International Journal of Advanced Technology and Engineering Exploration, Vol 8(82)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2021.874407

Research Article

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

Dipankar Das[1*] and Satyajit Chakrabarti[2]
Research Scholar, University of Engineering & Management, Kolkata, West Bengal, India[1]
Professor, University of Engineering & Management, Kolkata, West Bengal, India[2]

Received: 12-July-2021; Revised: 20-September-2021; Accepted: 24-September-2021

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

*Author for correspondence

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" ($Manuf_{Chem-Items}$) group.

To suggest an appropriate forecasting strategy for the WPIs having non-linear trends from the $Manuf_{Chem-Items}$ 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 $Manuf_{Chem-Items}$ 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 $Manuf_{Chem-Items}$ group having a non-linear trend ($WPI_{NonLinear}$) during this period.
- Model development for the $WPI_{NonLinear}$ 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 naïve 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 $Manuf_{Chem\text{-}Items}$ group, and identification of non-linear fit (Step3), (d) selection of the WPIs of $Manuf_{Chem\text{-}items}$ group showing non-linear trend (Step4), (e) modeling the proposed MLP to forecast $WPI_{NonLinear}$ (Step5), (f) forecast model building for the $WPI_{NonLinear}$ using other approaches (Step6), and (g) forecasting performance evaluation (Step7). The steps are discussed in detail in 3.1 to 3.7.

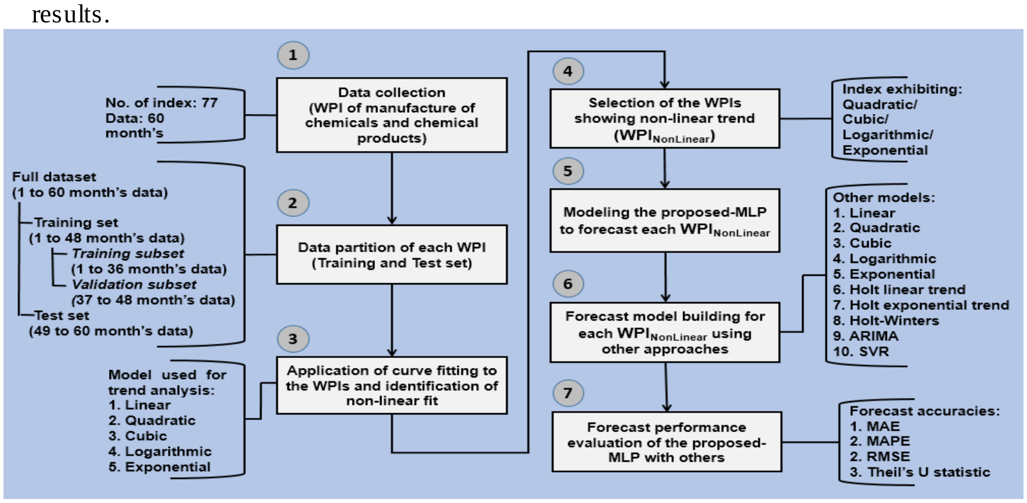

Figure 1 Methodology of MLP modeling of the $WPI_{NonLinear}$ of $Manuf_{Chem\text{-}Items}$ group

3.1Data collection (Step1)

We gathered the monthly data of all the seventy-seven commodities listed in the $Manuf_{Chem\text{-}Items}$ 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].

3.2Data partition (Step2)

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.

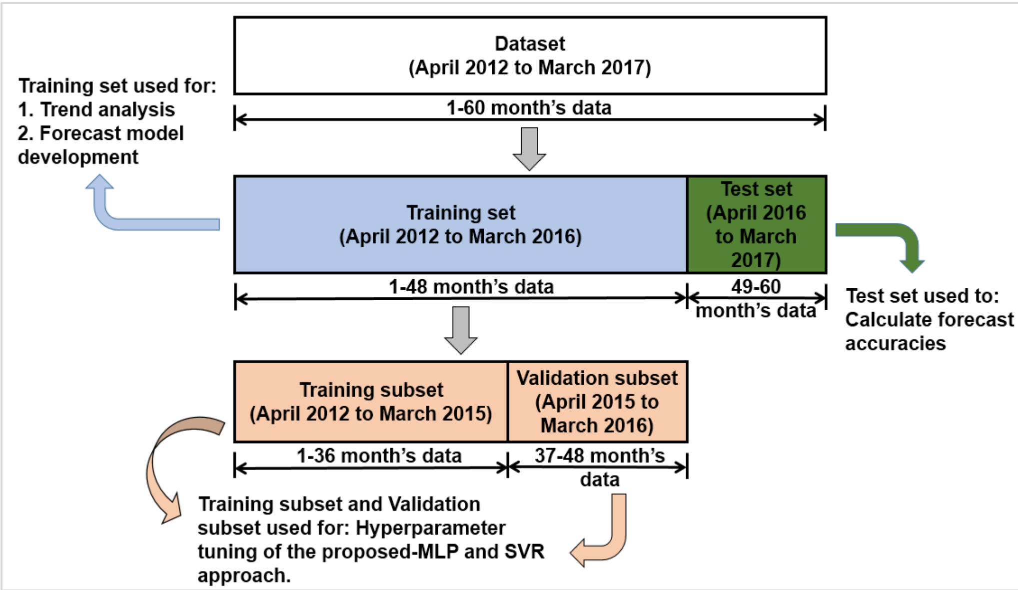

Figure 2 Data division scheme of WPIs of $Manuf_{Chem\text{-}Items}$ group

3.3Application of curve fitting to the WPIs of $Manuf_{Chem\text{-}Items}$ group and identification of non-linear fit (Step3)

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].

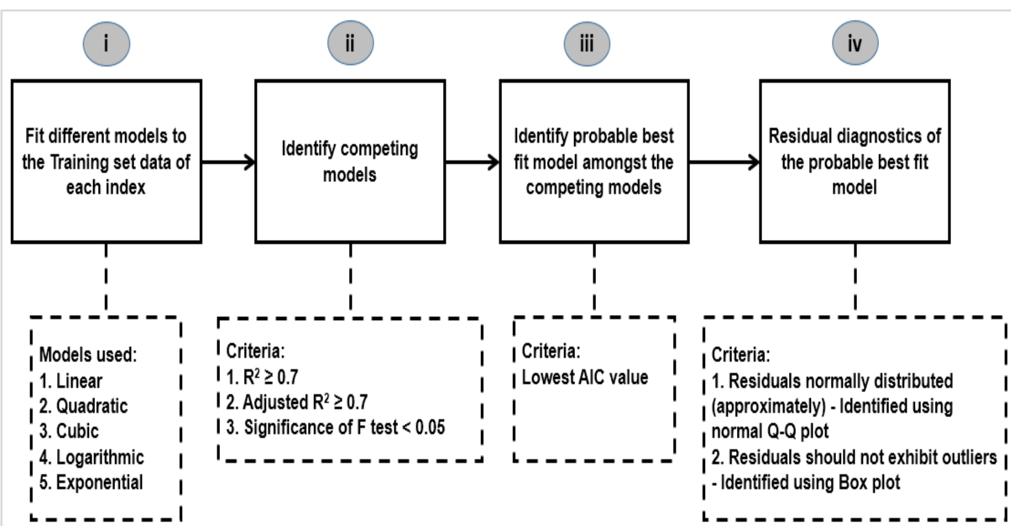

Figure 3 Curve fitting to the WPIs of $Manuf_{Chem\text{-}Items}$ group and best fit identification

3.4 Selection of the WPIs of Manuf$_{Chem\text{-}items}$ 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 WPINonLinear is portrayed in *Figure 4*.

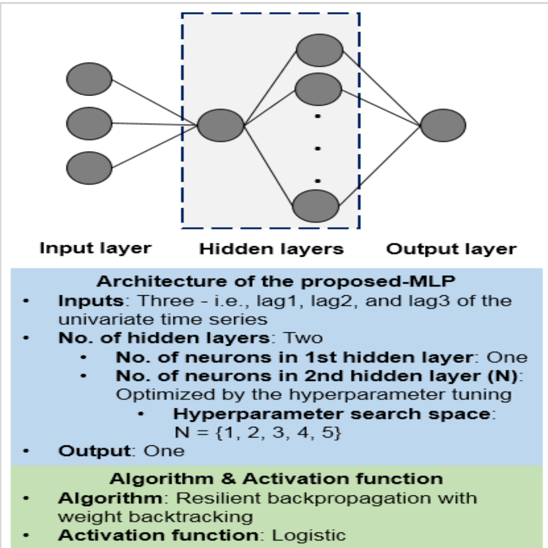

Figure 4 MLP architecture for forecasting WPI$_{NonLinear}$

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 trained twenty-five networks, combined their forecasts, and obtained an ensemble forecast. We combined them using the mode operator (based on the estimation of kernel density). We used the mlp () of R's nnfor package to build the models [30].

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

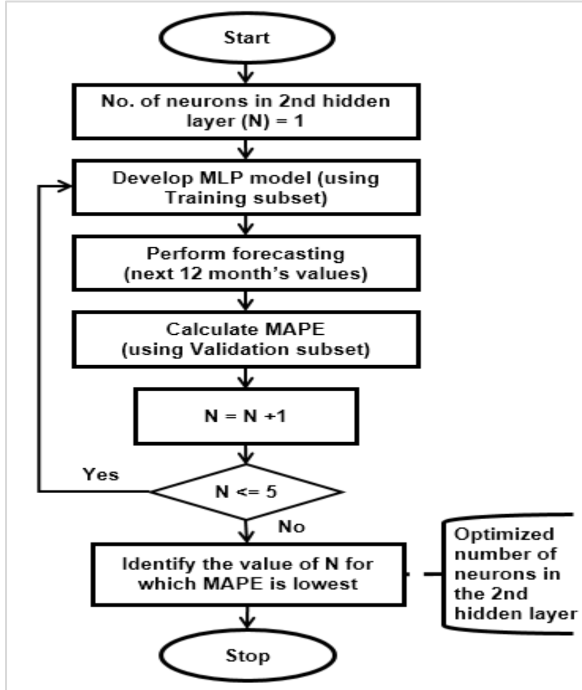

Figure 5 Hyperparameter tuning of the proposed MLP for WPI$_{NonLinear}$

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.

3.7Forecasting performance evaluation (Step7)

For each $WPI_{NonLinear}$ 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, equal to 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

4.1Curve fitting and trend analysis of seventy-seven WPIs of $Manuf_{Chem\text{-}Items}$ 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.

Table 1 Result of curve fit of WPI of organic solvent

Fit results	Model				
	L1	Q	C	L2	E
R^2	0.23	0.86	0.89	0.02	0.24
Adjusted R^2	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	NA	264.28	251.18		
Probable best fit	NA	NA	√	NA	NA

Findings: We observed that only two models, namely Q and C, had both R^2 and Adjusted $R^2 \geq 0.7$, 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*.

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*.

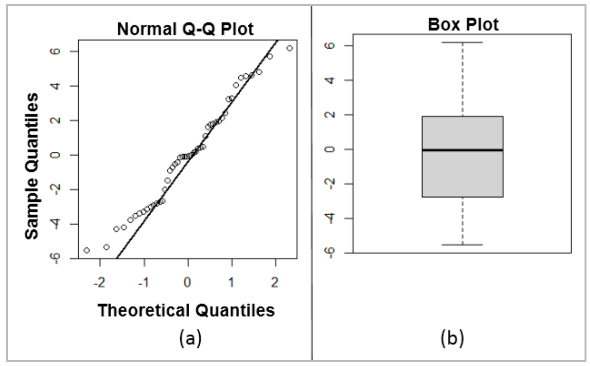

Figure 6 Residual analysis of probable best-fit 'C' model of WPI of organic solvent

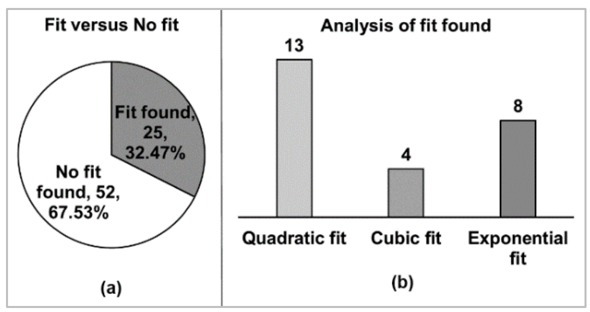

Figure 7 Findings of trend analysis using the curve fit of the seventy-seven WPIs of $Manuf_{Chem\text{-}Items}$ group

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 ($WPI_{NonLinear}$).

We listed the index code (used in this work) of these $WPI_{NonLinear}$, and their respective best-fits in *Table 2*.

Table 2 List of $WPI_{NonLinear}$ of $Manuf_{Chem\text{-}Items}$ group of India's WPI

No.	Name of the $WPI_{NonLinear}$	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

No.	Name of the $WPI_{NonLinear}$	Index code	Best-fit
4.	Ethyl acetate	V4	C
5.	Ethylene Oxide	V5	C
6.	Aniline (including PNA, ONA, OCPNA)	V6	Q
7.	Nitric Acid	V7	E
8.	Liquid air & other gaseous products	V8	E
9.	Alcohols	V9	C
10.	Urea	V10	E
11.	Ammonia gas	V11	Q
12.	Poly Vinyl Chloride (PVC)	V12	C
13.	Fungicide, liquid	V13	E
14.	Varnish (all types)	V14	E
15.	Tooth paste/Tooth Powder	V15	E
16.	Face/Body Powder	V16	E
17.	Mosquito coil	V17	E
18.	Polyester film(metalized)	V18	C
19.	Adhesive excluding gum	V19	C
20.	Hydrogen peroxide	V20	C
21.	Explosive	V21	Q
22.	Organic chemicals	V22	C
23.	Polyester chips or Polyethylene terepthalate (PET) chips	V23	C
24.	Viscose staple fibre	V24	Q
25.	Polyester fibre fabric	V25	C

4.2 Forecast model development of the $WPI_{NonLinear}$ using the proposed MLP approach

For each of the $WPI_{NonLinear}$ 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 $WPI_{NonLinear}$. The hyperparameter tuning resulted in the final models for each $WPI_{NonLinear}$. 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 $WPI_{NonLinear}$ 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	5.55	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

WPI	Hyperparameter tuning MAPE for 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	3/1/1/1
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.

Table 4 Performance of the MLP for forecasting the $WPI_{NonLinear}$

Forecast accuracy metrics	Criteria	No. of indices meeting the criteria	Remarks
MAPE	≤ 10	25	High model accuracy
Theil's U statistics	Close to zero	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 $WPI_{NonLinear}$ 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	$MAE_{MLP} < MAE_{L1}$	22	25
	$MAPE_{MLP} < MAPE_{L1}$	22	25
	$RMSE_{MLP} < RMSE_{L1}$	20	25
	Theil's U_{MLP} < Theil's U_{L1}	20	25
MLP and Q	$MAE_{MLP} < MAE_{Q}$	23	25
	$MAPE_{MLP} < MAPE_{Q}$	23	25
	$RMSE_{MLP} < RMSE_{Q}$	23	25
	Theil's U_{MLP}< Theil's U_{Q}	23	25
MLP and C	$MAE_{MLP} < MAE_{C}$	22	25
	$MAPE_{MLP} < MAPE_{C}$	22	25
	$RMSE_{MLP} < RMSE_{C}$	22	25
	Theil's U_{MLP}< Theil's U_{C}	22	25
MLP and L2	$MAE_{MLP} < MAE_{L2}$	18	25
	$MAPE_{MLP} < MAPE_{L2}$	18	25
	$RMSE_{MLP} < RMSE_{L2}$	17	25
	Theil's U_{MLP} < Theil's U_{L2}	17	25
MLP and E	$MAE_{MLP} < MAE_{E}$	22	25
	$MAPE_{MLP} < MAPE_{E}$	22	25
	$RMSE_{MLP} < RMSE_{E}$	20	25
	Theil's U_{MLP} < Theil's U_{E}	20	25
MLP and H1	$MAE_{MLP} < MAE_{H1}$	19	25

Models	Category	No. of WPI (MLP best)	Total no. of WPI
	$MAPE_{MLP} < MAPE_{H1}$	20	25
	$RMSE_{MLP} < RMSE_{H1}$	18	25
	Theil's $U_{MLP} <$ Theil's U_{H1}	18	25
MLP and H2	$MAE_{MLP} < MAE_{H2}$	19	25
	$MAPE_{MLP} < MAPE_{H2}$	19	25
	$RMSE_{MLP} < RMSE_{H2}$	19	25
	Theil's $U_{MLP} <$ Theil's U_{H2}	19	25
MLP and HW	$MAE_{MLP} < MAE_{HW}$	18	25
	$MAPE_{MLP} < MAPE_{HW}$	18	25
	$RMSE_{MLP} < RMSE_{HW}$	17	25
	Theil's $U_{MLP} <$ Theil's U_{HW}	17	25
MLP and A	$MAE_{MLP} < MAE_{A}$	13	25
	$MAPE_{MLP} < MAPE_{A}$	14	25
	$RMSE_{MLP} < RMSE_{A}$	13	25
	Theil's $U_{MLP} <$ Theil's U_{A}	13	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 $WPI_{NonLinear}$, we performed a comparison to find out which model performs best. We picked out the best-performing model amongst all compared models for each $WPI_{NonLinear}$. 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.

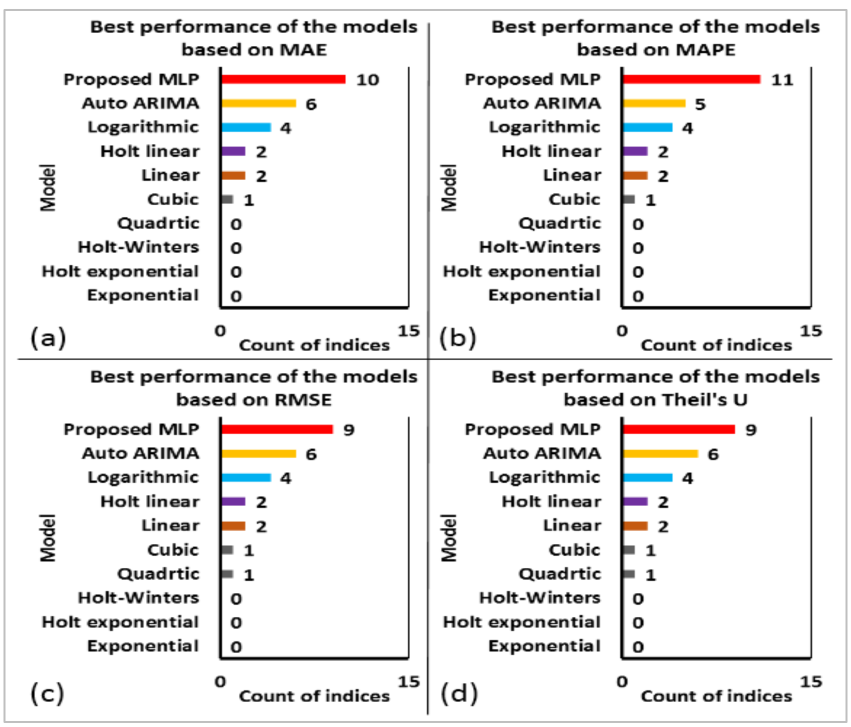

Figure 8 Total number of best performances of each model

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 $WPI_{NonLinear}$ 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 $WPI_{NonLinear}$ indices, we compared the SVR and the proposed MLP's forecast performance and identified the best-performing model. We counted the number of $WPI_{NonLinear}$ indexes for which the MLP performed best and displayed the results in *Table 8*.

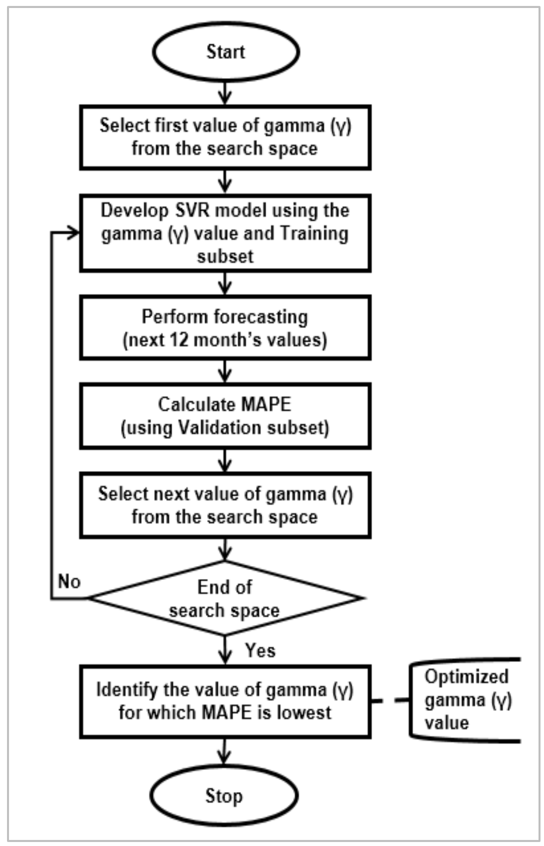

Figure 9 Hyperparameter tuning of SVR for $WPI_{NonLinear}$

Table 7 Hyperparameter tuning and optimized Gamma of the SVR models for twenty-five $WPI_{NonLinear}$ indices

WPI	Hyperparameter tuning: MAPE for					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

WPI	Hyperparameter tuning MAPE for					Optimized γ
	γ = 1	γ = 1.25	γ = 1.5	γ = 1.75	γ = 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	8.45	8.40	8.42	8.36	8.37	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	5.15	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 and SVR	$MAE_{MLP} < MAE_{SVR}$	14	25
	$MAPE_{MLP} < MAPE_{SVR}$	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.

Using different MAPE criteria, we examined the forecast MAPE of the SVR and the proposed MLP, and *Table 9* presents the results.

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

Model	Total number of indices meeting the criteria	
	MAPE ≤ 10	MAPE ≤ 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.

We analyzed the forecasting performances of our proposed model with the MLP models of Khashei and Hajirahimi [42], Lu et al. [43], and Herrera et al. [44] and listed the findings in *Table 10*.

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)	366.81	471.09	3.48
	Shenzhen Integrated Index	48 months (23% of the total number of observations)	1102.34	1405.16	9.81
	Nikkei 225	201 days (20% of the total number of observations)	100.03	123.29	0.98
Lu et al. (2020) [43]	Shanghai Composite Index (000001)	500 days (approximately 7% of the total number of observations)	37.58	49.80	
Herrera et al. (2019) [44]	Oil Brent	20% (app) of the total number of observations		17.34	17.92
	Oil WTI			14.72	16.56

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 $Manuf_{Chem-Items}$ 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 found any fits. In this present work, we focused on only the WPIs with non-linear fits identified through curve fitting.
- For forecasting the $WPI_{NonLinear}$ 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-MAPE less than equal to seven point five is twenty-five out of twenty-five, higher than all other models applied.

5.1Limitations

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 $\text{Manuf}_{\text{Chem-Items}}$ 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 $\text{Manuf}_{\text{Chem-Items}}$ group with non-linear trends and proposed an efficient forecasting approach for them. We analyzed each of the seventy-seven WPIs of the $\text{Manuf}_{\text{Chem-Items}}$ group exercising curve fitting, identified the WPIs with non-linear trends ($\text{WPI}_{\text{NonLinear}}$), and developed a forecasting approach applying MLP for these $\text{WPI}_{\text{NonLinear}}$ 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 $\text{Manuf}_{\text{Chem-Items}}$ 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., $\text{WPI}_{\text{NonLinear}}$ indices) by applying MLP

At first, we employed curve fitting to analyze the seventy-seven WPIs and determined the $\text{WPI}_{\text{NonLinear}}$ 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 $\text{WPI}_{\text{NonLinear}}$ 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 $\text{WPI}_{\text{NonLinear}}$ 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.

Acknowledgment
None.

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

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Dipankar Das is a Ph.D. scholar at the University of Engineering & Management, Kolkata, West Bengal, India. His research interests are Data Analytics, Time Series Analysis, Forecasting, Artificial Intelligence, and Machine Learning.

Email: dipankr.das@gmail.com

Dr. Satyajit Chakrabarti, Professor, Department of Computer Science and Engineering, University of Engineering & Management, Kolkata, West Bengal, India. His research interests are Data Science, Data Mining, Artificial Intelligence, and Nano Technology.

Email: satyajit.chakrabarti@iemcal.com

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_{A}	Mean Absolute Error of Auto ARIMA
16	MAE_{C}	Mean Absolute Error of Cubic
17	MAE_{E}	Mean Absolute Error of Exponential
18	MAE_{H1}	Mean Absolute Error of Holt's Linear Trend
19	MAE_{H2}	Mean Absolute Error of Holt's Exponential Trend
20	MAE_{HW}	Mean Absolute Error of Holt-Winters
21	MAE_{L1}	Mean Absolute Error of Linear
22	MAE_{L2}	Mean Absolute Error of Logarithmic
23	MAE_{MLP}	Mean Absolute Error of MLP
24	MAE_{Q}	Mean Absolute Error of Quadratic
25	MAE_{SVR}	Mean Absolute Error of Support Vector Regression
26	$Manuf_{Chem\text{-}Items}$	Manufacture of Chemicals and Chemical Products
27	MAPE	Mean Absolute Percentage Error
28	$MAPE_{A}$	Mean Absolute Percentage Error of Auto ARIMA
29	$MAPE_{C}$	Mean Absolute Percentage Error of Cubic
30	$MAPE_{E}$	Mean Absolute Percentage Error of Exponential
31	$MAPE_{H1}$	Mean Absolute Percentage Error of Holt's linear trend
32	$MAPE_{H2}$	Mean Absolute Percentage Error of Holt's exponential trend
33	$MAPE_{HW}$	Mean Absolute Percentage Error of Holt-Winters
34	$MAPE_{L1}$	Mean Absolute Percentage Error of Linear
35	$MAPE_{L2}$	Mean Absolute Percentage Error of Logarithmic
36	$MAPE_{MLP}$	Mean Absolute Percentage Error of MLP
37	$MAPE_{Q}$	Mean Absolute Percentage Error of Quadratic
38	$MAPE_{SVR}$	Mean Absolute Percentage Error of Support Vector Regression
39	ML	Machine Learning
40	MLP	Multi-Layer Perceptron
41	MSE	Mean Squared Error
42	Q	Quadratic
43	RBF	Radial Basis Function
44	RMSE	Root Mean Square Error
45	$RMSE_{A}$	Root Mean Square Error of Auto ARIMA
46	$RMSE_{C}$	Root Mean Square Error of Cubic
47	$RMSE_{E}$	Root Mean Square Error of Exponential
48	$RMSE_{H1}$	Root Mean Square Error of Holt's linear trend
49	$RMSE_{H2}$	Root Mean Square Error of Holt's Exponential Trend
50	$RMSE_{HW}$	Root Mean Square Error of Holt-Winters
51	$RMSE_{L1}$	Root Mean Square Error of Linear
52	$RMSE_{L2}$	Root Mean Square Error of Logarithmic
53	$RMSE_{MLP}$	Root Mean Square Error of MLP
54	$RMSE_{Q}$	Root Mean Square Error of Quadratic
55	$RMSE_{SVR}$	Root Mean Square Error of Support Vector Regression
56	SVM	Support Vector Machine
57	SVR	Support Vector Regression
58	Theil's U_{A}	Theil's U of Auto ARIMA
59	Theil's U_{C}	Theil's U of Cubic
60	Theil's U_{E}	Theil's U of Exponential
61	Theil's U_{H1}	Theil's U of Holt's linear trend
62	Theil's U_{H2}	Theil's U of Holt's exponential trend
63	Theil's U_{HW}	Theil's U of Holt-Winters
64	Theil's U_{L1}	Theil's U of Linear
65	Theil's U_{L2}	Theil's U of Logarithmic
66	Theil's U_{MLP}	Theil's U of MLP
67	Theil's U_{Q}	Theil's U of Quadratic
68	Theil's U_{SVR}	Theil's U of Support Vector Regression
69	TS	Time series
70	WPI	Wholesale Price Index
71	$WPI_{NonLinear}$	WPIs of $Manuf_{Chem\text{-}Items}$ group having non-linear trend