Forecasting non-linear WPI of manufacture of chemicals and chemical products in India: an MLP approach

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Abstract
Forecasting is an instrument of decision-making that makes predictions or estimates about the future based on historical data. Identifying a suitable strategy for forecasting a time series amongst the classical techniques (e.g., exponential smoothing, Auto-Regressive Integrated Moving Average (ARIMA)), Neural approach, and Support Vector Regression (SVR) - another widely used and popular machine learning-based approach, is challenging. The present work aimed at providing a simple (implementation wise), efficient (forecast accuracy wise), and state-of-art Multi-Layer Perceptron (MLP) approach for some selected macroeconomic indices (Wholesale Price Index - i.e., WPI) in India. We looked at the WPIs with non-linear trends identified using the curve-fit method. It’s known that the diverse Indian chemical industry contributes notably to India’s economic development. In this work, we analyzed the WPI of seventy-seven commodities/items of the ‘manufacture of chemicals and chemical products’ group in India. We detected the indices having non-linear trends by applying the curve-fit method. The curve-fit approach based on statistical rigor identifies the non-linear WPIs. Twenty-five out of seventy-seven indices exhibits non-linear trends. We developed a forecasting approach employing the MLP for these twenty-five non-linear WPIs. The proposed-MLP optimized by hyperparameter tuning offers high accuracy, prediction reliability, and prediction acceptability for all non-linear WPIs. The forecasting performances of the proposed-MLP compared with regression models (Linear, Quadratic, Cubic, Logarithmic, Exponential), exponential smoothing (Holt linear trend, Holt exponential trend, Holt-Winters), state-of-art Auto-ARIMA, and SVR. The MLP outperformed them all. In terms of Mean Absolute Percentage Error (MAPE), the MLP outperform Linear in 88%, Quadratic in 92%, Cubic in 88%, Logarithmic in 72%, exponential in 88%, Holt Linear in 80%, Holt Exponential in 76%, Holt-Winters in 72%, Auto-ARIMA in 56%, and SVR in 56% of cases. We suggest the application of the proposed approach as an alternative for forecasting these twenty-five non-linear WPIs.

Keywords
Curve fitting, Multilayer perceptron, Wholesale price index, ARIMA, Exponential smoothing, Support vector regression.

1. Introduction
Forecasting predicts/estimates the future by taking into account historical data. It's an instrument of decision-making that assists companies/enterprises/institutions in managing uncertainties. It allows the business to set up goals and create a budget. Forecasting helps us to anticipate changes and therefore guide us towards data-driven strategies and reasoned decisions/choices. It serves as a more proactive rather than a reactive measure.

There are several forecasting approaches for the univariate Time Series (TS) data, e.g., Auto-Regressive Integrated Moving Average (ARIMA) [1–3], Exponential Smoothing (ES) [4–6], Support Vector Regression (SVR) [7, 8, 9], neural approaches [10–12]. The recent studies show that the researchers employed these approaches for forecasting various TS data, e.g., stock prices [1, 2, 13], prices of agricultural products [4, 5, 6], the price index [10, 14].

India's chemical industry is highly diverse, covers a wide range of products, and has a large import and export base. More than two million people are working here. On the economic growth of India, this sector's contribution is notable. In the future, there
exists a significant opportunity for the industry's business/revenue growth.

In India, on the economic front, there exist several indicators. We can use these indicators to assess and forecast the performance of different sectors. We know that the Wholesale Price Index (WPI) is an indicator that monitors the price changes of goods before they reach the retail stage. The selling of these goods/items is in bulk and transacted between businesses. India's WPI series, the current one, has the base 2011-12 = 100 and lists seventy-seven commodities in the "manufacture of chemicals and chemical products" (ManufChem-Item) group.

To suggest an appropriate forecasting strategy for the WPIs having non-linear trends from the ManufChem-Item group in India that is simple (implementation wise) and efficient (forecast accuracy wise) and can act as a convenient alternative is a challenge. Motivated by this, the objectives of this work are as follows:

- Trend examination of the monthly WPIs of seventy-seven commodities of the ManufChem-Item group of India's current WPI series. The data is of forty-eight months, starting in April 2012 and ending in March 2016.
- Identification of the WPIs of ManufChem-Item group having a non-linear trend (WPINonLinear) during this period.
- Model development for the WPINonLinear indices suitable to render twelve months ahead forecasts.

In this work, we analyzed these seventy-seven WPIs, identified those that have non-linear trends by applying the curve fit, and developed forecast models for these identified WPIs. An Artificial Neural Network (ANN) is a computational tool used for solving complex problems Marini [15], non-linear data modeling Bertolaccini et al. [16], and suitable for learning non-linear relationships and modeling them [17]. In this work, for forecasting the non-linear WPIs, we employed the Multi-Layer Perceptron (MLP) - a class of ANN.

2. Literature review

Wadi et al. [1] found the best-fit ARIMA model for forecasting the closed price of Jordan's ASE, with p, d, and q parameters of 2, 1, and 1 correspondingly, and Root Mean Squared Error (RMSE)=4. For the banking stock data of Jordan's ASE, the ARIMA p=1, d=1, and q=2 suited most with RMSE=1.4 Almasarweh and Alwadi [2]. While forecasting the trucking prices in the US, Miller [3] found that the ARIMA with p=1, d=1, and q=0 best fitted to forecast the Truckload. BLS data. Azari [18] used ARIMA to predict the bitcoin price and witnessed increased MSE due to the price fluctuations of the bitcoins when working with the closing price. Hossain et al. [13] found the best-fitted ARIMA model for forecasting the banking stock data of Bangladesh's DSE is having p=0, d=2, and q=1 parameters and produced MAPE=1.632, and RMSE=0.046. Zhu et al. [19] used this approach using p=1, d=1, and q=1 to forecast COVID-19 cases in China. Katoch and Sidhu [20] forecast India's COVID-19 confirmed cases using the method having p=4, d=2, and q=7.

Talwar and Goyal [4] applied different ES approaches to predict Indian coriander price and observed Holt-Winters trend-adjusted model with alpha=1 and beta=0.06 performs best, and the model showed RMSE=100.11. In production forecasting of Thailand's crude palm oil, Suppalakpanya et al. [5] studied various ES techniques, observed that additive Holt-Winters and extended additive Holt-Winters exhibited the smallest MAPE. To forecast the price of potatoes in Turkey, Şahinli [6] used ARIMA, Holt-Winters additive, and Holt-Winters multiplicative approaches and found the ARIMA model with p=1, d=1, and q=2 is the best. Rasheed et al. [21] forecast the PKR's exchange rate using the ES technique and obtained MAPE=6.53. Sokannit and Chujai [22] applied the triple ES to forecast electricity (household consumption). Li et al. [23] found the multiplicative Holt-Winters is a suitable approach to predict the agriculture and forestry's gross output value in Guangxi, China. While performing the forecast of Indonesian construction companies' share prices, Ali [24] noted that Holt's double ES method is suitable for forecasting.

In forecasting the Spanish tourism demand, the SVR using RBF kernel outdid the ARMA approach Claveria et al. [7]. The SVR method with c=6 and gamma=0.01 beats the ARIMA model with p=0, d=1, and q=1 parameters, simple ES model with alpha=0.9, and Moving Average model in forecasting US crude oil prices He [8]. Carrasco et al. [25] examined the application of the Support Vector Machine (SVM) in predicting the London Metal Exchange's copper price and observed good performance of the approach. Kuizinienė et al. [9] forecast cryptocurrencies using SVR with a linear kernel and ARIMA, found that ARIMA beat SVR. Rohmah et al. [14] examined the SVR method's following four different Kernels in forecasting the
Consumer Price Index (CPI) of Indonesia: Linear, Polynomial, Spline, and Gaussian-RBF. The authors Rohmah et al. [14] observed that the Gaussian-RBF outperformed other kernels and found it more suitable for forecasting the CPI. In forecasting Hong Kong's property price index, the authors Abidoye et al. [10] contrasted the ARIMA methodology to two well-known AI approaches: (i) SVM and (ii) Artificial Neural Network (ANN) [10]. They employed the "backpropagation multilayer perceptron ensemble" algorithm to train the ANN. Airlangga et al. [11] compared the backpropagation-ANN and four ES methods - single, double, additive triple, and multiplicative triple for forecasting the Indonesian rice production where the former outperformed the ES methods. Spiliotis et al. [12] applied various statistical and ML approaches to predict Belgium's electricity prices, observed the MLP outperformed the naive Bayes, ES, multiple linear regression, and seasonal ARIMA approaches. To forecast the BCG vaccine demand in Cabanatuan city, the Philippines, the authors Alegado and Tumibay [26] found the MLP having 16/5/1 architecture showed MSE=31.79 and exceeded the ARIMA. To forecast the COVID-19 confirmed cases in Iran, Talkhi et al. [27] showed that the MLP performed well with a low Mean Absolute Percentage Error (MAPE) (5.72 approx.).

From the literature reviewed, the author's observations are the followings:

- Different ES approaches and ARIMA were widely employed on several TS data and provided efficient results (forecast accuracy wise).
- Researchers applied various machine learning approaches (e.g., neural approach, SVR) for univariate TS forecasting and obtained efficient results.
- In studies, the researchers pointed out the neural approaches are suitable for learning non-linear relationships and modeling them.

The authors further identified the following research gaps in the recent studies: application of the TS forecasting techniques - (a) regression models, (b) different ES techniques, (c) ARIMA approach, (d) MLP approach, and (e) SVR approach for forecasting the non-linear WPIs of India from the "manufacture of chemicals and chemical products" group.

The present work aims at bridging the gaps by identifying the non-linear WPIs from the said set, developing a simple (implementation wise), efficient (forecast accuracy wise), and state-of-art MLP approach for forecasting these non-linear WPIs, and comparing its performance with the results of other techniques to analyze the quality of the proposed approach.

### 3. Methodology

The methodology used is portrayed graphically in Figure 1. The authors employed the following seven distinct steps to approach their objectives: (a) data collection (Step1), (b) data partition (Step2), (c) application of curve fitting to the WPIs of ManufChem-Item group, and identification of non-linear fit (Step3), (d) selection of the WPIs of ManufChem-Item group showing non-linear trend (Step4), (e) modeling the proposed MLP to forecast WPI\textsubscript{NonLinear} (Step5), (f) forecast model building for the WPI\textsubscript{NonLinear} using other approaches (Step6), and (g) forecasting performance evaluation (Step7). The steps are discussed in detail in 3.1 to 3.7.

![Figure 1 Methodology of MLP modeling of the WPI\textsubscript{NonLinear} of ManufChem-Item group](image-url)
3.1 Data collection (Step 1)
We gathered the monthly data of all the seventy-seven commodities listed in the ManufChem-Items group of India’s current WPI series. The data is of sixty months, starting in April 2012 and ending in March 2017. We gathered the data from the data.gov.in platform [28].

3.2 Data partition (Step 2)
We partitioned the data into two parts - training and test sets. The training set is again further subdivided into the training and validation subsets. Figure 2 represents the data division scheme of the present work.

3.3 Application of curve fitting to the WPIs of ManufChem-Items group and identification of non-linear fit (Step 3)
For each WPI, Figure 3 describes the process of non-linear trend determination achieved through curve fitting. The curve best fitted gave us the result. We used the lm function of R’s stats package for fitting curves to data points [29].
3.4 Selection of the WPIs of Manuf-Chem-items group showing non-linear trend (Step4)
If a WPI showed Quadratic/ Cubic/ Logarithmic/ Exponential best fit, we identified it as a non-linear trend exhibiting index. The WPIs showing non-linear trend (WPI_{NonLinear}) is selected.

3.5 Modeling the proposed MLP to forecast WPI_{NonLinear} (Step5)
The MLP architecture offered to forecast the WPI_{NonLinear} is portrayed in Figure 4.

![MLP architecture for forecasting WPI_{NonLinear}](image)

**Figure 4** MLP architecture for forecasting WPI_{NonLinear}

We performed hyperparameter tuning of the MLP model for each WPI_{NonLinear} and used the tuned model for 12 months ahead forecasts. We applied lag1, lag2, and lag3 of the TS as inputs to the MLP with two hidden layers. Layer one consists of one neuron. We performed hyperparameter tuning to get the number of neurons in layer two (N) and obtain the optimized model. The hyperparameter search space is: N = {1,2,3,4,5}. The N value of the tuned model is the value at which the forecast-MAPE is the lowest. **Figure 5** presents the flowchart of the hyperparameter tuning of the proposed MLP.

For each WPI_{NonLinear}, we built the mlp model using its corresponding tuned hyperparameter and performed twelve months ahead forecasts.

![Hyperparameter tuning of the proposed MLP for WPI_{NonLinear}](image)

**Figure 5** Hyperparameter tuning of the proposed MLP for WPI_{NonLinear}

3.6 Forecast model building for the WPI_{NonLinear} using other approaches (Step6)
In this work, we employed widely accepted and used TS forecasting approaches to forecast and compared their performances with the proposed MLP. For each WPI_{NonLinear}, we developed the following models:
- Regression [31, 32]: Linear (L1), Quadratic (Q), Cubic (C), Logarithmic (L2), and Exponential (E)
- Exponential smoothing [5, 6]: Holt’s linear trend (H1), Holt’s exponential trend (H2), and Holt-Winters (HW)
- Auto ARIMA (A) [33, 34]
- SVR [10, 14]

We used R’s stats package to build the regression models [29]. To develop the exponential smoothing and automatic ARIMA models, we employed R software’s forecast package [35, 36]. We applied R software e1071 package [37] for developing the SVR model. For each WPI_{NonLinear} using each model, we performed twelve months ahead forecasts.
3.7 Forecasting performance evaluation (Step 7)

For each WPI using each model, we calculated the following accuracy metrics using the forecasts and the test set:

- Mean Absolute Error (MAE) [38]
- Mean Absolute Percentage Error (MAPE) [38]
- Root Mean Squared Error (RMSE) [38]
- Theil's U statistics [39]

We consider the forecast accuracy to be high if the MAPE is less than ten [40, 41], and the forecast to be (i) reliable and (ii) acceptable if Theil's U statistics close to zero [39, 41]. We evaluated the MLP's forecast performances and compared them with others.

4. Results

4.1 Curve fitting and trend analysis of seventy-seven WPIs of ManufChem-Items group

To illustrate the process, we used the WPI of Organic Solvent, applied five models on the training set, and determined the probable best fit. We gave the analysis outcome in Table 1. We developed the following models: L1, Q, C, L2, and E.

We illustrated the residual analysis of the identified model in Figure 6.

Findings: The residuals are approximately normally distributed and do not exhibit any outlier. Therefore, the cubic fit is the best.

We employed the curve fitting technique on each seventy-seven indexes, identified their best fits, and illustrated the summary of findings in Figure 7.

Findings: We observed that twenty-five out of seventy-seven indices exhibited best fits. The analysis of the fits found is as follows: (i) thirteen WPIs exhibited quadratic, (ii) four WPIs exhibited cubic, and (iii) eight WPIs exhibited exponential fits. Accordingly, we conclude, these twenty-five WPIs exhibit non-linear trends (WPINonLinear).

We listed the index code (used in this work) of these WPINonLinear, and their respective best-fits in Table 2.

Table 1 Result of curve fit of WPI of organic solvent

| Fit results | Model | L1 | Q | C | L2 | E |
|-------------|-------|----|---|---|----|---|
| R²          |       | 0.23 | 0.86 | 0.89 | 0.02 | 0.24 |
| Adjusted R² |       | 0.21 | 0.85 | 0.89 | - | 0.001 | 0.22 |
| F test      |       | 13.55 | 133.39 | 124.52 | 0.94 | 14.64 |
| Sig. of F test |   | <0.05 | <0.05 | <0.05 | 0.34 | <0.05 |
| Competing models | | NA | √ | √ | NA | NA |
| AIC         |       | 264.28 | 251.18 |
| Probable best fit | | NA | NA | √ | NA | NA |

Findings: We observed that only two models, namely Q and C, had both R² and Adjusted R² ≥ 0.7, and the significance of the F test < 0.05 and thus met the criteria to become competing models. Model ‘C’ had the lowest AIC, and we identified it as the probable best-fit model.

We illustrated the residual analysis of the identified model in Figure 6.

Table 2 List of WPINonLinear of ManufChem-Items group of India’s WPI

| No. | Name of the WPINonLinear | Index code | Best-fit |
|-----|--------------------------|------------|----------|
| 1.  | Organic Solvent          | V1         | C        |
| 2.  | Dye stuff/dyes incl. dye intermediates and pigments/colours | V2 | C |
| 3.  | Acetic acid and Its Derivatives | V3 | C |
4.2 Forecast model development of the WPI\textsubscript{NonLinear} using the proposed MLP approach

For each of the WPI\textsubscript{NonLinear} indices, Table 3 listed the hyperparameter tuning results.

Findings: We performed the hyperparameter tuning to obtain the optimized hyperparameter value, i.e., the number of neurons in the second hidden layer of the MLP for each WPI\textsubscript{NonLinear}. The hyperparameter tuning resulted in the final models for each WPI\textsubscript{NonLinear}. We observed that the final MLP model for ten indexes, namely V6, V10, V11, V13, V14, V15, V16, V17, V20, and V24, obtained 3/1/1/1 configurations. The final model of V7 is 3/1/2/1, whereas three indexes, namely V18, V19, and V22, attained 3/1/3/1 configurations. The following seven indexes obtained 3/1/4/1 configurations: V1, V2, V8, V12, V21, V23, and V25. For the remaining four, i.e., V3, V4, V5, and V9 indexes, 3/1/5/1 is the final model.

Table 3 Final MLP model of each WPI\textsubscript{NonLinear} index obtained by hyperparameter tuning

| WPI | Hyperparameter tuning | MAPE for | Final Model |
|-----|-----------------------|----------|-------------|
|     | N=1                   | N=2      | N=3        | N=4 | N=5 |         |
| V1  | 10.44                 | 10.56    | 10.47      | 10.36 | 10.53 | 3/1/4/1 |
| V2  | 14.73                 | 14.74    | 14.77      | 14.61 | 14.67 | 3/1/4/1 |
| V3  | 13                    | 13.49    | 13.02      | 12.92 | 12.87 | 3/1/5/1 |
| V4  | 3.83                  | 3.82     | 3.83       | 3.76  | 3.73  | 3/1/5/1 |
| V5  | 5.746                 | 5.746    | 5.735      | 5.729 | 5.728 | 3/1/5/1 |
| V6  | 4.14                  | 4.22     | 4.17       | 4.29  | 4.26  | 3/1/1/1 |
| V7  | 6.61                  | 6.47     | 6.52       | 6.5   | 6.54  | 3/1/2/1 |
| V8  | 0.91                  | 0.96     | 0.91       | 0.82  | 0.89  | 3/1/4/1 |
| V9  | 5.821                 | 5.436    | 5.41       | 5.436 | 5.408 | 3/1/5/1 |
| V10 | 1.24                  | 1.6      | 1.52       | 1.64  | 1.65  | 3/1/1/1 |
| V11 | 17.68                 | 17.69    | 17.71      | 17.72 | 17.78 | 3/1/1/1 |
| V12 | 8.45                  | 8.4      | 8.42       | 8.36  | 8.37  | 3/1/4/1 |
| V13 | 12.68                 | 12.71    | 12.68      | 12.71 | 12.7  | 3/1/1/1 |
| V14 | 5.53                  | 5.54     | 5.57       | 5.59  | 5.56  | 3/1/1/1 |
| V15 | 2.98                  | 3.05     | 3.02       | 3.04  | 3.03  | 3/1/1/1 |
| V16 | 1.2                   | 1.24     | 1.25       | 1.23  | 1.25  | 3/1/1/1 |
| V17 | 3.83                  | 4.6      | 7.08       | 6.98  | 6.98  | 3/1/1/1 |
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Hyperparameter tuning

| WPI | N=1 | N=2 | N=3 | N=4 | N=5 | Final Model |
|-----|-----|-----|-----|-----|-----|-------------|
| V18 | 5.181 | 5.171 | 5.147 | 5.17 | 5.152 | 3/1/3/1 |
| V19 | 2.18 | 2.18 | 2.17 | 2.19 | 2.17 | 3/1/3/1 |
| V20 | 8.13 | 8.26 | 8.24 | 8.27 | 8.24 | 3/1/3/1 |
| V21 | 1.339 | 1.341 | 1.326 | 1.324 | 1.357 | 3/1/4/1 |
| V22 | 3.905 | 3.9 | 3.897 | 3.9 | 3.889 | 3/1/3/1 |
| V23 | 11.2 | 10.93 | 11.13 | 10.37 | 11.37 | 3/1/4/1 |
| V24 | 1.4 | 1.5 | 1.57 | 1.55 | 1.57 | 3/1/1/1 |
| V25 | 4.24 | 4.69 | 3.98 | 3.96 | 4.01 | 3/1/4/1 |

4.3 Forecasting performance of the MLP

Table 4 lists the forecasting performances of the MLP.

| Forecast accuracy metrics | Criteria | No. of WPI (MLP best) | Remarks |
|---------------------------|----------|------------------------|---------|
| MAPE ≤ 10                | Close to zero | 25 | High model accuracy |
| Theil’s U statistics     |          | 25 | Forecast is (i) reliable and (ii) acceptable |

Findings: The MLP (proposed model) exhibits high model accuracy, along with reliable and acceptable forecasting for twenty-five out of twenty-five WPI\textsubscript{NonLinear} indices.

4.4 Comparison of forecast accuracies

We performed a comparative analysis of the forecast accuracies of the MLP (proposed) with the forecast accuracies of the following models: L1, Q, C, L2, E, H1, H2, HW, A. We assumed that a model’s forecasting performance is best if its forecast accuracy metric is less (than the other). We evaluated forecast accuracy metrics of the MLP with each of the nine models individually, counted the indices for which the proposed MLP performed best, and displayed the results in Table 5.

Table 5 Comparison of forecast accuracies of the MLP with nine models

| Models   | Category | No. of WPI (MLP best) | Total no. of WPI |
|----------|----------|------------------------|------------------|
| MLP and L1 | MAE\textsubscript{MLP} < MAE\textsubscript{L1} | 22 | 25 |
|          | MAPE\textsubscript{MLP} < MAPE\textsubscript{L1} | 22 | 25 |
|          | RMSE\textsubscript{MLP} < RMSE\textsubscript{L1} | 20 | 25 |
|          | Theil’s U\textsubscript{MLP} < Theil’s U\textsubscript{L1} | 20 | 25 |
| MLP and Q  | MAE\textsubscript{MLP} < MAE\textsubscript{Q} | 23 | 25 |
|          | MAPE\textsubscript{MLP} < MAPE\textsubscript{Q} | 23 | 25 |
|          | RMSE\textsubscript{MLP} < RMSE\textsubscript{Q} | 23 | 25 |
|          | Theil’s U\textsubscript{MLP} < Theil’s U\textsubscript{Q} | 23 | 25 |
| MLP and C  | MAE\textsubscript{MLP} < MAE\textsubscript{C} | 22 | 25 |
|          | MAPE\textsubscript{MLP} < MAPE\textsubscript{C} | 22 | 25 |
|          | RMSE\textsubscript{MLP} < RMSE\textsubscript{C} | 22 | 25 |
|          | Theil’s U\textsubscript{MLP} < Theil’s U\textsubscript{C} | 22 | 25 |
| MLP and L2 | MAE\textsubscript{MLP} < MAE\textsubscript{L2} | 18 | 25 |
|          | MAPE\textsubscript{MLP} < MAPE\textsubscript{L2} | 18 | 25 |
|          | RMSE\textsubscript{MLP} < RMSE\textsubscript{L2} | 17 | 25 |
|          | Theil’s U\textsubscript{MLP} < Theil’s U\textsubscript{L2} | 17 | 25 |
| MLP and E  | MAE\textsubscript{MLP} < MAE\textsubcript{E} | 22 | 25 |
|          | MAPE\textsubscript{MLP} < MAPE\textsubscript{E} | 22 | 25 |
|          | RMSE\textsubscript{MLP} < RMSE\textsubscript{E} | 20 | 25 |
|          | Theil’s U\textsubscript{MLP} < Theil’s U\textsubscript{E} | 20 | 25 |
| MLP and H1 | MAE\textsubscript{MLP} < MAE\textsubscript{H1} | 19 | 25 |
Findings: The proposed MLP surpassed others in connection with the total number of good performances for all four accuracy metrics when compared individually.

For each WPI\textsubscript{NonLinear}, we performed a comparison to find out which model performs best. We picked out the best-performing model amongst all compared models for each WPI\textsubscript{NonLinear}. For each model, we counted the total best performances. The overall comparison of the models shown in Figure 8 represents the number of best performances of each model.
Findings: The proposed MLP surpassed others in connection with the total number of good performances for all four-accuracy metrics when compared collectively.

Using different MAPE criteria, we examined the forecast MAPE of nine applied models and the proposed MLP, and Table 6 presents the results.

Table 6 Model comparison using different forecast MAPE criteria

| Model | The total number of indices, meeting the criteria | MAPE ≤ 10 | MAPE ≤ 7.5 |
|-------|-----------------------------------------------|----------|------------|
| L1    |                                              | 22       | 17         |
| Q     |                                              | 13       | 9          |
| C     |                                              | 11       | 8          |
| L2    |                                              | 21       | 15         |
| E     |                                              | 21       | 17         |
| H1    |                                              | 21       | 17         |
| H2    |                                              | 22       | 17         |
| HW    |                                              | 23       | 20         |
| A     |                                              | 25       | 24         |
| Proposed MLP approach | 25       | 25         |

Findings: Except for model A, the proposed MLP bettered others in connection with the total number of indices, meeting the following criteria: (i) MAPE ≤ 10 and (ii) MAPE ≤ 7.5. For MAPE ≤ 10, models 'A' and MLP performed the same. The MLP bettered model 'A' in connection with the other criterion, i.e., MAPE ≤ 7.5.

Notwithstanding the encouraging forecasting performances of the MLP-proposed and to test the prudence of this MLP approach, we compared the forecasting performance of the MLP with the SVR - another popular machine learning (ML) approach.

We performed hyperparameter tuning of the SVR model for each WPINonLinear and used the tuned model for 12 months ahead forecasts. We applied the RBF kernel for model development. For hyperparameter tuning, we used the training subset (to develop the model) and the validation subset (to calculate forecast-MAPE). The hyperparameter search space is given by gamma (γ) = {1, 1.25, 1.5, 1.75, 2}. The gamma value of the tuned model is the value at which the forecast-MAPE is the lowest. Figure 9 presents the flowchart of the hyperparameter tuning of the SVR. Table 7 listed the hyperparameter tuning results of the SVR approach for each of these twenty-five indices.

For each WPINonLinear indices, we compared the SVR and the proposed MLP's forecast performance and identified the best-performing model. We counted the number of WPINonLinear indexes for which the MLP performed best and displayed the results in Table 8.

Figure 9 Hyperparameter tuning of SVR for WPINonLinear

Table 7 Hyperparameter tuning and optimized Gamma of the SVR models for twenty-five WPINonLinear indices

| WPI | Hyperparameter tuning | Optimized Γ |
|-----|-----------------------|-------------|
|     | γ = 1 | γ = 1.25 | γ = 1.5 | γ = 1.75 | γ = 2 |        |
| V1  | 10.44 | 10.56  | 10.47  | 10.36  | 10.53 | 1.75   |
| V2  | 14.73 | 14.74  | 14.77  | 14.61  | 14.67 | 1.75   |
| V3  | 13.00 | 13.49  | 13.02  | 12.92  | 12.87 | 2      |
| V4  | 3.83  | 3.82   | 3.83   | 3.76   | 3.73  | 2      |
Hyperparameter tuning

| WPI   | $\gamma = 1$ | $\gamma = 1.25$ | $\gamma = 1.5$ | $\gamma = 1.75$ | $\gamma = 2$ |
|-------|---------------|-----------------|----------------|-----------------|--------------|
| V5    | 5.75          | 5.75            | 5.73           | 5.73            | 5.73         | 2            |
| V6    | 4.14          | 4.22            | 4.17           | 4.29            | 4.26         | 1            |
| V7    | 6.61          | 6.47            | 6.52           | 6.50            | 6.54         | 1.25          |
| V8    | 0.91          | 0.96            | 0.91           | 0.82            | 0.89         | 1.75          |
| V9    | 5.82          | 5.44            | 5.41           | 5.44            | 5.41         | 2            |
| V10   | 1.24          | 1.60            | 1.52           | 1.64            | 1.65         | 1            |
| V11   | 17.68         | 17.69           | 17.71          | 17.72           | 17.78        | 1            |
| V12   | 2.45          | 2.40            | 2.42           | 2.36            | 2.37         | 1.75          |
| V13   | 12.68         | 12.71           | 12.68          | 12.71           | 12.70        | 1            |
| V14   | 5.53          | 5.54            | 5.57           | 5.55            | 5.56         | 1            |
| V15   | 2.98          | 3.05            | 3.02           | 3.04            | 3.03         | 1            |
| V16   | 1.20          | 1.24            | 1.25           | 1.23            | 1.25         | 1            |
| V17   | 3.83          | 4.60            | 7.08           | 6.98            | 6.98         | 1            |
| V18   | 5.18          | 5.17            | 5.18           | 5.17            | 5.15         | 1.5           |
| V19   | 2.18          | 2.18            | 2.17           | 2.19            | 2.17         | 1.5           |
| V20   | 8.13          | 8.26            | 8.24           | 8.27            | 8.24         | 1            |
| V21   | 1.34          | 1.34            | 1.33           | 1.32            | 1.36         | 1.75          |
| V22   | 3.90          | 3.90            | 3.90           | 3.90            | 3.90         | 1.5           |
| V23   | 11.20         | 10.93           | 11.13          | 10.37           | 11.37        | 1.75          |
| V24   | 1.40          | 1.50            | 1.57           | 1.55            | 1.57         | 1            |
| V25   | 4.24          | 4.69            | 3.98           | 3.96            | 4.01         | 1.75          |

Table 8 Comparison of the SVR and the proposed MLP's forecast accuracies

| Models | Category | No. of WPI (MLP best) | Total no. of WPI |
|--------|----------|-----------------------|-----------------|
| MLP    | MAE$_{MLP} <$ MAE$_{SVR}$ | 14 | 25 |
| SVR    | MAE$_{MLP} <$ MAE$_{SVR}$ | 14 | 25 |
|        | RMSE$_{MLP} <$ RMSE$_{SVR}$ | 14 | 25 |
|        | Theil’s $U_{MLP} <$ Theil’s $U_{SVR}$ | 14 | 25 |

Findings: The proposed MLP surpassed the SVR in connection with the total number of best performances for all four accuracy metrics.

Table 9 Comparison of Proposed MLP and SVR using different MAPE criteria

| Model | Total number of indices meeting the criteria | MAPE $\leq 10$ | MAPE $\leq 7.5$ |
|-------|---------------------------------------------|----------------|----------------|
| Proposed MLP | 25 | 25 |
| SVR | 22 | 22 |

Findings: The MLP is a clear winner for both MAPE less than equal to 10 and 7.5.

Table 10 Performance comparison of the proposed MLP with the MLP models of others

| Authors                | Details                        | Forecast horizon | Forecast accuracy metrics (MAE, RMSE, MAPE) |
|------------------------|--------------------------------|------------------|------------------------------------------|
| Khashei and Hajirahimi (2019) [42] | Dow Jones Industrial Average Index | 60 months (25% of the total number of observations) | MAE 366.81, RMSE 471.09, MAPE 3.48 |
|                        | Shenzhen Integrated Index       | 48 months (23% of the total number of observations) | MAE 1102.34, RMSE 1405.16, MAPE 9.81 |
|                        | Nikkei 225                     | 201 days (20% of the total number of observations) | MAE 100.03, RMSE 123.29, MAPE 0.98 |
| Lu et al. (2020) [43]  | Shanghai Composite Index (000001) | 500 days (approximately 7% of the total number of observations) | MAE 37.58, RMSE 49.80 |
| Herrera et al. (2019) [44] | Oil Brent | 20% (app) of the total number of observations | MAE 17.34, RMSE 17.92, MAPE 3.48 |
|                        | Oil WTI                        |                  | MAE 14.72, RMSE 16.56 |
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| Authors | Details | Forecast horizon | Forecast accuracy metrics |
|---------|---------|------------------|--------------------------|
|         |         |                  | MAE | RMSE | MAPE |
| Oil Dubai |        |                  | 20.29 | 20.43 |       |
| Coal AU  |        |                  | 12.80 | 11.54 |       |
| Gas US   |        |                  | 0.78  | 23.72 |       |
| Gas Russia |       |                  | 2.68  | 32.88 |       |
| Our work | Twenty-five non-linear trends exhibiting WPI of the ManufChem-Items group of India | 12 months (20% of the total number of observations) | 0.64* | 0.81* | 0.56* |

* Best performance of the proposed MLP obtained for index V2

Findings: The proposed MLP surpassed others in connection with the best performances for the three-accuracy metrics - MAE, RMSE, and MAPE.

A complete list of abbreviations is shown in Appendix I.

5. Discussions

In this work, the authors intended to develop a simple (implementation wise), efficient (forecast accuracy wise), and state-of-art MLP approach for the non-linear indexes of the ManufChem-Items group from the Indian WPI series for bridging the gaps identified from the past studies. The outcomes of the present work are as follows:

- We observed that twenty-five out of seventy-seven WPIs, i.e., thirty-two point four seven percent exhibited non-linear fits. The rest of the WPIs (67.53%) could not find any fits. In this present work, we focused on only the WPIs with non-linear fits identified through curve fitting.
- For forecasting the WPINonLinear indices, we proposed and developed a simple and efficient MLP approach. The model exhibits high model accuracy (MAPE ≤ ten), along with reliable and acceptable forecasting (Theil's U statistics close to zero) for twenty-five out of twenty-five indices, i.e., for hundred percent cases.
- We compared the forecast accuracies (MAE, MAPE, RMSE, and Theil's U) of the proposed MLP with the other applied models (L1, Q, C, L2, E, H1, H2, HW, A, and SVR). We observed that the proposed MLP exhibited the lowest MAE, MAPE, RMSE, and Theil's U statistics for the maximum number of indices when compared MLP versus a single model (i.e., individual comparison) and MLP versus all models (i.e., compared collectively). Therefore, we witnessed the model (MLP) achieved better forecast accuracies than others and outperformed others.
- The precision of the proposed MLP is also better than others. For the proposed MLP, the count of the total number of indices showing forecast-

5.1 Limitations

We proposed and developed an MLP approach for the WPINonLinear indexes of the ManufChem-Items group from the Indian WPI series. Out of seventy-seven WPIs, fifty-two WPIs could not exhibit any best fit and therefore remain out of the scope of this work. We have not examined the performance of the proposed MLP on these sets of WPIs to judge the forecastability of our proposed model on the TS dataset that could not show any clear trends. In the present work, we compared the performance of the proposed model on a limited set (twenty-five) of WPIs exhibiting non-linear trends. Exploring the hyperparameters (e.g., number of hidden layers, number of neurons) of the MLP is another challenging area for future work.

6. Conclusion and future work

Time-series forecasting acts as an instrument of decision-making, produces estimations about the future based on historical data. The suggestion of an appropriate forecasting strategy that is simple (implementation wise) and efficient (forecast accuracy wise) for a time-series dataset and that (proposed approach) can act as a convenient alternative is challenging. This work provides a state-of-art alternative forecasting strategy for some selected WPIs in India. The proposed method applies the MLP - a neural approach to model and forecast the non-linear WPIs. For each WPI, the proposed-MLP employs historical data of the univariate series as inputs, uses optimized hyperparameter, trains multiple networks, combines their forecast values, and obtains an ensemble forecast. We looked at the WPIs with non-linear trends identified using the curve-fit method. The curve-fit approach based on statistical rigor identifies the non-linear WPIs.

The chemical industry is a multiple-product industry and one of the fastest-growing in India. There are
seventy-seven individual items in the ManufChem Items group of India's present WPI. Identification of the trends of these seventy-seven WPIs and proposing an efficient forecasting approach for the WPIs from the group that exhibits non-linear trends is indeed challenging. In this work, we identified the WPIs of the ManufChem Items group with non-linear trends and proposed an efficient forecasting approach for them. We analyzed each of the seventy-seven WPIs of the ManufChem Items group exercising curve fitting, identified the WPIs with non-linear trends (WPINonLinear), and developed a forecasting approach applying MLP for these WPINonLinear indices. The proposed model is suitable to render twelve months ahead forecasts.

The novel contributions of this work are the following:

- Identification of the WPIs of the ManufChem Items group with non-linear trends using the curve-fit method
- Development of a simple (implementation wise) and efficient (forecast accuracy wise) forecasting approach for these WPIs (i.e., WPINonLinear indices) by applying MLP

At first, we employed curve fitting to analyze the seventy-seven WPIs and determined the WPINonLinear indices. We observed that twenty-five out of seventy-seven WPIs - i.e., approximately thirty-two point five percent of indices exhibit non-linear trends. The majority of the fits are quadratic - i.e., thirteen out of twenty-five.

Next, we developed forecasting models for these twenty-five WPINonLinear indices using the following ten models: (i) MLP (proposed approach), (ii) Linear, (iii) Quadratic, (iv) Cubic, (v) Logarithmic, (vi) Exponential, (vii) Holt linear trend, (viii) Holt exponential trend, (ix) Holt-Winters, and (x) Auto-ARIMA. The MLP (proposed approach) exhibits high model accuracy, along with reliable and acceptable forecasting for twenty-five out of twenty-five WPINonLinear indices. The proposed approach also surpassed others in connection with the following:

- Total number of best performances when compared individually
- Total number of best performances when compared with all others at the same time
- MAPE less than equal to seven point five

Notwithstanding the promising forecasting performance of the MLP (proposed approach) and to test its prudence, we examined the proposed-MLP's performance against SVR's performance and noted that the proposed MLP surpassed the SVR in connection with the following:

- Total number of best performances
- MAPE less than equal to ten
- MAPE less than equal to seven point five

According to our findings, the proposed-MLP outperformed the regression, exponential smoothing, Auto ARIMA, and SVR methods on different accuracy metrics applying varied criteria. Therefore, we suggest the proposed MLP is a suitable alternative for forecasting these twenty-five WPINonLinear indices for the next twelve months. Additionally, validating the proposed approaches' accuracy and suitability on different sets of indices with non-linear trends or indices that do not show any trends creates a new research direction. Exploring the hyperparameters of the MLP by expanding the search space to achieve better efficiency is another area in the future scope of this work.

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Conflicts of interest
The authors have no conflicts of interest to declare.

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Appendix I

| S. No. | Abbreviation | Description |
|-------|-------------|-------------|
| 1     | A           | Auto ARIMA  |
| 2     | AIC         | Akaike’s Information Criteria |
| 3     | ANN         | Artificial Neural Network |
| 4     | ARIMA       | Auto-Regressive Integrated Moving Average |
| 5     | C           | Cubic       |
| 6     | CPI         | Consumer Price Index |
| 7     | E           | Exponential |
| 8     | ES          | Exponential Smoothing |
| 9     | H1          | Holt’s Linear Trend |
| 10    | H2          | Holt’s Exponential Trend |
| 11    | HW          | Holt-Winters |
| 12    | L1          | Linear      |
| 13    | L2          | Logarithmic |
| 14    | MAE          | Mean Absolute Error |
| 15    | MAE<sub>A</sub> | Mean Absolute Error of Auto ARIMA |
| 16    | MAE<sub>C</sub> | Mean Absolute Error of Cubic |
| 17    | MAE<sub>E</sub> | Mean Absolute Error of Exponential |
| 18    | MAE<sub>H1</sub> | Mean Absolute Error of Holt’s Linear Trend |
| 19    | MAE<sub>H2</sub> | Mean Absolute Error of Holt’s Exponential Trend |
| 20    | MAE<sub>HW</sub> | Mean Absolute Error of Holt-Winters |
| 21    | MAE<sub>LI</sub> | Mean Absolute Error of Linear |

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22 MAE<sub>L1</sub> Mean Absolute Error of Logarithmic
23 MAE<sub>MLP</sub> Mean Absolute Error of MLP
24 MAE<sub>E</sub> Mean Absolute Error of Quadratic
25 MAE<sub>SVR</sub> Mean Absolute Error of Support Vector Regression
26 MAE<sub>WPIChemicals and Chemical Products</sub> Manufacture of Chemicals and Chemical Products
27 MAPE Mean Absolute Percentage Error
28 MAPE<sub>A</sub> Mean Absolute Percentage Error of Auto ARIMA
29 MAPE<sub>C</sub> Mean Absolute Percentage Error of Cubic
30 MAPE<sub>E</sub> Mean Absolute Percentage Error of Exponential
31 MAPE<sub>H1</sub> Mean Absolute Percentage Error of Holt’s linear trend
32 MAPE<sub>H2</sub> Mean Absolute Percentage Error of Holt’s exponential trend
33 MAPE<sub>HW</sub> Mean Absolute Percentage Error of Holt-Winters
34 MAPE<sub>L1</sub> Mean Absolute Percentage Error of Linear
35 MAPE<sub>L2</sub> Mean Absolute Percentage Error of Quadratic
36 MAPE<sub>MLP</sub> Mean Absolute Percentage Error of MLP
37 MAPE<sub>Q</sub> Mean Absolute Percentage Error of Quadratic
38 MAPE<sub>SVR</sub> Mean Absolute Percentage Error of Support Vector Regression
39 MLP Multi-Layer Perceptron
40 MSE Mean Squared Error
41 Q Quadratic
42 RBF Radial Basis Function
43 RMSE Root Mean Square Error
44 RMSE<sub>A</sub> Root Mean Square Error of Auto ARIMA
45 RMSE<sub>C</sub> Root Mean Square Error of Cubic
46 RMSE<sub>E</sub> Root Mean Square Error of Exponential
47 RMSE<sub>H1</sub> Root Mean Square Error of Holt’s linear trend
48 RMSE<sub>H2</sub> Root Mean Square Error of Holt’s exponential trend
49 RMSE<sub>HW</sub> Root Mean Square Error of Holt-Winters
50 RMSE<sub>L1</sub> Root Mean Square Error of Linear
51 RMSE<sub>MLP</sub> Root Mean Square Error of MLP
52 RMSE<sub>Q</sub> Root Mean Square Error of Quadratic
53 RMSE<sub>SVR</sub> Root Mean Square Error of Support Vector Regression
54 SVM Support Vector Machine
55 SVR Support Vector Regression
56 Theil’s <sub>U</sub> Theil’s U of Auto ARIMA
57 Theil’s <sub>U</sub> Theil’s U of Cubic
58 Theil’s <sub>U</sub> Theil’s U of Exponential
59 Theil’s <sub>U</sub> Theil’s U of Holt’s linear trend
60 Theil’s <sub>U</sub> Theil’s U of Holt’s exponential trend
61 Theil’s <sub>U</sub> Theil’s U of Holt’s Winters
62 Theil’s <sub>U</sub> Theil’s U of Holt’s exponential trend
63 Theil’s <sub>U</sub> Theil’s U of Holt-Winters
64 Theil’s <sub>U</sub> Theil’s U of Linear
65 Theil’s <sub>U</sub> Theil’s U of Logarithmic
66 Theil’s <sub>U</sub> Theil’s U of MLP
67 Theil’s <sub>U</sub> Theil’s U of Quadratic
68 Theil’s <sub>U</sub> Theil’s U of Support Vector Regression
69 TS Time series
70 WPI Wholesale Price Index
71 WP<sub>FinalLinear</sub> WPIs of Manufactures’ group having non-linear trend