
**ISSN:** 2456-1452
Maths 2021; 6(3): 08-12

www.mathsjournal.com
Received: 11-01-2021
Accepted: 06-03-2021

**Srikanth C**
Research Scholar, Department of Statistics, Kakatiya University, Warangal, Telangana, India

**K Balaraju**
Research Scholar, Department of Statistics, Kakatiya University, Warangal, Telangana, India

**A Rajendra Prasad**
Professor, Department of Statistics, Kakatiya University, Warangal, Telangana, India

**Corresponding Author:**
**Srikanth C**
Research Scholar, Department of Statistics, Kakatiya University, Warangal, Telangana, India

# Forecasting petrol prices in India using neural networks models

**Srikanth C, K Balaraju and A Rajendra Prasad**

**Abstract**
The work presented in this research paper constitutes a contribution to modeling and forecasting the monthly average petrol price per liter in Delhi using Feed Forward Neural Networks models. The model performance is on training and test samples measured using Mean Absolute Error (MAE), Mean Absolute and Percentage Error (MAPE,) and Root Mean Square Error (RMSE). The results show that feed forward neural networks (FFNN) models could be utilized to forecast the average petrol prices in Delhi city.

**Keywords:** FFNN, AIC, SBC, MAE, MAPE, RMSE

## 1. Introduction
Petrol is majorly consumed in the transport sector. In this, the majority of the consumption is accounted by two-wheelers and cars. Petrol is used in detergents which are used to clean the dishes and wash clothes. This detergent contains petrochemical glycerin which is the derivative of petrol. Oil-based paints and paint additives are produced from petrochemicals. Synthetic rubber is produced from petrochemicals that are used to make car tires, rubber sholes, or shoes. Petrol is also used to make plastic. The rise in petrol prices can affect badly the poor and middle-class people who use petrol for their transport vehicles. By better understanding the future petrol prices, one can plan a monthly budget for petrol. The government can also take appropriate decisions to maintain petrol prices as low as possible.
M. Sulaiga Beevi , K. Senthamarai Kannan , S. Syed Ali Fathima (2020) [13]: used Double Exponential Smoothing, ARIMA and Fuzzy time series models for forecasting the daily petrol prices. Ibina E.O., Igwe N.O., Oyah M.P. and Okonta C.A(2020), used ARIMA models for forecasting the stock market prices of Benne cement and Akshara Cement in Nigeria. Chukwudike C. Nwokike, Bright C. Offorha, Maxwell Obubu, Chukwuma B. Ugoala, Henry I. Ukomah (2020), used SARIMA models for forecasting the monthly rainfall in Nigeria. Murali Krishna, K., Konda Reddy, N. and Raghavender Sharma, M. (2019) [14]: used ARIMA and Artificial Neural Networks models for forecasting the daily prices of gold in India. Lemuel Clark P. Velasco1, Daisy Lou L. Polestico2, Gary Paolo O. Macasieb (2019) [11], used Hybrid Model of Autoregressive Integrated Moving Average and Artificial Neural Network for electricity load Forecasting. Sudeshna Gosh (2017), proposed ARIMA models to forecast the cotton exports of India. Destaings Nyongesa Nyongesa, Adolphus Wagala (2016) are used ARIMA models for forecasting the diesel prices in Kenya. Kumar Manoj and and Anand Madhu (2012), used Box-Jenkins ARIMA models to forecast sugarcane production in India. Jamal Fattah, Latifa Ezzine, Zineb Aman, Haj El Moussami, and Abdeslam Lachhab (2018), proposed modeling and forecasting the demand in a food company using ARIMA models. Ayodele Ariyo Adebiyi, Aderemi Oluyinka Adewumi, and Charles Korede Ayo (2014) [2], used ARIMA and Artificial neural networks models for stock price prediction. Krishna Reddy, M. and Naveen Kumar, B. (2011) [9]: used Time delay neural networks for forecasting foreign exchange rates. Rangsan Nochai, Titida Nochai (2006) [16]: used ARIMA model for forecasting Oil palm prices in Thailand. Destaings Nyongesa Nyongesa, Adolphus Wagala (2016) [5]: used ARIMA model for forecasting the diesel prices in Kenya. J.Jaya Selvi, R.Kaviya Shree, J. Krishnan (2018): used ARIMA models for forecasting the crude oil prices in India.

## 2. Materials and Methods

A historical data of monthly average petrol price per liter from January-2010 to December -2020 of Delhi are collected from Petroleum Planning and Analysis Cell, Ministry of Petroleum and Natural Gas, Government of India. The Box-Jenkins ARIMA and FFNN models are developed and discussed in this paper for modeling and forecasting the monthly average petrol price per liter. SPSS software is used for statistical analysis, modeling, and forecasting of average petrol price per liter in Delhi city.

## 3. Methodology

### 3.1 Neural Networks Model

Artificial neural network models are inspired by biological neural networks (animal brains). These are interconnected groups of nodes. The following figure shows the architecture of a multilayer feed-forward neural network.

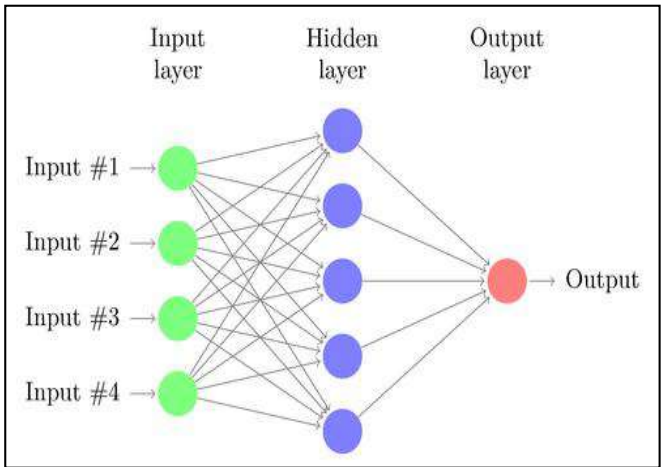


**Fig 1:** Neural Network Architecture

Feed-Forward neural networks (FFNN) structure is a three-layered network and it consists of an input layer, a hidden layer, and an output layer. The data is processing from the input layer, hidden layer, and output layers. Each layer of nodes receives inputs from the previous layers. The outputs of the nodes in one layer are inputs to the next layer. The only one input neuron is needed for developing FFNN models, and it is representing the previous month petrol price that is lag1. The table-1 gives the information about number of input neurons, rescaling method, number of hidden layers, activation function, dependent variable and optimization function.

**Table 1:** Network Information

| | | | |
|---|---|---|---|
| Input Layer | Covariates | 1 | lag1 |
| | Number of Units[a] | 1 | |
| | Rescaling Method for Covariates | Standardized | |
| Hidden Layer(s) | Number of Hidden Layers | 1 | |
| | Number of Units in Hidden Layer 1[a] | 4 | |
| | Activation Function | Hyperbolic tangent | |
| Output Layer | Dependent Variables | 1 | Petrol prices |
| | Number of Units | 1 | |
| | Rescaling Method for Scale Dependents | Standardized | |
| | Activation Function | Identity | |
| | Error Function | Sum of Squares | |
| a. Excluding the bias unit | | | |

## 4. Results and Discussion

The time plot of monthly average price per liter of petrol from January 2010 (Rs/L.32.92) to December 2020 (Rs/L.83.22 ) is given in figure 2.

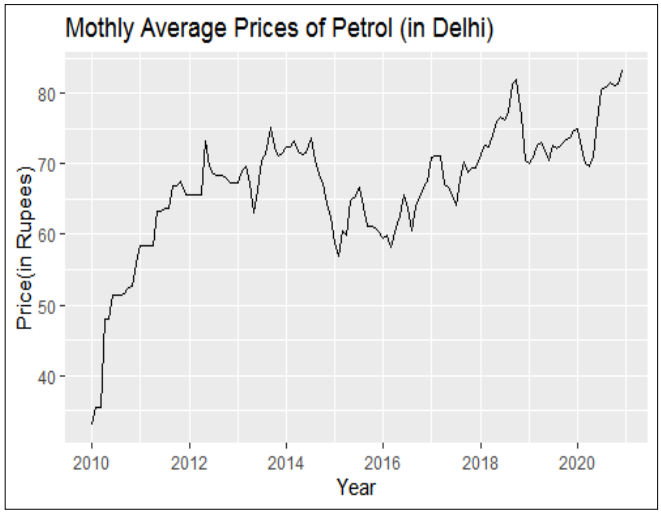


**Fig 2:** Monthly average petrol prices per liter in Delhi
Descriptive Statistics

**Table 2:** Descriptive Statistics of the petrol prices

| Statistics | Count | Mean | Median | Mode | Standard Deviation | Sample Variance | Kurtosis | Skewness | Minimum | Maximum |
|---|---|---|---|---|---|---|---|---|---|---|
| Petrol price (Yt) | 132 | 66.80 | 67.91 | 65.64 | 8.69 | 75.55 | 3.04 | -1.24 | 32.92 | 83.22 |
| lag1 of Petrol | 131 | 66.72 | 67.77 | 65.64 | 8.61 | 74.06 | 3.15 | -1.31 | 32.92 | 81.92 |

From table2, It is observed that, petrol prices range from Rs.32.92 to 83.22, mean is Rs.66.84, standard the deviation is 8.69, and average squared deviations from the mean, that is variance Rs.75.55.

The whole data was divided as training data (January-2010 to December-2018) and test data (January-2019 to December-2020). The model is to be developed on training data and validate on the test data.

### Feed Forward Neural Networks Model

The total number of input neurons needed in this model is one, and it represents the values of lag1 (previous month average petrol price). In this model, only one output unit is needed and it indicates the forecasts of petrol price in India. The hyperbolic tangent function is taken as an activation function under the back-propagation algorithm. The FFNN model was trained till the testing sample error is smaller than

the training sample. There is no simple method to decide the ideal number of hidden units without preparing and testing. The best way to find the least number of hidden units is the trial and error method. In practice, one can use either forward selection or backward selection to determine the hidden layer units. The forward selection method is applied, in which, select few concealed neurons at that point record the system performance by computing the MAE, MAPE, and RMSE. Next increase the number of hidden neurons one by one, trail, and test until the error is acceptably small or no improvement is noted. The accompanying outcomes are acquired for the given partition test.

**Table 3:** Results for forward selection method

| Number of Neurons in the layers | | | Error measures | | |
|---|---|---|---|---|---|
| **input** | **hidden** | **output** | **MAE** | **MAPE** | **RMSE** |
| 1 | 1 | 1 | 1.63 | 2.14 | 2.07 |
| 1 | 2 | 1 | 1.56 | 2.06 | 2.00 |
| 1 | 3 | 1 | 1.70 | 2.23 | 2.15 |
| 1 | 4 | 1 | 1.50 | 1.99 | 1.94 |
| 1 | 5 | 1 | 1.53 | 2.02 | 1.97 |

From the above table, the ideal number of covered neurons in the hidden layer is 4 and the the optimum network is 1-4-1 since the selected network has minimum MAE, MAPE and RMSE.

The layout of the FFNN Model is given below.

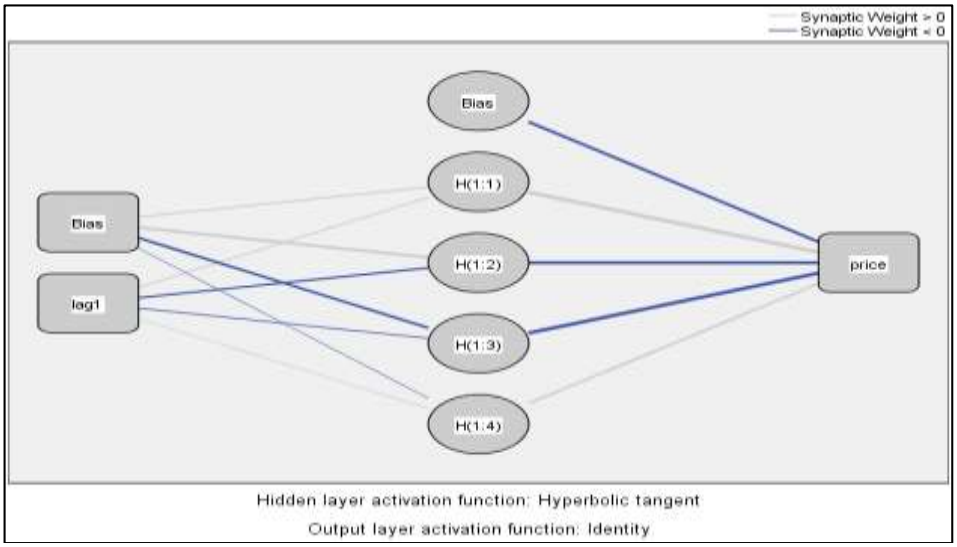


**Fig 3:** FFNN model for prediction of monthly petrol prices.

The FFNN model is developed using SPSS software and the model parameters are presented in the following table.

**Table 4:** Parameter Estimates

| Predictor | | Predicted | | | | |
|---|---|---|---|---|---|---|
| | | Hidden Layer 1 | | | | Output Layer |
| | | **H(1:1)** | **H(1:2)** | **H(1:3)** | **H(1:4)** | **price** |
| Input Layer | (Bias) | .527 | .728 | -.580 | -.147 | |
| | lag1 | .356 | -.551 | -.273 | .224 | |
| Hidden Layer 1 | (Bias) | | | | | -.625 |
| | H(1:1) | | | | | 1.263 |
| | H(1:2) | | | | | -.882 |
| | H(1:3) | | | | | -1.209 |
| | H(1:4) | | | | | .572 |

The hidden neurons are

$H_{(1:1)}$ = Tanh[0.527+0.356 $\bar{Y}_{t-1}$] $H_{(1:2)}$ =Tanh[0.728-0.551 $\bar{Y}_{t-1}$]

$H_{(1:3)}$ =Tanh[-0.580-0.273 $\bar{Y}_{t-1}$]

$H_{(1:4)}$ =Tanh[-0.147-0.224 $\bar{Y}_{t-1}$]

Where $\bar{Y}_{t-1} = (\frac{Y_{t-1} - mean}{sd}) = (\frac{Y_{t-1} - 66.72}{8.61})$ is the rescaled input variable.

The forecasting model is

$\hat{Y}_t$ = 66.72 + 8.61* [-0.625+1.263$H_{(1:1)}$-0.882$H_{(1:2)}$-1.2091$H_{(1:3)}$+ 0.572$H_{(1:4)}$]

The performance of the FFNN model in the fitting and forecasting stage is given below.

**Table 5:** FFNN Model performance

| Data set | MAE | MAPE | RMSE |
|---|---|---|---|
| Training set | 1.77 | 2.85 | 2.37 |
| Test set | 1.41 | 1.88 | 1.88 |

The FFNN model has smaller error measures in the training and test samples. Therefore FFNN model can be used for forecasting the monthly petrol prices.

From the above study, it is observed that 1-4-1 FFNN models can be used for forecasting the petrol prices in India. The forecasts are given below.

## 5. Conclusion

The forecasts from models were presented below.

**Table 6:** Forecasts using FFNN Models

| Month-Year | Original Values | Forecasts | | Month-Year | Original values | Forecasts |
|---|---|---|---|---|---|---|
| Jan-19 | 70.02 | 70.59 | | Jan-20 | 75.01 | 74.75 |
| Feb-19 | 70.83 | 70.15 | | Feb-20 | 72.23 | 74.94 |
| Mar-19 | 72.54 | 70.93 | | Mar-20 | 70.15 | 72.28 |
| Apr-19 | 72.93 | 72.58 | | Apr-20 | 69.59 | 70.28 |
| May-19 | 71.94 | 72.95 | | May-20 | 71.04 | 69.74 |
| Jun-19 | 70.42 | 72.00 | | Jun-20 | 76.1 | 71.13 |
| Jul-19 | 72.71 | 70.54 | | Jul-20 | 80.43 | 75.96 |
| Aug-19 | 72.10 | 72.74 | | Aug-20 | 80.95 | 79.87 |
| Sep-19 | 72.71 | 72.15 | | Sep-20 | 81.56 | 80.31 |
| Oct-19 | 73.46 | 72.74 | | Oct-20 | 81.06 | 80.82 |
| Nov-19 | 73.69 | 73.46 | | Nov-20 | 81.31 | 80.4 |
| Dec-19 | 74.81 | 73.68 | | Dec-20 | 83.22 | 80.61 |

The forecasts from FFNN models were presented below.

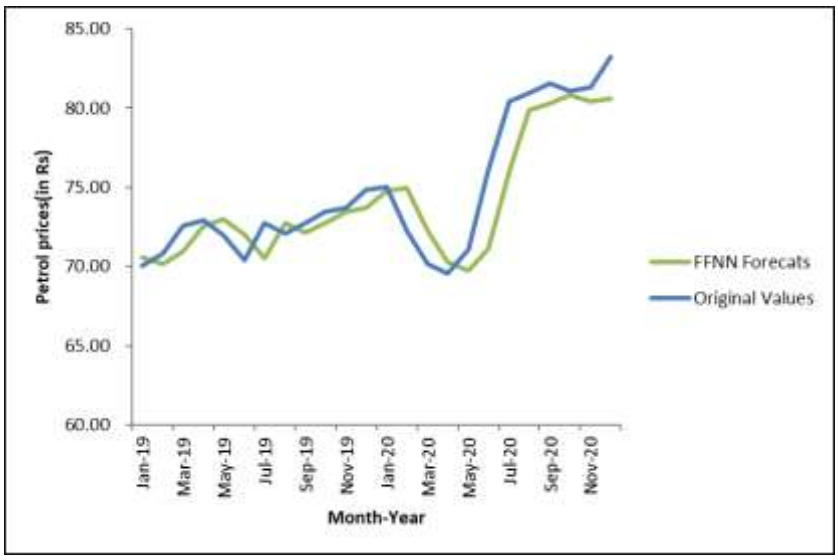


**Fig 4:** Out of Sample forecasts FFNN models on test data

## 7.References


1. Aarti Mehta Sharma and Saina Baby Gold Price Forecasting in India using ARIMA modeling 2015.
2. Ayodele Ariyo Adebiyi, Aderemi Oluyinka Adewumi, Charles Korede Ayo. Comparison of ARIMA and Artificial neural networks models for stock price prediction, Journal of Applied Mathematics 2014.
3. Banhi Guha, Gautam Bandyopadhyay. Gold Price Forecasting Using ARIMA Model 2016.
4. Box GEP, Jenkins GM, Reinsel GC. Time Series Analysis, Forecasting and Control, Prentice, Hall, 3rd edition 1994.
5. Destaings Nyongesa Nyongesa, Adolphus Wagala. Non Linear Time Series Modeling of the Diesel Prices in Kenya, International Journal of Academic Research in Economics and Management Science 2016, 5.
6. Ette Harrison Etuk, Tariq Mahgoub Mohamed. Time Series Analysis of Monthly Rainfall data for the Gadaref rainfall station, Sudan, by Sarima Methods 2014.
7. Peter Zhang G. Neural Networks in Business Forecasting, Idea Group Publishing 2004.
8. Balaraju K, Jakkula Srinivas, Rajendraprasad A. Bootstrapping methods and some aspects 2020.
9. Krishna Reddy M, Naveen Kumar B. Forecasting INR/USD exchange rates 2011.
10. Ranga Rao K, Naveen Kumar, Krishna Reddy M. A new method of forecasting south-west monsoon rainfall 2012.
11. Lemuel Clark P, Velasco, Daisy Lou L. Polestico2, Gary Paolo O. Macasieb A Hybrid Model of Autoregressive Integrated Moving Average and Artificial Neural Network for Load Forecasting, (IJACSA) International Journal of Advanced Computer Science and Applications 2019;10(11).

12. Mohammad Almasarweh, AL Wadi S. ARIMA Model in Predicting Banking Stock Market Data 2018.
13. Sulaiga Beevi M, Senthamarai Kannan K, Syed Ali S, Fathima. Univariate Time Series Models For Fuel Price, International Journal of Science & Technology Research, 2020, 9.
14. Murali Krishna K, Konda Reddy N, Raghavender Sharma M. Forecasting of daily prices of Gold in India using ARIMA and FFNN model, International Journal of Engineering and Advanced Technology (IJEAT) 2019;8(3).
15. Murali Krishna K, Raghavander Sharma M, Konda Redyy N. Forecasting INR/USD Exchange Rates using Hybrid and Neural Network Model, TEST Engineering and, Management Journal 2020.
16. Rangsan Nochai, Titida Nochai. ARIMA model for forecasting oil palm prices, Proceedings of the 2nd IMT-GT Regional Conference on Mathematics 2006.
17. Srikanth C, Rajendra Prasad A. Forecasting of Egg Prices data using Time Series Models –I, International Journal of Information and Computing Science 2020.