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An Approach for Prediction of Weekly Prices of Green Chili in Sri Lanka: Application of Artificial Neural Network Techniques

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ABSTRACT

Purpose: *Predicting the prices of crops is a principal task for producers, suppliers, governments and international businesses. The purpose of the study is to forecast the prices of green chili, which is a cash crop in Sri Lanka. Artificial neural networks were applied as they help to extract important insights from the bulk of data with a scientific approach.*

Research Method: *The Time Delay Neural Network (TDNN), Feedforward Neural Network (FFNN) with Levenberg-Marquardt (LM) algorithm and FFNN with Scaled Conjugate Gradient (SCG) algorithm were employed on weekly average retail prices of green chili in Sri Lanka from the 1st week of January 2011 to the 4th week of December 2018. The performance of models was evaluated through the Mean Squared Error (MSE), Mean Absolute Error (MAE) and Normalized Mean Squared Error (NMSE).*

Findings: *Among the three methods implemented, the FFNN model using the LM algorithm exhibited the highest accuracy with a minimum MSE of 0.0033, MAE of 0.0437 and NMSE of 0.2542. The model built using the SCG algorithm fitted data with a minimum MSE of 0.0033, MAE of 0.0458 and NMSE of 0.2549. Among the fitted TDNN models, the model with 8 input delays were a better model with an MSE of 0.0036, MAE of 0.0470 and NMSE of 0.3221. FFNNs outperformed TDNN in forecasting green chili prices of Sri Lanka.*

Originality/ Value: *The neural network approach in forecasting the prices of green chili provides more accurate results to make decisions based on the trends and to identify future opportunities.*

Keywords: *Green Chili, Feedforward Neural Network, Levenberg-Marquardt algorithm, Prediction, Scaled Conjugate Gradient algorithm, Time Delay Neural Network*

INTRODUCTION

Agriculture plays a prominent role in the economy of Sri Lanka. Over 24% of the total labor force of Sri Lanka is engaged in agriculture, and it contributes 7.42% to the national GDP (Plecher, 2020a; Plecher, 2020b). Green chili is one of the most important cash crops cultivated in Sri Lanka, consumed as a condiment. The main chili cultivating districts are Anuradhapura, Puttalam, Monaragala, Vavuniya, Kurunegala, and Mahaweli System H. It is cultivated in two seasons annually as Yala and Maha. According to the review done by Hector Kobbekaduwa, Agrarian Research Institute supply from major green chili production areas has slightly increased during November 2019 (Priyankara, 2019). Hence, the retail price of green chili was decreased by 37% compared to the same period of the previous year. Furthermore, high retail price fluctuations can be observed every year.

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One of the major complications in the Sri Lankan economy is the substantial price fluctuation in agricultural products due to uneven supply throughout the year. Green chili is one such perishable agricultural product that has exhibited large price fluctuations from time to time due to various factors such as government policies, trade agreements, and adverse weather conditions on cultivation. Farmers and consumers get stressed due to the lack of education regarding the unpleasant price fluctuations, and it creates various political and social issues. Further, these inconsistencies led to bankrupts of farmers and sellers. To overcome these complications, reliable mechanisms are required to foresee the upcoming variations of prices which can be used to take required decisions, control price variations, and avoid adverse economic phenomena. Moreover, these forecasted findings should be shared with the farmers too.

The application of advanced data mining techniques in addressing these complicated economic problems has an emerging requirement. This study is mainly focused on identifying the behavior of price variations, modeling, and forecasting weekly open market average retail prices of green chili in Colombo, Sri Lanka, using appropriate artificial neural network (ANN) techniques. The contribution of this study is forecasting prices of green chili; one of the most important cash crops in Sri Lanka using ANNs.

Cash crops' prices are often subjected to high fluctuations due to the imbalance between supply and demand. It occurs as a result of the supply being affected by various environmental and economic factors. As agricultural product prices often show seasonal fluctuations along with the seasonal cultivation of crops, many researchers have employed traditional time series techniques to forecast prices. For instance, Pradeep & Wickramasinghe, (2015) studied retail and wholesale prices of five vegetables in the up-country and forecasted the monthly prices using the Auto-Regressive Integrated Moving Average (ARIMA) method. Similarly, Bogahawatta, (1987) conducted a study to explore the behavior of the prices of vegetables and agricultural commodities using ARIMA and Seasonal Auto-Regressive Integrated Moving Average (SARIMA) approaches.

The basic assumption of the classical time series models is that the considered time series data follows a normal distribution, and it is linear (Adhikari & Agrawal, 2013). The popularity of these models is mainly because of their flexibility and simplicity of illustrating varieties of time series with the Box-Jenkins methodology in modeling the data. For instance, the ARIMA model consists of several sub-classes as Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA) and SARIMA models (Box & Jenkins, 1970; Adhikari & Agrawal, 2013). However, the critical limitation of these models is the normal distribution assumption with the constant variance in the residuals which is inadequate in many practical situations. Alternatively, the literature has proposed different data mining techniques in time-series forecasting which exhibit lesser limitations and higher performance compared to classical time-series models.

However, the comparison between traditional methods and ANN techniques in the literature have proven that agricultural commodity prices can be forecasted more accurately using ANN techniques. In 2020, three approaches: SARIMA, Holt-Winter's Seasonal method, and Long Short-term Memory (LSTM) neural network were implemented and tested by two researchers for forecasting areca nuts in prices in India and it was found that the LSTM model outperformed the other two classical models (Sabu & Kumar, 2020). In forecasting short-term wholesale prices of tomatoes in China, ANN models were employed against classical time series models, and it was evident that FFNN outperformed the fitted ARIMA model in forecasting one day or one week ahead prices (Li *et al*. 2010). In cash crop price analysis, data mining was used as one of the most sophisticated tools in the research field. Based on the complexity of price prediction of vegetables, the use of data mining techniques like neural networks with advanced features such as self-adapt, self-study and, high fault tolerance has contributed to building up effective models. The Backpropagation neural network (BPNN) prediction model has been employed on forecasting weekly tomato prices in the Coimbatore market and has been found that the neural network is one way of predicting, non-linear time-ordered data on market prices of vegetables (Nasira & Hemageetha, 2012).

The forecasting of a time-series can be approached in two ways: Univariate approach and multivariate approach. Both approaches can be considered in forecasting prices of vegetables. Past studies considered other macroeconomic variables such as seasonality, population size, perishable nature, consumer interest and farmers' knowledge on the behavior of the prices when applying multivariate approach in forecasting (Bogahawatta, 1987; Pradeep & Wickramasinghe, 2013). However, in the multivariate approach, there are many limitations that result in less contribution to the economic and finance sectors as most of the macroeconomic variables are available as monthly data whereas in economics and finance, it is required to handle weekly and daily data. Moreover, multivariate models are not very much suitable in out-of-sample prediction (Tambi, M. K., 2005; Newaz, M. K., 2008). Hence, to overcome such problems in handling weekly and daily data, it is recommended to use univariate models that are able to model and forecast economic and financial variables with the details of past values of the data and the possible other values such as past and current values of error terms.

Many data mining techniques have been employed and tested to identify the most appropriate method to gain the highest accuracy in forecasting vegetable prices. The BPNN model in forecasting monthly prices of Lentinus edodes (i.e. a mushroom species native to East Asia) in the Beijing Xinfadi wholesale market using the previous four months' data as input and the latter one-month data as output, exhibits high accuracy on price trend prediction and also indicated that BPNN has the reference value for the price prediction of Lentinus edodes. The prediction results for the same data showed that the BPNN model is worse than the results obtained from the Radial Basis neural network (RBFN) and further it was inferior to the neural network based on genetic algorithm (GA). An integrated model has been proposed to illuminate the shortcomings of these individual models and gain the highest accuracy. In this integrated model, prices were forecasted through separate models and constructed an FFNN model by taking forecasted results as inputs and actual results as output (Luo, *et al*. 2010).

The prediction of market prices of agricultural products is more complicated than commercial products due to the collusion of many factors such as climate, supply, and demand, etc. Due to the complexity in collecting the data of impacting factors accurately and timely, the historical vegetable prices can be used as experimental materials for future forecasting in ANN models (Luo *et al*. 2010). Further, various economic indices have been used as input variables to forecast cash crop prices. For example, the BPNN model implemented to forecast monthly prices of sticky rice in Thailand has used eight input parameters: the gross domestic products (GDP), money supply, interest rate, US currency baht per dollar (THB/USD), exchange rate dong per dollar (DONG/USD), Consumer Price Index (CPI), sticky rice yield (metric ton) and rice export price (million USD) (Tongnoy & Chen, 2018).

A comparison of three neural network architectures was carried out in 2009 to identify an ANN model that can predict the US Dollar against Sri Lankan Rupee (USD/LKR) with a higher accuracy level. Here, two static neural network models were employed: FFNN with the Backpropagation (BPR) algorithm and FFNN with SCG algorithm and compared the accuracy with a dynamic neural network: TDNN. It was found that the FFNN model trained with the SCG algorithm is the best static neural network among the two approaches used. Further, the best-performed TDNN model has outperformed the best static model in forecasting unseen data (Chandrasekara & Tilakaratne, 2009).

There are many real-world scenarios where future events must be predicted based on historical data. Although perfect predictions can hardly ever be made, neural networks can be used to obtain adequate predictions in many instances. Neural networks have been used for a variety of functions, such as classification, clustering, function approximation, and optimization.

Every task requires different networks and learning algorithms. In some scenarios, the prediction problem is a special case of function approximation problems representing functional values using time series. For many of the above functions, it was empirically found that neural networks to be at least as successful as classical statistical methods which are partly due to the use of non-parametric estimators, making no assumptions about input distributions and non-linear node functions. Contrastingly, non-parametric, and non-linear statistical models are much more complex and harder to implement than neural networks (Mehrotra *et al*. 1997).

Many models have been employed in modeling and forecasting prices of perishable cash crops in local as well as in global markets. Even though, in Sri Lanka, the use of sophisticated tools like ANN methods is yet not used satisfactorily to monitor the complexities that arise in cash crop price forecasting. Despite the fact that green chili prices exhibit huge retail price variations every year, only classical models have been applied to forecast green chili prices in Sri Lanka. Therefore, it would be very appropriate to use advanced ANNs to closely monitor the retail price fluctuations of green chili in Sri Lanka.

MATERIALS AND METHODS

Even though, the historical prices of green chili had reported highly irregular behavior, the use of ANN techniques has not widely employed to capture this phenomenon. The main objective of this study is to identify the behavior of price variations, model them effectively with the use of ANN techniques to forecast weekly open market average retail prices of green chili in Colombo with higher accuracy. The study was conducted using weekly average retail prices of green chili from the 1st week of January 2011 to the 4th week of December 2018 in Sri Lanka. It is required to observe the measurements of a study regularly: on a daily basis or weekly basis to make more accurate forecasts (Orrebrant & Hill, 2014). Therefore, this study used weekly data in the analysis.

The prices of the green chili were obtained from the website of the Department of Census and Statistics, Sri Lanka. Three different ANN approaches were built using the trial-and-error method with the parameter adjustments in this study, namely, TDNN, FFNN with LM algorithm and FFNN with SCG algorithm for the standardized data as this form contributes equally to the data. Initial 80% of the data from the first week of the 2011 January to the second week of 2018 January were used to train the models, 15% where the third week of 2018 January to the third week of 2019 May to validate and the remaining 5% of the data, fourth of week of 2019 May to 2019 October third week were used to test the models. The performance criteria, MSE, MAE and NMSE which were calculated using Equation 1-3 were used to evaluate the performance of built models under the three approaches.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2 \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\widehat{Y}_i - Y_i\right| \tag{2}$$

$$NMSE = \frac{1}{\sigma^2 n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2 \tag{3}$$

where n is the sample size, is the ith observed value and $\hat{Y}_i$ is the predicted value of the ith observation and $\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2$.

The TDNN is a dynamic model based on time lags and provides a better ANN with higher lags dependence (Reese, 2001). Initially, models were built for different epochs of 100, 200 and 500 accompanied by different numbers of hidden layers and hidden neurons. Then the model with the lowest errors was selected and the activation functions were changed in each hidden layer to acquire lower MSE, MAE and NMSE values. Finally, the time delays were adjusted and found a better model to use in forecasting the prices of green chili.

FFNN is a static ANN where the nodes of the network do not consist of a cycle behavior (Huang *et al*. 2004). LM algorithm is considered to be the most effective procedure for FFNN due to training precision (Ampazis *et al*. 2000). However, there are drawbacks due to the extensive number of variables and cost functions. In the SCG algorithm, a search is carried out in the conjugate directions with a fast convergence ability (Johansson *et al*. 1991). For the FFNN, the potential input variables of lags and Moving Averages (MA) were assessed through the Pearson correlation coefficient and Spearman's rank-order correlation. A similar training process, as in the TDNN was carried out for the FFNN with LM and SCG algorithms for selecting a better model among different epochs with the minimum error values and then changed activation functions for each hidden layer. Then for the LM algorithm parameters learning rate and momentum values were changed between 0 and 1, as the learning rate is used to adapt the weights of the network while momentum is used to avoid the local minimum problem. In the SCG algorithm Sigma (σ) and Lambda (λ) parameters were adjusted, to detect the variation of the weight in the second derivative approximation and adjust the indefiniteness of the Hessian matrix (Moller, 1990).

RESULTS AND DISCUSSION

As a first step of the analysis, an exploratory analysis was carried out to observe the distribution and behavior of weekly green chili prices. There were no missing values found in the dataset and the original series was used for further analysis. According to the time series plot (Figure 01), there is a slight upward trend, non-constant variance and a clear seasonal pattern in weekly retail prices of green chili. Moreover, high fluctuations can be observed in prices from the first week of May 2014 to the third week of August 2016. Further, for the considered time period, the average value of the weekly price is Rs.356.22 per kg and, the lowest and highest values are Rs.127.03 per kg in the fourth week of March 2012 and Rs.978.21 per kg in the first week of December 2015 respectively. TDNN model was implemented as a dynamic model and moving averages and lags were used as input variables for FFNN models. The correlations among the moving averages (MA), lags (previous values of the same series) and the original series were used to analyze the suitability of the suggested input variables. The Table 01 represents the correlations among the aforementioned input variables and the original price series and it was observed that there exist high positive correlations among MA4, lag1, lag2 and lag3 with the original price series.

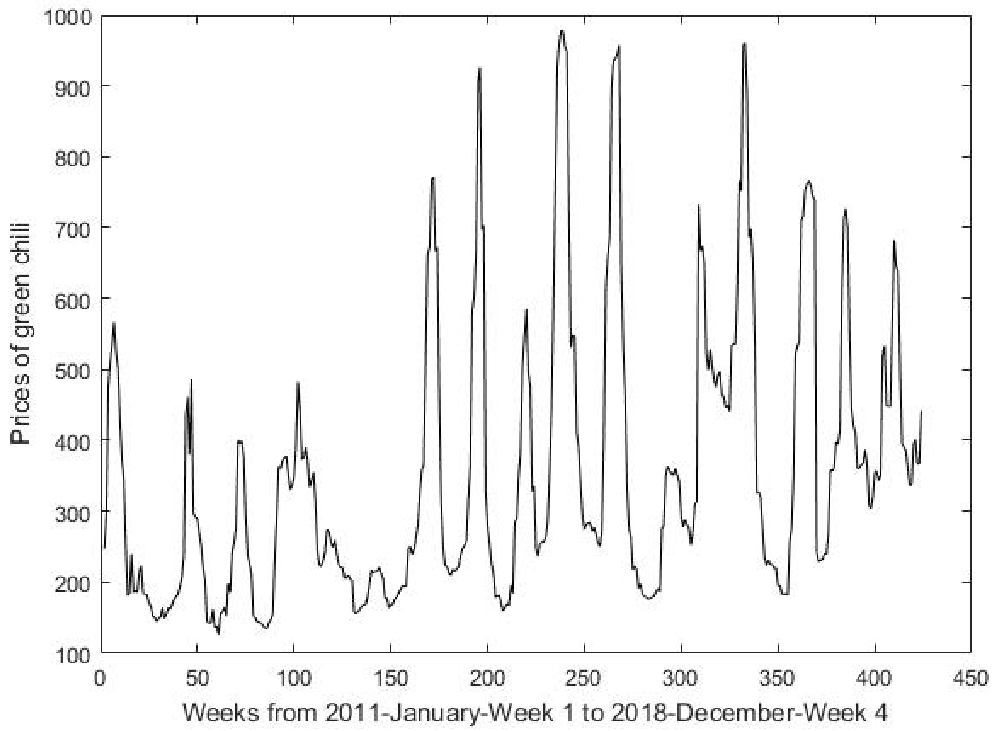

Figure 01: Weekly Prices of Green Chili

Table 01: Correlations between suggested input variables and original price series

	DATA	MA4	MA8	MA12	MA16	MA20	MA24
DATA	1	0.806819	0.590478	0.416943	0.322941	0.312516	0.358116
MA4	0.806819	1	0.904067	0.729955	0.582318	0.505673	0.499772
MA8	0.590478	0.904067	1	0.925942	0.787569	0.67466	0.624671
MA12	0.416943	0.729955	0.925942	1	0.942003	0.83295	0.749333
MA16	0.322941	0.582318	0.787569	0.942003	1	0.953318	0.867967
MA20	0.312516	0.505673	0.67466	0.83295	0.953318	1	0.962887
MA24	0.358116	0.499772	0.624671	0.749333	0.867967	0.962887	1
LAG1	0.934797	0.919621	0.725149	0.539352	0.418734	0.381345	0.407617
LAG2	0.837515	0.977344	0.83563	0.652196	0.512583	0.449919	0.455012
LAG3	0.716256	0.977416	0.91386	0.749815	0.600188	0.514541	0.498146
LAG4	0.57337	0.920009	0.955392	0.827931	0.677641	0.572625	0.535362
LAG5	0.432138	0.807914	0.955495	0.881932	0.741225	0.62276	0.566185
LAG6	0.302011	0.675962	0.9144	0.909916	0.79026	0.665093	0.591167
LAG7	0.179586	0.535538	0.836931	0.910329	0.823565	0.699181	0.610222
DATA	LAG1	LAG2	LAG3	LAG4	LAG5	LAG6	LAG7
MA4	0.934797	0.837515	0.716256	0.57337	0.432138	0.302011	0.179586
MA8	0.919621	0.977344	0.977416	0.920009	0.807914	0.675962	0.535538
MA12	0.725149	0.83563	0.91386	0.955392	0.955495	0.9144	0.836931
MA16	0.539352	0.652196	0.749815	0.827931	0.881932	0.909916	0.910329
MA20	0.418734	0.512583	0.600188	0.677641	0.741225	0.79026	0.823565
MA24	0.381345	0.449919	0.514541	0.572625	0.62276	0.665093	0.699181
LAG1	0.407617	0.455012	0.498146	0.535362	0.566185	0.591167	0.610222
LAG2	1	0.935083	0.83797	0.716784	0.573928	0.433239	0.303542
LAG3	0.935083	1	0.935205	0.838299	0.717164	0.574578	0.434292
LAG4	0.83797	0.935205	1	0.935357	0.838501	0.717593	0.575373
LAG5	0.716784	0.838299	0.935357	1	0.935399	0.838833	0.718202
LAG6	0.573928	0.717164	0.838501	0.935399	1	0.935569	0.839113
LAG7	0.433239	0.574578	0.717593	0.838833	0.935569	1	0.935641
DATA	0.303542	0.434292	0.575373	0.718202	0.839113	0.935641	1

Time Delay Neural Network (TDNN)

The TDNN model training was commenced with a single hidden layer and a hidden neuron with the 'tansig' activation function. Subsequently, the number of hidden neurons and hidden layers was increased and trained the models while having other parameters constant (initially with 100 epochs and 3 input delays). MSE, MAE and NMSE performance measures were used to detect the better model among different networks as shown in Table 02., for the different number of hidden layers and hidden neurons. The same process was carried for 200 and 500 epochs and the summary is illustrated in Table 03.

Table 02: Performance measurements of TDNN for different hidden layers and hidden neurons for 100 epochs

Epoch 100									
Hidden layer	Hidden neurons	MSE	MAE	NMSE	Hidden layer	Hidden neurons	MSE	MAE	NMSE
1	1	0.0054	0.0575	0.4920	3	2,2,3	0.0051	0.0556	0.4687
1	2	0.0047	0.0544	0.4313	3	2,2,4	0.0055	0.0583	0.5009
1	3	0.0046	0.0510	0.4242	3	2,3,1	0.0055	0.0583	0.5085
1	4	0.0047	0.0548	0.4320	3	2,3,2	0.0049	0.0543	0.4459
2	1,1	0.0057	0.0603	0.5211	3	2,3,3	0.0050	0.0550	0.4573
2	1,2	0.0054	0.0557	0.4930	3	2,3,4	0.0051	0.0551	0.4665
2	1,3	0.0051	0.0557	0.4709	3	2,4,1	0.0055	0.0585	0.5068
2	1,4	0.0052	0.0581	0.4800	3	2,4,2	0.0050	0.0554	0.4603
2	2,1	0.0049	0.0546	0.4516	3	2,4,3	0.0058	0.0608	0.5328
2	2,2	0.0057	0.0605	0.5237	3	2,4,4	0.0050	0.0556	0.4640
2	2,3	0.0055	0.0587	0.5035	3	3,1,1	0.0053	0.0573	0.4835
2	2,4	0.0047	0.0527	0.4342	3	3,1,2	0.0052	0.0559	0.4778
2	3,1	0.0060	0.0626	0.5529	3	3,1,3	0.0051	0.0560	0.4652
2	3,2	0.0058	0.0629	0.5365	3	3,1,4	0.0045	0.0541	0.4108
2	3,3	0.0064	0.0638	0.5846	3	3,2,1	0.0058	0.0627	0.5303
2	3,4	0.0052	0.0577	0.4760	3	3,2,2	0.0050	0.0562	0.4575
2	4,1	0.0050	0.0569	0.4641	3	3,2,3	0.0062	0.0607	0.5662
2	4,2	0.0071	0.0654	0.6556	3	3,2,4	0.0054	0.0561	0.4982
2	4,3	0.0059	0.0633	0.5453	3	3,3,1	0.0052	0.0568	0.4821
2	4,4	0.0053	0.0563	0.4877	3	3,3,2	0.0058	0.0609	0.5286
3	1,1,1	0.0053	0.0572	0.4882	3	3,3,3	0.0053	0.0584	0.4905
3	1,1,2	0.0057	0.0597	0.5204	3	3,3,4	0.0057	0.0632	0.5258
3	1,1,3	0.0050	0.0553	0.4574	3	3,4,1	0.0051	0.0568	0.4679
3	1,1,4	0.0049	0.0553	0.4538	3	3,4,2	0.0051	0.0554	0.4648
3	1,2,1	0.0050	0.0560	0.4626	3	3,4,3	0.0054	0.0597	0.4918
3	1,2,2	0.0049	0.0560	0.4520	3	3,4,4	0.0062	0.0628	0.5659
3	1,2,3	0.0056	0.0596	0.5146	3	4,1,1	0.0056	0.0590	0.5104
3	1,2,4	0.0053	0.0576	0.4836	3	4,1,2	0.0048	0.0557	0.4372
3	1,3,1	0.0047	0.0564	0.4355	3	4,1,3	0.0054	0.0611	0.4974
3	1,3,2	0.0050	0.0552	0.4593	3	4,1,4	0.0051	0.0535	0.4706
3	1,3,3	0.0047	0.0535	0.4348	3	4,2,1	0.0059	0.0625	0.5393
3	1,3,4	0.0046	0.0500	0.4217	3	4,2,2	0.0051	0.0555	0.4644
3	1,4,1	0.0049	0.0542	0.4469	3	4,2,3	0.0054	0.0606	0.4944
3	1,4,2	0.0056	0.0583	0.5134	3	4,2,4	0.0052	0.0547	0.4765
3	1,4,3	0.0048	0.0570	0.4377	3	4,3,1	0.0058	0.0598	0.5365
3	1,4,4	0.0051	0.0573	0.4700	3	4,3,2	0.0056	0.0630	0.5160
3	2,1,1	0.0046	0.0493	0.4225	3	4,3,3	0.0052	0.0567	0.4764
3	2,1,2	0.0052	0.0603	0.4792	3	4,3,4	0.0056	0.0582	0.5156
3	2,1,3	0.0043	0.0505	0.3928	3	4,4,1	0.0058	0.0581	0.5353
3	2,1,4	0.0052	0.0547	0.4774	3	4,4,2	0.0050	0.0574	0.4589
3	2,2,1	0.0055	0.0586	0.5072	3	4,4,3	0.0056	0.0608	0.5134
3	2,2,2	0.0053	0.0580	0.4831	3	4,4,4	0.0074	0.0699	0.6792

Table 03: Summary of performance measurements of selected TDNN for different epochs

Epochs	Network architecture	MSE	MAE	NMSE
100	2,1,3	0.0043	0.0505	0.3928
200	3,2,4	0.0039	0.0508	0.3586
500	4,2,2	0.0041	0.0480	0.3769

From the above selected three models under three different epochs, the model [3 2 4] (i.e. 3 hidden layers and 3, 2 and 4 hidden neurons in each layer) which was trained with 200 epochs was selected for further training as it exhibits the lowest MSE value (0.0039), lowest NMSE values (0.3586) and a lower MAE (0.0508).

As the next step, the transfer functions in each hidden layer were changed in the above selected model to detect the least MSE, MAE and NMSE values. (Table 04.)

Table 04: Performance measurements of selected TDNN with different transfer functions

Epoch 200					
Transfer function 1	Transfer function 2	Transfer function 3	MSE	MAE	NMSE
Tansig	Tansig	Tansig	0.0039	0.0508	0.3586
Tansig	Tansig	Logsig	0.0054	0.0593	0.4994
Tansig	Tansig	Purelin	0.0052	0.0555	0.4747
Tansig	Logsig	Tansig	0.0044	0.0514	0.4016
Tansig	Logsig	Logsig	0.0055	0.0610	0.5042
Tansig	Logsig	Purelin	0.0056	0.0582	0.5170
Tansig	Purelin	Tansig	0.0055	0.0600	0.5074
Tansig	Purelin	Logsig	0.0057	0.0623	0.5248
Tansig	Purelin	Purelin	0.0042	0.0525	0.3842
Logsig	Tansig	Tansig	0.0050	0.0552	0.4553
Logsig	Tansig	Logsig	0.0050	0.0563	0.4635
Logsig	Tansig	Purelin	0.0057	0.0592	0.5198
Logsig	Logsig	Tansig	0.0051	0.0569	0.4679
Logsig	Logsig	Logsig	0.0051	0.0592	0.4653
Logsig	Logsig	Purelin	0.0055	0.0586	0.5029
Logsig	Purelin	Tansig	0.0062	0.0661	0.5742
Logsig	Purelin	Logsig	0.0052	0.0579	0.4815
Logsig	Purelin	Purelin	0.0049	0.0547	0.4476
Purelin	Tansig	Tansig	0.0051	0.0561	0.4677
Purelin	Tansig	Logsig	0.0050	0.0505	0.4601
Purelin	Tansig	Purelin	0.0048	0.0534	0.4421
Purelin	Logsig	Tansig	0.0055	0.0588	0.5066
Purelin	Logsig	Logsig	0.0067	0.0658	0.6131
Purelin	Logsig	Purelin	0.0052	0.0554	0.4781
Purelin	Purelin	Tansig	0.0051	0.0549	0.4702
Purelin	Purelin	Logsig	0.0046	0.0536	0.4226
Purelin	Purelin	Purelin	0.0053	0.0557	0.4870

Table 05: Performance measurements of selected TDNN with different Input delays

Epochs 200			
Input delays	MSE	MAE	NMSE
1	0.0051	0.0533	0.4660
2	0.0044	0.0532	0.4013
3	0.0039	0.0508	0.3586
4	0.0049	0.0541	0.4471
5	0.0046	0.0527	0.4055
6	0.0056	0.0622	0.5015
7	0.0039	0.0480	0.3515
8	0.0036	0.0470	0.3221
9	0.0048	0.0558	0.4302
10	0.0040	0.0509	0.3528

Still, the least error measurements are observed in the network model with the 'tansig' functions. Next, different input delays were applied for the aforementioned model as in Table 05.

It was found that the minimum MSE, MAE and NMSE values are recorded when the input delay is 8.

As discussed above, from all the TDNN models trained with varying parameters, the network which indicated the least MSE of 0.0036, MAE of 0.0470 and NMSE of 0.3221 was selected as a better model for forecasting green chili prices. The structure of this network consists of 3 hidden layers with 3, 2, and 4 hidden neurons in each layer respectively (Figure 02). The 'tansig' activation function was used in each hidden layer, while the default activation function 'pureline' was used for the output layer, and the network was trained with 8 input delays at 200 epochs.

Figure 03 illustrates the time series plots of the outperformed model selected from TDNN. It shows the actual values of open market retail prices of green chili in point marks and predicted values of open market retail prices of green chili in asterisk marks of the test data from the fourth week of 2019 May to 2019 October. It implies that the fitted model captures the behavior of the original series well.

Feedforward Neural network (FFNN)s

The significant lags which are inputs to the FFNN were identified using the ACF and PACF plots in Figure 04. Further, the moving averages (MA) were considered as inputs. Since weekly prices were used for the analysis first, MA4, MA8, MA12, MA20, MA24 were assumed as appropriate moving averages as inputs to the model.

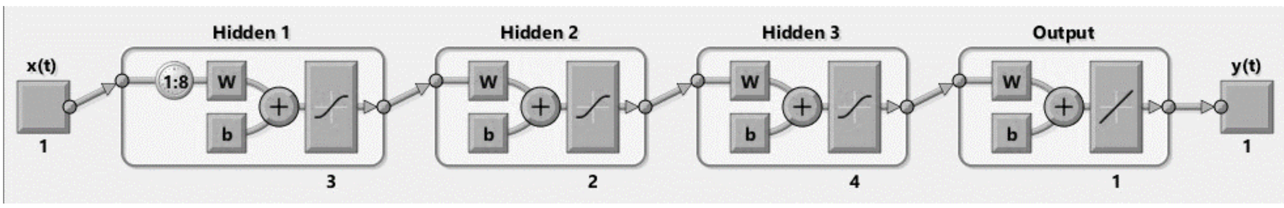

Figure 02: Network architecture of better performed TDNN model

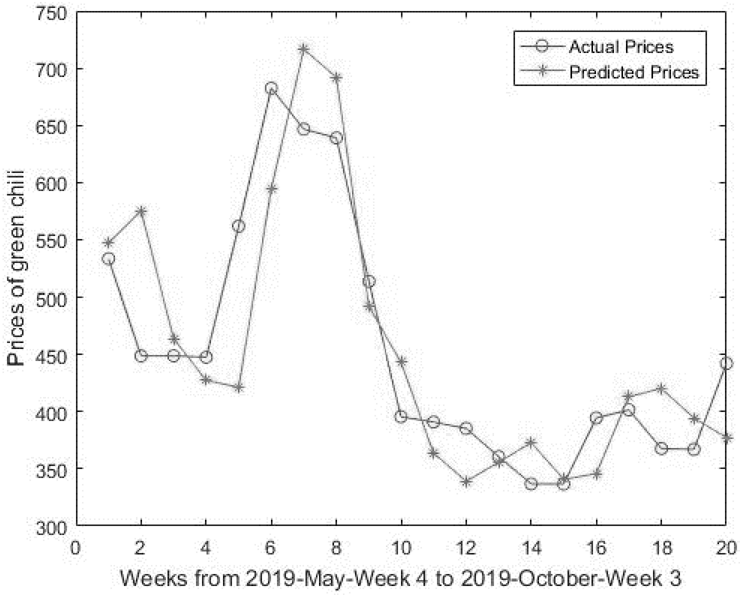

Figure 03: Time series plots of actual and predicted of test data in best performed TDNN model

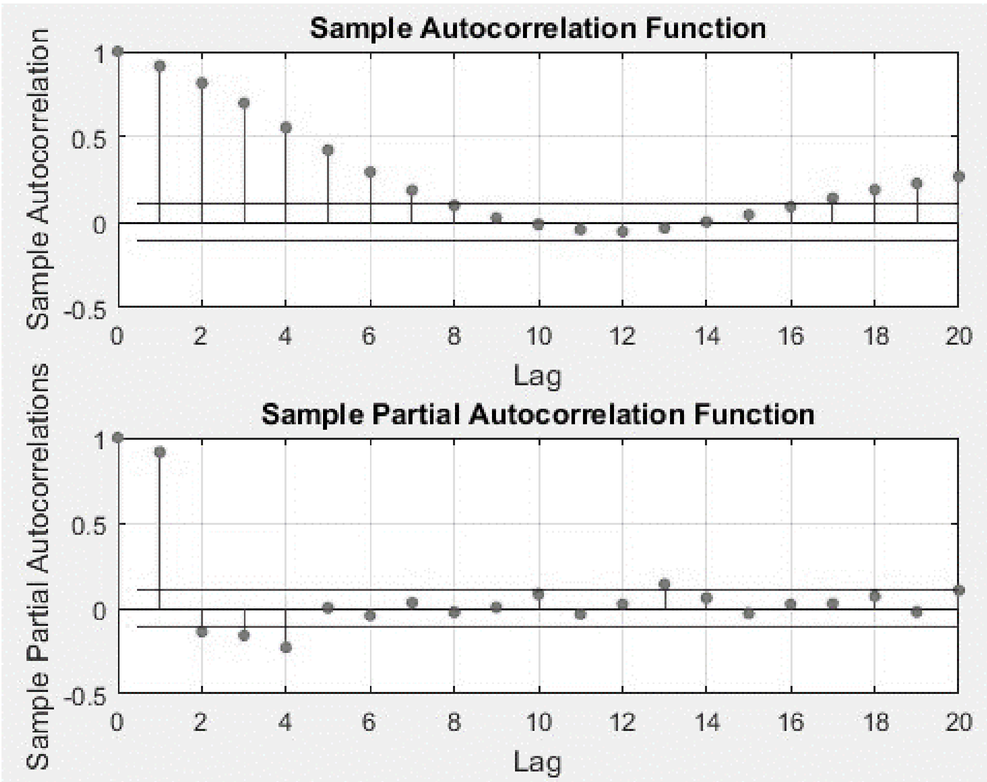

Figure 04: ACF and PACF plots

Even as, lag 1, lag 2, lag 3, lag 4, lag 5, lag 6 and lag 7 were found to be significant (Figure 04), they were considered for further analysis for input variable combinations along with above mentioned MAs. From the aforementioned set of variables, appropriate inputs with higher Pearson correlation coefficient and Spearman's rank-order correlation were kept in the input combinations and removed least correlated inputs. Different input combinations were employed and finally, Lag1, lag2, lag 3, and 4MA were selected as the better combinations for the FFNN based on the performance measures.

Feedforward Neural Network with LM algorithm

After selecting the suitable input combination, started to train models for different epochs of 100, 200 and 500 similarly in TDNN. The values for the performance measures were observed accordingly. Two most appropriate models with minimum error values for 200 and 500 epochs were selected as the model trained with 100 epochs exhibited comparatively high MSE, MAE and NMSE. Table 06 illustrates the observed values for the performance measures.

According to the above Table, the model, which had two hidden layers with one and four hidden neurons respectively, was selected as the most appropriate model for training further. Transfer functions of the selected model were changed and observed the performance measures. The model with 'tansig' function between all hidden layers was selected as the most suitable model. As the next step, the selected model was trained with the different learning rates as in Table 07.

The MSE of the better-performed model was 0.0033 and then it was followed by 0.0437 and 0.2542 in MAE and NMSE respectively by fine-tuning of the learning rate parameter between 0 and 1. Then the momentum was changed from 0.0001 to 1 for assessing further improvements of the above selected model which is illustrated in Table 08.

Table 06: Summary of performance measurements of selected FFNN for different epochs

Epochs	Network architecture	MSE	MAE	NMSE
200	3,1	0.0038	0.0460	0.3077
500	1,4	0.0033	0.0437	0.2542

Table 07: Performance measurements of selected FFNN with LM algorithm with different learning rates

Learning rate	MSE	MAE	NMSE	Learning rate	MSE	MAE	NMSE
0.0001	0.0048	0.0517	0.3982	0.01	0.0033	0.0437	0.2542
0.0002	0.0038	0.049	0.4834	0.011	0.0036	0.0453	0.3457
0.0003	0.004	0.0484	0.3253	0.012	0.0038	0.0484	0.3595
0.0004	0.0042	0.0515	0.3499	0.02	0.0041	0.0501	0.3338
0.0005	0.0041	0.0458	0.6827	0.03	0.0044	0.0535	0.3953
0.0006	0.0042	0.051	0.3477	0.04	0.0054	0.0602	0.3489
0.0007	0.0039	0.0486	0.3628	0.05	0.0039	0.049	0.3378
0.0008	0.0057	0.061	0.4279	0.06	0.0042	0.051	0.3503
0.0009	0.0042	0.0511	0.3576	0.07	0.0038	0.0467	0.3727
0.001	0.0041	0.0469	0.3647	0.08	0.0042	0.0512	0.3508
0.002	0.0042	0.0512	0.3509	0.09	0.0034	0.0443	0.3514
0.003	0.0043	0.0525	0.3587	0.1	0.0046	0.0562	0.3593
0.004	0.0041	0.0508	0.3634	0.2	0.0041	0.051	0.3678
0.005	0.0041	0.0502	0.3482	0.3	0.0046	0.048	0.3989
0.006	0.0041	0.0524	0.389	0.4	0.0044	0.0514	0.3822
0.007	0.0049	0.0529	0.367	0.5	0.0039	0.0475	0.3495
0.008	0.0037	0.0473	0.3805	0.6	0.0038	0.0484	0.3432
0.009	0.0042	0.0514	0.3537	0.7	0.0045	0.0544	0.3732
0.0097	0.0039	0.0493	0.3903	0.8	0.004	0.0495	0.3591
0.0098	0.0037	0.0474	0.4464	0.9	0.0038	0.0473	0.3376
0.0099	0.0042	0.0518	0.3536	1	0.0039	0.0488	0.3689

Table 08: Performance measurements of selected FFNN with LM algorithm with different learning rates

Momentum	MSE	MAE	NMSE	Momentum	MSE	MAE	NMSE
0.0001	0.0042	0.0499	0.3329	0.04	0.0042	0.0523	0.3653
0.0002	0.0044	0.0503	0.33	0.05	0.0064	0.0655	0.3438
0.0003	0.004	0.0463	0.338	0.06	0.0036	0.0469	0.3462
0.0004	0.0042	0.0512	0.3469	0.07	0.0039	0.048	0.3197
0.0005	0.0043	0.0526	0.3542	0.08	0.0041	0.0486	0.3452
0.0006	0.0047	0.0532	0.3293	0.09	0.0041	0.0504	0.3274
0.0007	0.0043	0.0522	0.3466	0.1	0.0042	0.0512	0.3506
0.0008	0.0042	0.0512	0.3078	0.2	0.0044	0.0533	0.3414
0.0009	0.0043	0.0512	0.3381	0.3	0.004	0.0474	0.3515
0.001	0.0039	0.0478	0.3179	0.4	0.0043	0.0526	0.3641
0.002	0.0039	0.0485	0.3318	0.5	0.0041	0.0502	0.3406
0.003	0.004	0.0498	0.3332	0.6	0.0038	0.0489	0.3821
0.004	0.004	0.0484	0.3388	0.7	0.0041	0.0486	0.4764
0.005	0.0039	0.0477	0.3722	0.8	0.0042	0.0504	0.3573
0.006	0.0037	0.0456	0.3327	0.88	0.0038	0.0472	0.3466
0.007	0.004	0.0495	0.3332	0.89	0.0041	0.0505	0.3504
0.008	0.0042	0.0512	0.3545	0.9	0.0033	0.0437	0.2542
0.009	0.0036	0.0475	0.4381	0.91	0.0037	0.0455	0.3503
0.01	0.0039	0.0479	0.3595	0.92	0.0043	0.0458	0.4217
0.02	0.0039	0.0488	0.3224	1	0.0048	0.0559	0.3325
0.03	0.0051	0.0606	0.3896				

As observed values in Table 08, the model with the momentum of 0.9 was selected as the better model for forecasting the open market retail prices of green chili.

The optimal FFNN with the LM algorithm was selected with 500 epochs with 2 hidden layers of 1 and 4 hidden neurons along with the activation functions 'tansig' in the hidden layers and output layer with the 'purelin' activation function. Further, it consists of a learning rate of 0.01 and momentum of 0.9 which indicate the better performance as 0.0033, 0.0437 and 0.2542 for the MSE, MAE and NMSE respectively. Figure 05 illustrates the network architecture of the selected FFNN model with the LM algorithm.

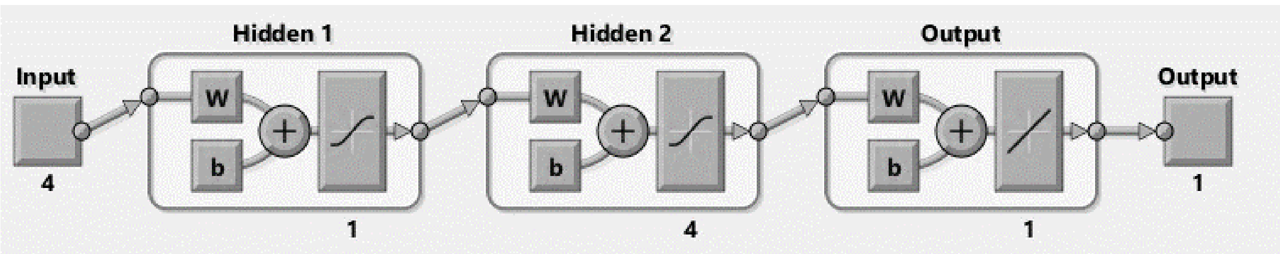

Figure 05: Network architecture of better performed FFNN with LM algorithm

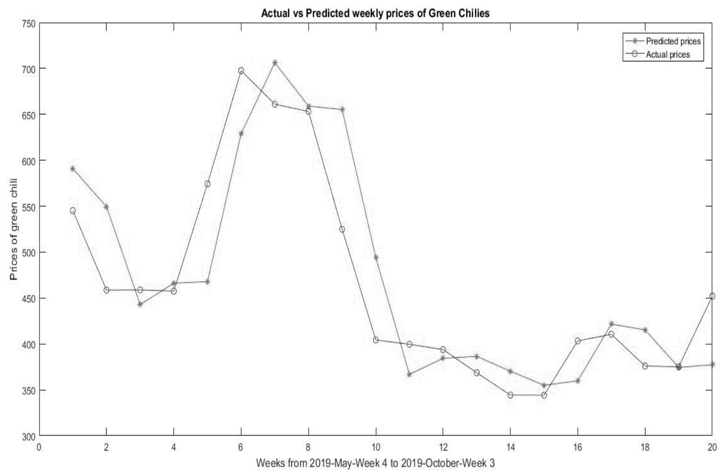

Figure 06: Time series plots of actual and predicted of test data in best performed FFNN with LM algorithm

Figure 06 illustrates the time series plots of the better-performed FFNN model with the LM algorithm. It exhibits that the fitted model captures the behavior of the original series well.

Feedforward Neural Network with SCG algorithm

Firstly, MSE, MAE and NMSE were identified for the trained models with FFNN with SCG algorithm for the different number of hidden layers and hidden neurons. Table 09 indicates the best selected models with the least MSE, MAE and NMSE among 100, 200 and 500 epochs.

For the selected model (4,1) from 100 epochs, the transfer functions were changed to detect the least MSE, MAE and NMSE values. The least performance errors are observed in the model with the 'tansig' and 'tansig' transfer functions in the two hidden layers respectively. Next, the different combinations of Sigma and Lambda were checked for the selected model as in Table 10.

Table 09: Summary of performance measurements of selected models in FFNN with SCG algorithm

Epochs	Network architecture	MSE	MAE	NMSE
100	4,1	0.0033	0.0458	0.2549
200	1,4,1	0.0029	0.0466	0.3065
500	4,4,4	0.0033	0.0441	0.3012

Table 10: Performance measurements of selected FFNN with SCG algorithm with different Sigma and Lambda values

Sigma	Lambda	MSE	MAE	NMSE
5.00E-05	5.00E-05	0.0084	0.074	0.3834
5.00E-05	5.00E-06	0.0027	0.0439	0.3329
5.00E-06	5.00E-05	0.0054	0.0617	0.2982
5.00E-06	5.00E-06	0.008	0.0709	0.4593
5.00E-06	5.00E-07	0.0053	0.0531	0.4343
5.00E-05	5.00E-07	0.0033	0.0458	0.2549
5.00E-07	5.00E-06	0.0094	0.0768	0.454
5.00E-07	5.00E-07	0.0071	0.0654	0.435
5.00E-07	5.00E-08	0.0085	0.0721	0.536

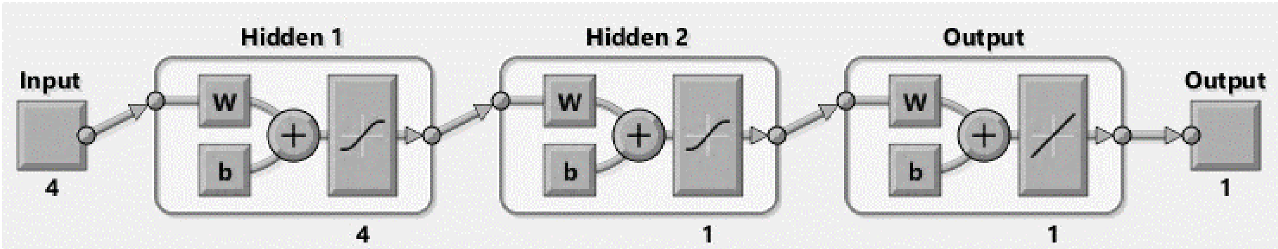

Figure 07: **Network architecture of better performed FFNN with SCG algorithm.**

A better model was identified with the network structure of 2 hidden layers; 4 and 1 hidden neurons with 'tansig' transfer function for each layer and having sigma and lambda values of 5e and 5erespectively at 100 epochs. The default activation function: 'purelin' was used for the output layer. Out of the implemented FFNNs with SCG algorithm, the least MSE of 0.0033, MAE of 0.0458 and NMSE 0.2549 values were observed under this network structure. Figure 07 illustrates the better performed network architecture for FFNN with SCG algorithm.

The time series plots of the best-performed model selected from the implemented FFNNs with the SCG algorithm are presented in Figure 08. As per the movements of the actual values and the predicted values of test data from the fourth week of 2019 May to 2019 October, it was evident that the implemented model reproduces the fluctuations of the original series of open market retail prices of green chili well.

Model Comparison

Three better performing ANN models could be identified using each of the aforementioned ANN techniques and a summary is presented in Table 11, with the network architectures and performance measures.

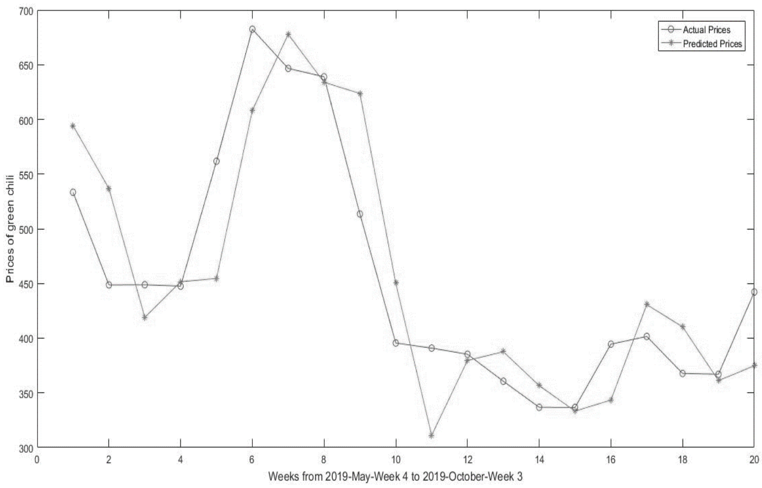

Figure 08: **Time series plots of actual and predicted of test data in best performed FFNN with SCG algorithm**

Table 11: **Comparisons of ANN techniques**

ANN techniques	Epochs	Hidden layers	Hidden neurons	MSE	MAE	NMSE
TDNN	200	3	3, 2, 4	0.0036	0.0470	0.3221
FFNN with LM algorithm	500	2	1, 4	0.0033	0.0437	0.2542
FFNN with SCG algorithm	100	2	4, 1	0.0033	0.0458	0.2549

As stated in Table 11., the TDNN model exhibits the highest error values in terms of MSE, MAE and NMSE compared to the other two models implemented. The TDNN was implemented as a univariate model and it was the only dynamic ANN architecture implemented and tested under this study. From the two static models: FFNN with LM algorithm and FFNN with SCG algorithm, the model with LM algorithm has outperformed the SCG algorithm as it indicates the lowest MSE, MAE and NMSE values of 0.0033, 0.0437 and 0.2542 respectively. The TDNN model comprises comparatively a large number of hidden neurons (nine neurons) compared to FFNN models. Altogether, the FFNN model with LM algorithm can be used in predicting the prices of green chili with higher accuracy. Nevertheless, all the models stated in Table 11 are appropriate to use in forecasting the open market retail prices of green chili in Sri Lanka. Further, the results from the study of Kushan *et al*., (2020) indicated that the ARIMA (1,1,3) $(1,1,1)_{[24]}$ model was capable in capturing the weekly prices of the green chili in Sri Lanka from the first week of January 2011 to the fourth week of December 2018 with a MAE of 63.8518. Hence, the proposed model by this study exhibit better-performance with a lower MAE of 0.0437 compared to the study of Kushan *et al*., (2020). Further, this is the first attempt in applying the ANNs for forecasting weekly open market average retail prices of green chili in Colombo Sri Lanka.

CONCLUSIONS

Forecasting the prices of crops is a vital procedure that affects the economy of a country. Green chili is one of the important crash crops in Sri Lanka. This study contributes to predicting the weekly prices of green chili using ANN techniques. According to the final outcomes of the trained neural network models, TDNN (dynamic) model indicates the highest error values and from the two static models, FFNN with the LM algorithm outperformed the other model and it can be identified as the most efficient method for forecasting the weekly prices of green chili. The study will provide an idea about the future price behavior of weekly prices of green chili in Sri Lanka.

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