(0.046)	(0.010)	(0.092)	(0.048)	(0.013)

Note The figures in parentheses are p-values of their respective figures

selecting best model for better forecasting in all the selected markets and results are shown in Annexure I. The performance of different models are evaluated on the basis of RMSE and MAPE. The various fitted ARIMA models are identified by above process and presented in Table 4. The evaluation criterion suggested that the best fit model for Agra market was {(1,0,1)(1,1,0)}$_{[12]}$ followed by Burdwan {(2,0,0) (2,1,1) $_{[12]}$}, Ahmedabad {(3,0,1) (1,1,1) $_{[12]}$}, Azadpur {(1,0,1) (1,1,0) $_{[12]}$}, Mumbai {(1,0,1) (0,1,1) $_{[12]}$}, Bangalore {(1,1,2) (0,0,0)$_{[12]}$} and Jalandhar {(2,0,1) (0,0,0)$_{[12]}$}. Additionally, among all the selected markets, the value of RMSE ranged between 232.76 to 571.98 among all the selected markets of India. However, the lowest value of RMSE recorded in Bangalore that suggest ARIMA {(1,1,2) (0,0,0)} $_{[12]}$ is the best price forecasting model among all the markets.

Non-linear test

Before proceeding with the TDNN, it is important to find whether the residuals of the best fitting ARIMA model of the selected markets are non-linear or not. If there is nonlinearity, then nonlinear models must be used to test for nonlinearity in the data. The study used BDS non-linearity model to test the residuals of the ARIMA model. The results of nonlinearity test presented in Table 5, reveal strong rejection of linearity in the case of residuals of the price series. In other words, the analysis has indicated the existence of some hidden structure left unaccounted in the residuals of

Table 4 Comparison of prediction performance of the selected models for the potato prices of selected markets of India

Market Name	ARIMA			Artificial Neural Network		
	Model	RMSE	MAPE	Layers	RMSE	MAPE
Agra	(1,0,1)	484.662	23.79	5:2s:11	303.16	16.27
	(1,1,0)$_{[12]}$	(129.221)	(11.47)		(68.47)	(5.74)
Burdwan	(2,0,0)	432.105	29.45	3:2s:11	299.73	20.14
	(2,1,1) $_{[12]}$	(119.072)	(6.93)		(82.74)	(5.63)
Ahmedabad	(3,0,1)	543.378	39.66	1:4s:11	216.49	12.49
	(1,1,1) $_{[12]}$	(136.013)	(9.52)		(61.96)	(4.03)
Azadpur	(1,0,1)	571.98	56.38	2:2s:11	265.99	24.15
	(1,1,0)$_{[12]}$	(142.26)	(7.28)		(103.76)	(6.49)
Mumbai	(1,0,1)	454.491	16.259	2:6s:11	242.56	11.54
	(0,1,1) $_{[12]}$	(131.52)	(8.289)		(77.14)	(4.86)
Bangalore	(1,1,2)	232.76	6.740	1:3s:11	213.47	5.93
	(0,0,0) $_{[12]}$	(164.91)	(7.316)		(72.53)	(2.99)
Jalandhar	(2,0,1)	334.484	40.55	2:3s:11	213.68	28.52
	(0,0,0) $_{[12]}$	(144.177)	(21.874)		(50.47)	(9.24)

Note The figures in parentheses are error measures of the training dataset

Table 5 Brock- Dechert-Scheinkman (BDS) test for nonlinearity for residuals

Markets	Epsilon=0.5		Epsilon=1		Epsilon=1.5		Epsilon=2	
	M=2	M=3	M=2	M=3	M=2	M=3	M=2	M=3
Agra	52.518	988.988	43.251	642.487	36.505	436.952	35.065	334.129
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Burdwan	37.657	665.255	31.026	388.723	25.729	284.006	23.176	237.714
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ahmedabad	56.453	1270.850	44.216	693.013	45.197	690.244	45.557	688.368
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Azadpur	42.159	770.840	34.339	466.604	34.588	453.985	36.154	452.599
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mumbai	56.71	1210.48	44.23	697.58	45.47	686.77	40.56	558.11
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bangalore	-4.85	-2.42	697.5	-31.21	206.35	-13.79	172.17	-19.75
	(0.00)	(0.015)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Jalandhar	-86.88	-38.64	-17.56	-7.64	-86.88	-38.64	-242.75	-108.34
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note The figures in parentheses are the respective p-value

linear model in selected potato markets. The test recommended the nonlinear model, i.e, Time Delay Neural Network (TDNN) for better price forecasting of potato.

Time delay Neural Network (TDNN)

The study has divided the datasets into two parts i.e., training set and testing set. The last 24 months of the monthly prices have been considered for testing purpose. Forecast models and its performance was tested using testing set. The summary of the fitted neural network model is given in Table 4. We have selected one hidden layer for best TDNN for this study. For this study, we have followed an iterative approach to select the hidden node, and we eventually chose one output node for better forecasting. We go through the different input nodes from 1 to 5 and the number of hidden nodes 2 to 6 for each selected market (Annexure II). TDNN model with one hidden layer is represented as I: Hs: Ol, where I is the number of nodes in the input layer, H is the number of nodes in the hidden layer, O is the number of nodes in the output layer, s denotes the logistic sigmoid transfer function, and l indicates the linear transfer function. The results of TDNN are summarized in Table 4 and Figure 2. We exercised different TDNN model at manual mode for each market, out of total 25 TDNN models that were tried, the best fit model for each market was identified based on the smallest value of RMSE and MAPE (Annexure II). The best fit TDNN model market was identified with 5 perceptron input layer and 2 perceptron hidden layer with one output (5:2s:1l) for Agra market of India. Likewise, the best TDNN for Burdwan market was 3:2s:1l followed by Ahmedabad (1:4s:1l), Azadpur (2:2s:1l), Mumbai (2:6s:1l), Bangalore (1:3s:1l) and Jalandhar (2:3s:1l). In all the selected markets, this network performed better than other competing networks for potato prices. Among all the markets, Bangalore market was performed best (with minimum value of RMSE 213) in India (Table 4 and Figure 2) with the selected Neural Network model. In Table 4, we have compared the results for the best in between ARIMA and TDNN models in terms of RMSE and MAPE for each market. We can see that for both the price series, the value of evaluation criterion (RMSE and MAPE) are comparatively lower in TDNN model than in ARIMA model. These lower value of RMSE and MAPE signifies that TDNN is better performing model. Nonetheless, in the study, we have used a variety of ARIMA models. However, all of the markets' pricing sets were nonlinear in character, which might be attributed to a nonlinear time series data set. In the nutshell, the results revealed that the TDNN model in general provided a better forecast

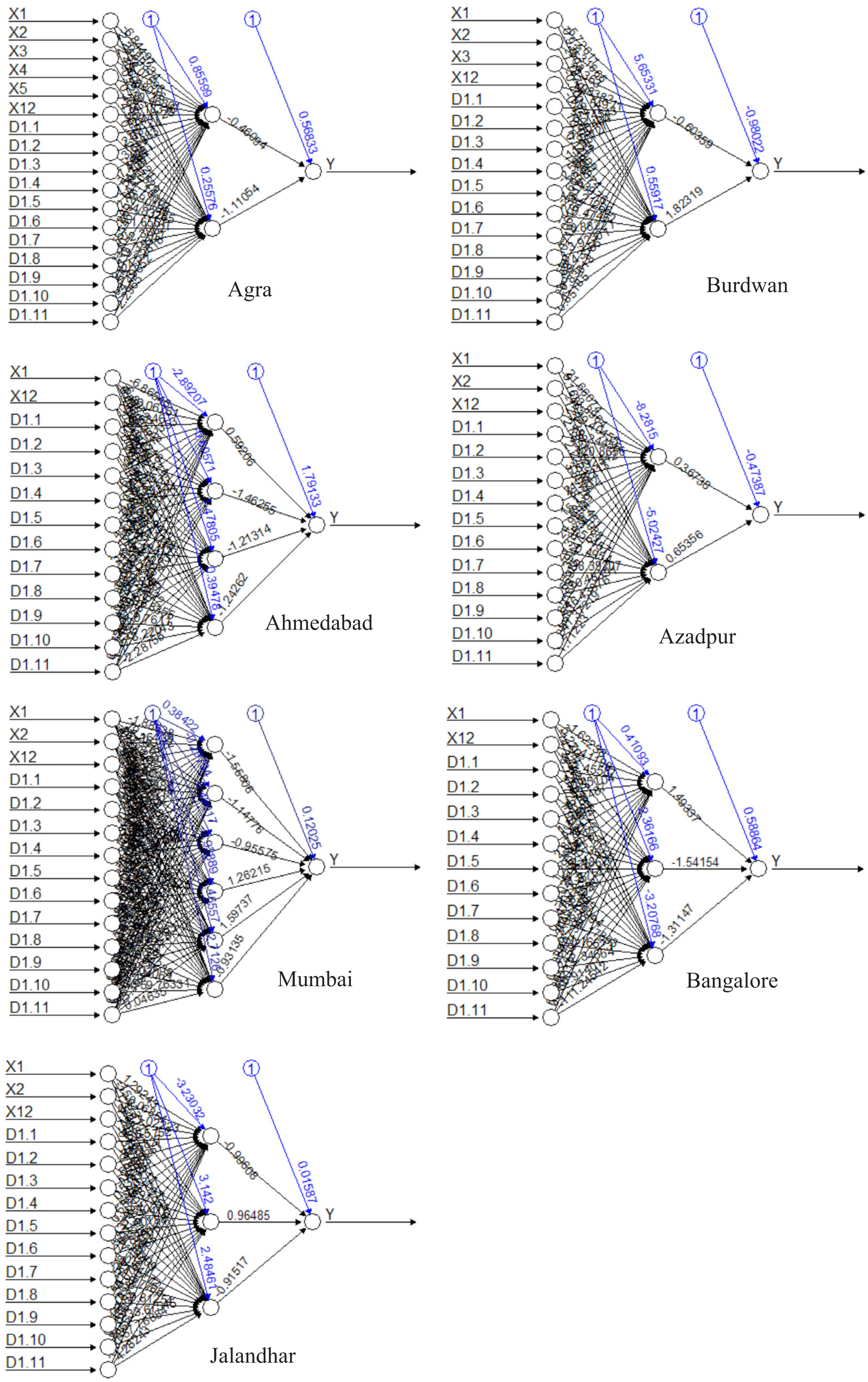
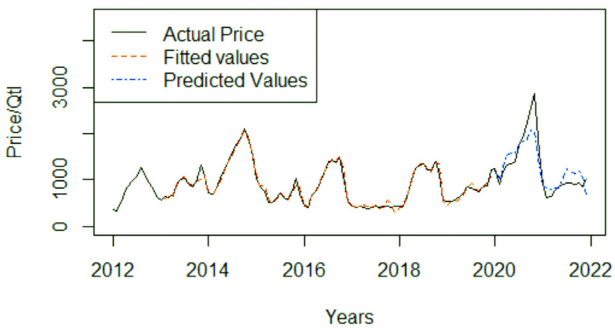
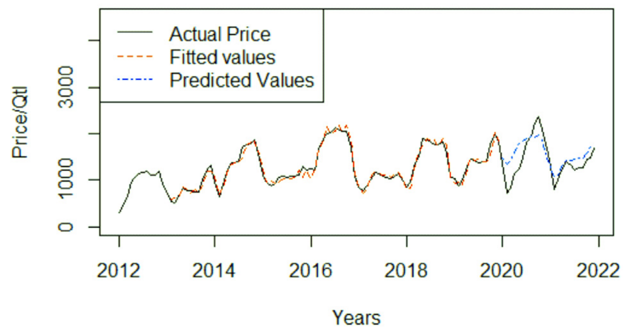


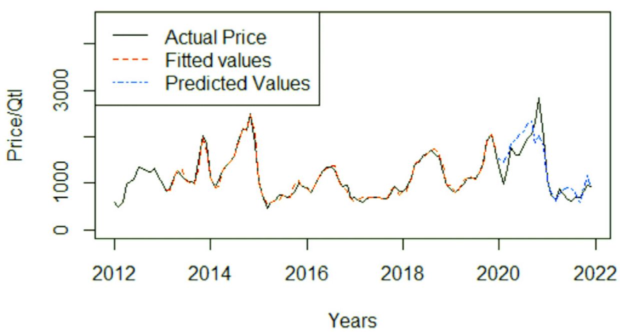
Figure 2 Artificial Neural Network layers for the potato prices of major markets in India



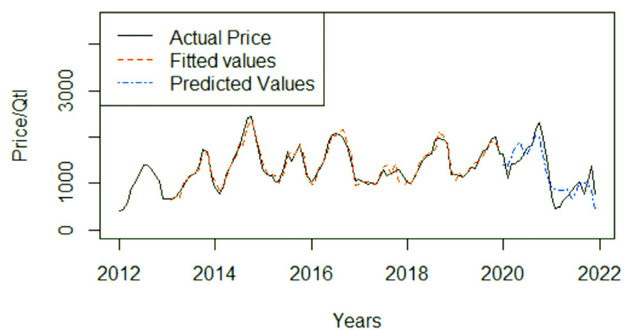
Agra



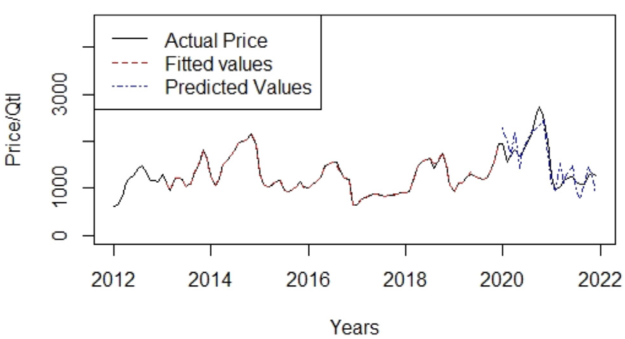
Burdwan



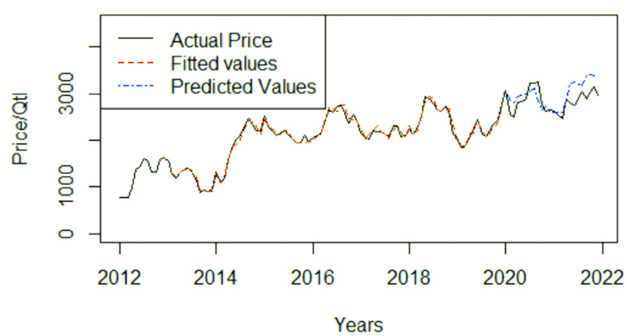
Ahmedabad



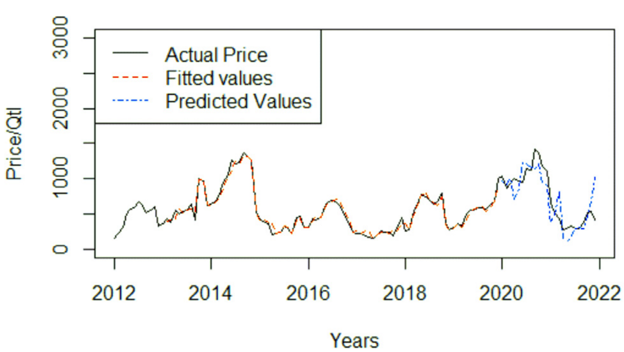
Azadpur



Mumbai



Bangalore



Jalandhar

Figure 3 Actual vs. fitted price series of selected markets of India by using ANN Model

Table 6 Diebold–Mariano (DM) test to see the forecasting power across models

Markets	Training set		Testing set	
	DM	p-value	DM	p-value
Agra	2.731	0.01	2.037	0.05
Burdwan	2.432	0.02	3.272	0.00
Ahmedabad	4.634	0.00	5.131	0.00
Azadpur	2.470	0.02	4.041	0.00
Mumbai	3.316	0.00	2.629	0.01
Bangalore	6.102	0.00	2.093	0.04
Jalandhar	3.068	0.00	3.752	0.00

accuracy in terms of RMSE and MAPE values as compared to the linear model, i.e., ARIMA (Figure 3).

To this end, Diebold–Mariano test (Diebold and Mariano, 1995) was applied for statistical comparison of forecasting performance among the ARIMA and TDNN models. It is found that the predictive accuracy of TDNN are significantly different than that of ARIMA models for all the selected markets (Table 6).

Conclusions

Timely and precise price forecasting of agricultural commodities have significance in the scenario of Indian agriculture, as this enables all the stakeholders associated with particularly perishable crops to take accurate decisions regarding the production and marketing. The agricultural time series datasets are asymmetric, meaning they are non-normal, nonlinear, and nonstationary. Pre-processing of the datasets is required for this purpose as our study compared two types of model, ARIMA and TDNN, as this exercise is demanding and getting popularity in this research area of agricultural marketing. In this study for empirical evaluation, forecasting of potato prices of all the selected markets across India have been carried out. Our results elucidate that potato price volatility is asymmetric in all of India's chosen markets. Additionally, the study compared the ARIMA and TDNN models for forecasting potato prices and the results found that TDNN performed better than ARIMA, it is considered as the best fit model with respect to minimum RMSE and MAPE value. The study put forward that our efforts must be focused on machine learning techniques like neural network for designing market intelligence system, as these models handles the violation of traditional time series techniques assumptions. However, combination of statistical methods with these soft computing techniques and the local information to the farmers, traders and policymakers is still lacking. The synergy of these would help to provide accurate and timely price forecast.

References

Barathi, R, Havaldar Y N, Meregi S N, Patil G M and Patil B L. 2011. A study on market integration of Ramanagaram and Siddlaghatta markets and forecasting of their prices and arrivals. *Karnataka Journal of Agricultural Science* 24(3): 347-349. http://dx.doi.org/10.18782/2582-2845.7856

Box, G E P and G M Jenkins. 1976. *Time series analysis: forecasting and control*, *Second Edition,* Holden Day, St. San Francisco, CA; United States.

Brock, W, Dechert W, Scheinkman J, and LeBaron B. 1996. A test for independence based on the correlation dimension, *Econometric Reviews* 15(3): 197-235. https://doi.org/10.1080/07474939608800353

Chavas, J P,Hummels D and Wright B D 2014. *The economics of food price volatility*. University of Chicago Press. https://www.nber.org/books-and-chapters/economics-food-price-volatility

Cheng, B and Titterington D M. 1994. Neural networks: a review from a statistical perspective. *Statistical Science* 9 (1): 2–54

Darbellay, G A and Slama M. 2000. Forecasting the short-term demand for electricity: do neural networks stand a better chance?. *International Journal of Forecasting* 16(1):71-83. https://www.researchgate.net/publication/240169091_Forecasting_the_short-term_demand_for_electricity

Dickey D and W Fuller. 1979. Distribution of the estimators for autoregressive time series with a unit root, *Journal of American Statistical Association*, 74(366): 427-431. https://www.jstor.org/stable/2286348

Diebold, F X, Mariano R S. 1995. Comparing predictive accuracy. *Journal of Business Economics and Statistics* 13:253–263

Gupta A K, Rao V S and Singh A K. 2018. Forecasting of arrivals and prices of chickpea in Chhattisgarh. *International Journal of Agricultural Statistics Science* 14(1): 421-426. https://www.researchgate.net/publication/331687234_Forecasting_of_arrivals_and_prices_of_Chickpea_in_Chhattisgarh

Gupta, A K, Patra C and Singh A K. 2019. Forecasting market prices of soybean in Ujjain market (Madhya Pradesh). *Green Farming* 10(6): 752-755. file:///C:/Users/S/Downloads/20.A.K.GuptaC.PatraA.K.Singh-ForecastingMarketprices-P-7792752-755%20(1).pdf

Jha, G K and Sinha K. 2013. Agricultural price forecasting using neural network model: an innovative information delivery system. *Agricultural Economics Research Review* 26(2): 229-239. http://dx.doi.org/10.22004/ag.econ.162150

Jha, G K, Thulasiraman P and Thulasiram R K. 2009. PSO based neural network for time series forecasting. Proceedings of the International Joint Conference on Neural Networks. Atlanta, USA. pp. 1422-1427. https://doi.org/10.1109/IJCNN.2009.5178707

Chin K, and Arthur R. 1996. Neural network vs. conventional methods of forecasting. *The Journal of Business Forecasting* 14(4): 17–22. https://www.proquest.com/openview/8e9276b8614741cf246d953ac6c6d806/1?pq-origsite=gscholar&cbl=28144#:~:text=In%20neural%20networks%20one%20does,input%20and%20output%20data%20…&text=Conventional%20forecasting%20models%0rely%20on,project%20the%20variables%20of%20interest.

Kalkuhl, M. Von Braun, J. and Torero, M., 2016. *Food price volatility and its implications for food security and policy*, 1st Edition, Springer Open, Washington DC, USA http://dx.doi.org/10.1007/978-3-319-28201-5

Kumar, S, Gupta, A K, Arora, K and Vatta K. 2022. Effect of rainfall in predicting tomato prices in India: An application of SARIMAX and NARX Model. *Journal of Agricultural Development and Policy* 32 (2): 159-164. http://www.isadp.in/publication/paper2.pdf

Lama A, Jha G K, Paul R K and Gurung B. 2015. Modelling and forecasting of price volatility: an application of GARCH and EGARCH models. *Agricultural Economics Research Review* 28(1):73-82. https://doi.org/10.22004/ag.econ.206582

Li, G Q, Xu S W and Li Z M. 2010. Short-term price forecasting for agro-products using artificial neural networks. *Agriculture and Agricultural Science Procedia* 1: 278-287. https://mail.google.com/mail/u/0/#inbox/FMfcgzGmtNbQZNHMCXvvBnBqjMKQxsPC?projector=1&messagePartId=0.1

Elkateb M M,, Solaiman K, Al-Turki Y. 1998. A comparative study of medium-weather-dependent load forecasting using enhanced artificial/fuzzy neural network and statistical techniques. *Neurocomputing* 23 (1-3): 3–13. https://www.sciencedirect.com/science/article/abs/pii/S0925231298000769

Paul R K, Alam W, Paul A K. 2014. Prospects of livestock and dairy production in India under time series framework. *Indian Journal of Animal Science* 84(4):130–134. http://krishi.icar.gov.in/jspui/handle/123456789/42806

Paul, R K and Garai S. 2021. Performance comparison of wavelets-based machine learning technique for forecasting agricultural commodity prices. *Soft Computing*, *25*(20): 12857-12873. https://doi.org/10.1007/s00500-021-06087-4(0123456789().,-volV)(0123456789()

Paul, R K, Gurung B, Paul A K. 2015. Modelling and forecasting of retail price of Arhar dal in Karnal, Haryana. *Indian Journal of Agricultural Science* 85(1):69–72. https://www.researchgate.net/publication/271218018_Modelling_and_Forecasting_of_Retail_Price_of_Arhar_Dal_in_Karnal_Haryana

Paul, R K, Paul A K, Bhar L M. 2020. Wavelet-based combination approach for modeling sub-divisional rainfall in India. Theoretical and Applied Climatology 139(3–4): 949–963. https://www.researchgate.net/publication/337226229_Wavelet-based_combination_approach_for_modeling_sub-divisional_rainfall_in_India

Paul, R K, Sinha K. 2016. Forecasting crop yield: a comparative assessment of ARIMAX and NARX model. *RASHI* 1(1):77–85. https://krishi.icar.gov.in/jspui/bitstream/123456789/42733/2/vol1__12.pdf

Phillips, P C B and P Perron. 1988. Testing for a unit root in time series regression, *Biometrika* 75 (2): 335-346. https://www.jstor.org/stable/2336182

Schnepf R 1999. Assessing agricultural commodity price variability. Economic Research Service/United States

Department of Agriculture-Agricultural Outlook. https://agris.fao.org/agris-search/search.do?recordID=US201302946639

Shapiro, S S and Wilk M B. 1965. An analysis of variance test for normality (complete samples *Biometrika* 52 (3 &4): 591–611. doi:10.1093/biomet/52.3-4.591.

Sharma H. 2015. Applicability of ARIMA models in wholesale wheat market of Rajasthan: An Investigation. *Economic affairs* 60(4): 687- 691. http://dx.doi.org/10.5958/0976-4666.2015.00096.0

Singh, D K, Pynbianglang K and Pandey N K. 2017. Market arrival and price behaviour of potato in Agra district of Uttar Pradesh*.* *Economic Affairs*, 62(2): 341. https://ndpublisher.in/admin/issues/EAv62no2r.pdf

Sreepriya, P and Sidhu J S. 2020. An analysis of market arrival and price behavior of potato in India. *Economic Affairs*. 65(1): 9-15. http://dx.doi.org/10.30954/0424-2513.1.2020.2

Hill T, O'Connor M, Remus W. 1996. Neural network models for time series forecasts, Management Science 42(7): 1082–1092.

Wang, X, Smith K A, and Hyndman R J. 2006. Characterstic-based clustering for time-series data. *Data mining and Knowledge Discovery* 13(3): 335-364.

White, H. 1989. Learning in artificial neural networks: a statistical perspective. *Neural Computation* 1(4): 425–464. https://ieeexplore.ieee.org/document/6796856

Zhang D, Chen S, Ling L and Xia Q 2020. Forecasting agricultural commodity prices using model selection framework with time series features and forecast horizons. IEEE Access. https://doi.org/10.1109/ACCESS.2020.2971591

Zhang, G, Patuwo B E and Hu M Y. 1998. Forecasting with artificial neural networks: the state of the art. *International Journal of Forecasting* 14(1): 35-62. https://doi.org/10.1016/S0169-2070(97)00044-7

Received 4 October 2021 Accepted 17 March 2022

Annexure I

Parameters estimates and fitting performance of different models by using ARIMA for the Potato Prices of Major Markets

Model	AR_1	AR_2	AR_3	MA_1	MA_2	SAR_1	SAR_2	SMA_1	SMA_2	Mean	RMSE	MAPE
Agra												
Auto ARIMA	0.832**			0.589**				0.109	0.633**	880.887**	720.59	25.747
(1,0,1) (0,0,2)	(0.059)			(0.089)				(0.108)	(0.1573)	(185.187)	(125.506)	(11.476)
ARIMA	0.875**			0.539**		-0.767**					484.662	12.552
(1,0,1) (1,1,0)	(0.062)			(0.099)		(0.065)					(129.221)	(11.469)
ARIMA	1.33**	-0.436**				-0.794**		0.065			519.207	21.552
(2,0,0) (1,1,1)	(0.104)	(0.106)				(0.093)		(0.178)			(131.41)	(12.178)
ARIMA (1,0,1)	0.875**			0.54**		-0.767**		-0.004			484.774	23.762
(1,1,1)	(0.062)			(0.103)		(0.1)		(0.188)			(129.221)	(11.469)
ARIMA	1.335**	-0.441**				-0.768**					530.167	20.986
(2,0,0) (1,1,0)	(0.102)	(0.104)				(0.066)					(131.544)	(12.195)
Burdwan												
Auto ARIMA				0.38		0.135*	0.573**				721.412	52.7
(0,1,1) (2,0,0)				(0.103)		(0.076)	(0.089)				(129.396)	(8.216)
ARIMA	0.912**			0.379**		-0.782**	-0.084**				536.77	39.277
(1,0,1) (2,1,0)	(0.057)			(0.12)		(0.121)	(0.134)				(124.759)	(7.286)
ARIMA	1.443**	-0.517*		-0.147		-0.536**		-0.287			480.604	33.659
(2,0,1) (1,1,1)	(0.376)	(0.362)		(0.457)		(0.193)		(0.284)			(123.517)	(7.299)
ARIMA	0.918**			0.393**		-0.579**		-0.284			521.267	37.849
(1,0,1) (1,1,1)	(0.057)			(0.114)		(0.182)		(0.278)			(123.924)	(7.246)
ARIMA	1.289**	-0.355**				-0.003	0.402**	-0.896*			432.105	29.451
(2,0,0) (2,1,0)	(0.109)	(0.115)				(0.299)	(0.148)	(0.452)			(119.072)	(6.929)
Ahmedabad												
Auto ARIMA	0.508**	0.629**	-0.434**	0.971**		0.402**				1127.797**	709.802	32.388
(3,0,1) (1,0,0)	(0.102)	(0.117)	(0.102)	(0.04)		(0.099)				(162.892)	(158.2)	(11.018)
ARIMA	0.857**			0.536**		0.606**	-0.244**				603.39	54.337
(1,0,1) (2,1,0)	(0.062)			(0.097)		(0.118)	(0.128)				(164.972)	(11.478)
ARIMA (2,0,1)	1.364**	-0.511**		0.008		0.202		-1.00**			552.567	39.604
(1,1,1)	(0.209)	(0.196)		(0.249)		(0.13)		(0.325)			(140.938)	(10.002)
ARIMA	1.371**	-0.505**		-1.00**		0.227*	0.054	-0.999**			557.581	46.423
(2,1,1) (2,1,1)	(0.095)	(0.097)		(0.131)		(0.13)	(0.145)	(0.296)			(142.146)	(9.891)
ARIMA	0.478**	0.667**	-0.414**	1.00**		0.217**		-1.00**			543.378	39.657
(3,0,1) (1,1,1)	(0.103)	(0.099)	(0.106)	(0.09)		(0.128)		(0.387)			(136.013)	(9.52)

Contd...

Mumbai									
Auto ARIMA	0.793**		0.575**				1246.807**	733.119	25.28
(1,0,1) (0,0,0)	(0.071)		(0.088)				(109.592)	(147.088)	(9.421)
ARIMA (1,0,1)	0.834**		0.556**					618.332	36.16
(0,1,0)	(0.066)		(0.089)					(187.055)	(12.112)
ARIMA (1,1,1)	-0.096**		0.576**		0.954**	-0.885*		763.763	51.754
(1,0,1)	(0.195)		(0.155)		(0.336)	(0.508)		(148.839)	(9.078)
ARIMA (2,0,1)	0.838**	-0.011	0.527**			-0.999**		456.049	16.257
(0,1,1)	(0.209)	(0.207)	(0.177)			(0.24)		(131.514)	(8.294)
ARIMA (1,0,1)	0.828**		0.535**			-0.999**		454.491	16.259
(0,1,1)	(0.076)		(0.099)			(0.239)		(131.518)	(8.289)
Azadpur									
Auto ARIMA	0.835**		0.402**		-0.593**			151.232	7.302
(1,0,1) (1,1,0)	(0.068)		(0.127)		(0.086)			(142.255)	(7.28)
ARIMA (2,0,1)	0.375**	0.401**	0.877**					656.92	65.852
(0,1,0)	(0.196)	(0.189)	(0.136)					(175.242)	(9.368)
ARIMA (1,1,1)	-0.396*		0.731**		0.999**	0.959**		854.839	85.716
(1,0,1)	(0.231)		(0.177)		(0.004)	(0.096)		(134.323)	(8.204)
ARIMA (1,1,1)	-0.517**		0.799**		-0.104**	0.999**		863.603	86.038
(1,1,1)	(0.181)		(0.13)		(0.122)	(0.221)		(120.609)	(6.423)
ARIMA (1,1,0)	0.221**				-0.113	1.00**		883.67	88.318
(1,1,1)	(0.107)				(0.119)	(0.214)		(123.765)	(6.7)
Bangalore									
Auto ARIMA			0.341**					263.625	8.173
(0,1,1) (0,0,0)			(0.107)					(165.567)	(7.354)
ARIMA (1,0,1)	0.867**		0.418**					373.848	9.482
(0,1,0)	(0.059)		(0.122)					(203.116)	(7.737)
ARIMA (2,1,0)	0.296**	-0.168						233.989	6.713
(0,0,0)	(0.103)	(0.102)						(165.235)	(7.321)
ARIMA (1,1,2)	0.182		0.1255	-0.148				232.755	6.74
(0,0,0)	(0.955)		(0.947)	(0.324)				(164.912)	(7.316)
ARIMA (1,1,1)	-0.269		0.601**					785.389	23.895
(0,1,0)	(0.282)		(0.233)					(206.964)	(7.839)
Jalandhar									
Auto ARIMA	0.618**							577.134	98.314
(1,0,0) (0,0,0)	(0.083)							(169.072)	(218.076)
ARIMA (1,1,1)	0.897**		1.000**					467.996	93.176
(0,0,0)	(0.053)		(0.031)					(145.405)	(20.059)
ARIMA (1,0,1)	0.832**		0.142**				535.399**	338.594	40.286
(0,0,0)	(0.068)		(0.076)				(95.597)	(144.387)	(21.895)
ARIMA (1,0,1)	0.923**		-0.012		-0.69**			366.402	69.008
(1,1,0)	(0.05)		(0.127)		(0.077)			(134.617)	(21.605)
ARIMA (2,0,1)	0.406**	0.374**	-0.565**				53547**	334.484	40.554
(0,0,0)	(0.113)	(0.147)	(0.272)				(98.998)	(144.177)	(21.874)

Notes The figures in parentheses are the standard error of coefficients and error measures of the training group; ***p<0.01, *p<0.05, ·p<0.10.

Annexure II

Model Structure and fitting performance of different models by using TDNN for the Potato Prices of Major Markets

Model	Agra			Burdwan			Ahmedabad			Azadpur			Mumbai			Bangalore			Jalandhar		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
1:2s:1l	369.72	571.92	22.92	520.04	420.01	44.56	329.41	251.06	21.26	460.92	405.5	46.19	779.24	636.03	49.81	338.29	252.43	8.55	247.5	575.94	147.37
	(95.03)	(66.02)	(9.38)	(97.84)	(71.81)	(7.02)	(102.32)	(71.7)	(7.3)	(105.41)	(84.97)	(6.71)	(99.44)	(68.77)	(6.32)	(100.76)	(81.62)	(4.71)	(79.07)	(55.46)	(15.14)
1:3s:1l	399.74	348.08	87.02	326.99	282.9	22.99	304.68	233.63	18.35	395.44	335.95	29.86	493.69	430.03	32.87	213.47	166.77	5.93	259.29	220.06	83.4
	(55.95)	(39.93)	(5.54)	(85.58)	(59.07)	(5.64)	(77.84)	(54.29)	(5.41)	(77.63)	(60.38)	(4.78)	(70.77)	(45.31)	(4.16)	(72.53)	(52.43)	(2.99)	(60.02)	(42.64)	(11.53)
1:4s:1l	358.2	297.01	22.23	389.05	314.43	23.84	216.49	151.92	12.49	447.82	395.15	43.61	348.35	305.01	20.31	233.06	212.15	7.43	242.41	154.64	19.34
	(35.89)	(23.94)	(3.28)	(73.39)	(46.44)	(4.34)	(61.96)	(40.42)	(4.03)	(49.42)	(35.38)	(2.92)	(47.56)	(27.47)	(2.49)	(44.2)	(29.77)	(1.67)	(47.37)	(28.02)	(7.88)
1:5s:1l	395.89	315.33	26.71	552.93	275.1	23.02	443.17	367.13	42.28	338.57	302.93	31.13	382.58	697.44	19.14	322.87	269.88	9.52	278.14	222.69	30.58
	(21.71)	(14.1)	(2.02)	(56.39)	(30.61)	(2.7)	(48.41)	(27.87)	(2.82)	(31.62)	(20.28)	(1.74)	(32.6)	(17.37)	(1.54)	(23.92)	(13.64)	(0.74)	(44.58)	(24.66)	(6.94)
1:6s:1l	448.77	331.07	25.11	529.93	455.79	37.93	474.35	565.11	62.45	367.42	393.44	40.85	451.86	393.71	28.26	259.25	210.97	7.32	250.44	215.6	38.53
	(15.36)	(9.07)	(1.31)	(43.9)	(18.8)	(1.51)	(36.99)	(19.05)	(1.87)	(25.6)	(14.89)	(1.29)	(24.9)	(13.03)	(1.14)	(9.99)	(4.9)	(0.27)	(40.78)	(19.84)	(5.54)
2:2s:1l	333.86	244.59	20.03	394.97	331.77	27.95	346.77	291.07	27.22	265.99	231.77	24.15	409.58	381.04	27.95	227.39	181.95	9.99	218.01	145.94	22.79
	(91.37)	(61.25)	(8.37)	(95.25)	(68.31)	(6.71)	(95.65)	(68.92)	(7.01)	(103.76)	(81.01)	(6.49)	(84.31)	(57.64)	(5.48)	(74.19)	(56.49)	(3.06)	(78.14)	(54.85)	(15.81)
2:3s:1l	357.52	289.45	25.64	364.9	306.56	23.21	499.17	337.96	58.82	487.06	440.8	44.19	326.14	209.08	10.58	324.6	241.63	5.31	213.68	162.71	28.52
	(47.96)	(32.03)	(4.38)	(76.34)	(48.72)	(4.64)	(66.37)	(44.94)	(4.59)	(67.31)	(48.22)	(3.89)	(58.59)	(36.25)	(3.48)	(46.45)	(33.23)	(1.82)	(50.47)	(35.06)	(9.24)
2:4s:1l	562.65	477.81	47.52	517.86	459.95	33.27	539.29	455.67	43.25	416.24	341.49	35.2	444.38	362.31	23.15	331.47	264.1	9.28	311.69	258.29	43.89
	(28.19)	(17.25)	(2.37)	(55.53)	(30.54)	(2.73)	(45.04)	(28.43)	(3)	(45.83)	(29.44)	(2.48)	(30.73)	(16.89)	(1.62)	(23.19)	(14.8)	(0.81)	(37.59)	(23.58)	(6.28)
2:5s:1l	673.98	587.99	59.01	562.65	426.41	27.22	562.76	484.15	30.98	475.7	427.79	41.77	307.4	243.77	15.14	423.25	317.44	11.61	238.5	187.72	29.09
	(18.26)	(10.25)	(1.33)	(44.66)	(21.23)	(1.77)	(33.08)	(19.03)	(1.97)	(27.18)	(15.07)	(1.31)	(17.22)	(8.38)	(0.77)	(7.39)	(4.65)	(0.26)	(22.28)	(13.84)	(3.91)
2:6s:1l	528.82	371.82	30.71	444.71	341.18	26.42	567.57	411.58	33.53	392.78	264.37	34.83	323.51	261.67	19.89	323.49	286.54	10.05	279.78	234.55	45.02
	(14.66)	(7.55)	(0.99)	(36.89)	(14.94)	(1.14)	(24.03)	(11.3)	(1.19)	(21.34)	(9.4)	(0.82)	(15.38)	(6.39)	(0.57)	(4.45)	(2.33)	(0.13)	(18.09)	(9.52)	(2.79)
3:2s:1l	387.89	312.1	27.21	299.73	252.85	20.14	380.18	282.68	24.64	502.34	382.77	49.66	242.56	194.88	11.54	287.97	245.31	8.83	434.98	332.71	82.89
	(77.62)	(52.64)	(6.99)	(82.74)	(59.55)	(5.63)	(85.56)	(62.15)	(6.34)	(97.6)	(77.72)	(6.12)	(77.14)	(52.5)	(4.86)	(74.67)	(58.27)	(3.21)	(74.74)	(50.17)	(14.09)
3:3s:1l	429.67	340.03	31.74	395.04	361.37	26.98	446.96	392.77	34.33	354.24	293.61	32.1	586.52	509.59	37.53	247.99	200.7	7.12	290.97	211.46	42.41
	(43.73)	(27.62)	(3.66)	(57.45)	(36.93)	(3.45)	(45.56)	(33.22)	(3.48)	(54.23)	(37.65)	(2.9)	(48.79)	(30.89)	(2.88)	(37.74)	(28.05)	(1.55)	(41.19)	(29.68)	(7.28)
3:4s:1l	633.71	496.75	45.12	434.79	392.82	29.07	477.43	379.01	35.63	362.33	308.65	30.35	454.21	379.28	27.81	392.26	325.79	11.04	398.23	310.02	73.4
	(23.03)	(13.95)	(1.87)	(40.54)	(21.63)	(1.83)	(27.04)	(18.42)	(1.92)	(27.73)	(18.64)	(1.48)	(29.37)	(16.67)	(1.53)	(16.47)	(10.68)	(0.58)	(21.93)	(15.34)	(3.89)
3:5s:1l	598..31	510.49	44.37	771.38	467.73	33.57	438.07	353.48	30.66	360.63	315.09	32.06	509.88	426.98	29.76	514.28	431.1	15.03	792.02	686.68	133.76
	(12.67)	(6.94)	(0.86)	(28.76)	(11.98)	(0.92)	(16.12)	(10.54)	(1.12)	(13.34)	(8.22)	(0.69)	(16.5)	(7.81)	(0.69)	(6.01)	(3.55)	(0.2)	(14.47)	(9.76)	(2.42)
3:6s:1l	514.08	371.4	26.95	934.19	774.05	57.73	584.04	433.78	47.49	626.32	534.08	50.84	517.08	466.25	31.73	431.59	345.01	12.01	359.01	263.08	46.61
	(9.54)	(4.68)	(0.61)	(26.42)	(9.07)	(0.69)	(15.42)	(10.02)	(1.07)	(8.74)	(5.01)	(0.43)	(12.95)	(5.05)	(0.44)	(4.98)	(2.13)	(0.12)	(11.74)	(7.07)	(1.72)
4:2s:1l	402.26	312.76	26.79	393.81	337.57	33.49	564.66	448.88	32.33	735.9	393.11	75.28	273.97	255.64	17.34	291.42	236.03	8.33	483.54	415.84	95.44
	(78.8)	(54.07)	(7.37)	(76.65)	(54.68)	(5.31)	(84.07)	(64.87)	(6.55)	(86.13)	(63.64)	(5.05)	(71.86)	(49.5)	(4.6)	(70.69)	(55.89)	(3.04)	(64.37)	(43.61)	(11.43)
4:3s:1l	473.05	356.23	31.72	347.29	251.77	16.14	527.36	386.19	28.35	358.64	311.5	32.07	310.64	244.64	15.7	370.8	322.35	11.77	486.58	377.62	89.81
	(37.07)	(22.69)	(2.87)	(47.89)	(30.83)	(2.89)	(43.82)	(33.42)	(3.52)	(53.64)	(38.18)	(3.04)	(39.92)	(25.08)	(2.33)	(27.71)	(19.61)	(1.07)	(42.41)	(27.52)	(7.34)
4:4s:1l	379.98	313.45	28.94	634.69	510.26	96.66	668.98	415.27	38.49	417.66	338.23	39.31	441.12	293.46	15.47	342.42	276.87	5.75	345.6	281.21	63.11
	(15.98)	(9.22)	(1.18)	(26.82)	(14.17)	(1.23)	(22.73)	(15.12)	(1.59)	(19.3)	(12.81)	(1.03)	(25.52)	(11.91)	(1.1)	(11.08)	(7.14)	(0.39)	(18.01)	(11.41)	(2.85)

Contd...

Model	Agra			Burdwan			Ahmedabad			Azadpur			Mumbai			Bangalore			Jalandhar		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
4:5s:11	624.76	570.29	50.61	476.94	377.9	26.07	652.91	562.23	47.5	539.18	463.43	47.19	405.92	342.38	22.87	404.23	343.02	12.14	623.47	496.95	101.21
	(8.35)	(4.38)	(0.53)	(15.36)	(7.58)	(0.61)	(12.78)	(8.81)	(0.96)	(12.92)	(6.55)	(0.54)	(10.46)	(4.38)	(0.41)	(3.33)	(2.12)	(0.11)	(13.91)	(8.18)	(2.01)
4:6s:11	381.75	269.5	20.12	415.3	357.59	28.35	518.14	382.85	27.37	447.23	386.79	35.7	383.01	317.15	11.05	375.86	313.26	10.86	430.16	373.68	68.66
	(5.47)	(2.33)	(0.29)	(9.56)	(4.16)	(0.34)	(10.69)	(6.68)	(0.71)	(8.83)	(4.51)	(0.37)	(8.63)	(4.15)	(0.3)	(1.82)	(0.97)	(0.05)	(9.66)	(5.14)	(1.28)
5:2s:11	303.16	221.76	16.27	401.06	343.11	28.74	643.76	473.36	31.6	569.43	470.6	54.88	606.35	230.94	41.23	317.86	283.64	10.24	270.8	224.38	50.26
	(68.47)	(44.13)	(5.74)	(70.82)	(49.87)	(4.69)	(74.23)	(53.16)	(5.55)	(78.13)	(59.3)	(4.53)	(61.5)	(43.2)	(4.13)	(58.15)	(44.3)	(2.35)	(70.34)	(45.16)	(12.83)
5:3s:11	522.54	470.87	43.97	417.08	351.41	28.56	416.13	338.53	32.76	424.13	322.64	33.09	300.41	256.12	17.27	272.06	233.37	8.32	663.53	531.54	120.38
	(30.86)	(17.07)	(2.17)	(40.16)	(25.47)	(2.41)	(36.87)	(25.26)	(2.69)	(43.76)	(30.48)	(2.43)	(25.76)	(18.51)	(1.72)	(27.15)	(18.67)	(0.99)	(34.14)	(22.33)	(5.89)
5:4s:11	565.79	458.59	40.4	389.94	303.88	20.39	462.35	375.61	35.01	396.42	283.74	22.23	288.96	239.94	14.63	336.66	272.24	24.47	586.39	435.07	82.96
	(15.62)	(6.65)	(0.81)	(16.21)	(9.24)	(0.72)	(21.09)	(13.29)	(1.46)	(19.83)	(12.36)	(0.99)	(13.65)	(7.55)	(0.69)	(8.21)	(5.29)	(0.28)	(14.84)	(9.56)	(2.41)
5:5s:11	904.94	785.87	68.48	453.94	366.39	25.05	511.92	454.38	38.03	459.62	354.91	42.14	361.57	315.72	20.94	465.72	410.65	14.92	459.08	401.19	77.13
	(8.67)	(3.09)	(0.38)	(9.78)	(5.41)	(0.43)	(11.46)	(6.32)	(0.65)	(11.05)	(5.13)	(0.4)	(3.35)	(2.17)	(0.19)	(3.43)	(2.04)	(0.11)	(7.42)	(4.5)	(1.1)
5:6s:11	733.89	521.29	39.11	440.94	350.98	23.32	459.94	369.39	34.32	340.7	262.43	27.92	400.39	308.92	17.14	309.1	258.3	8.89	380.76	314.98	70.13
	(4.58)	(2.03)	(0.25)	(7.24)	(3.31)	(0.25)	(9.51)	(5.11)	(0.52)	(9.69)	(4.3)	(0.34)	(3.41)	(1.78)	(0.16)	(1.62)	(1.02)	(0.05)	(6.07)	(3.54)	(0.78)

Note The figures in parentheses are the error measures of the training group