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Soft Computing-Based Ensemble Technique for WPI Estimation in India's Textile Sector

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Abstract

The current work presents a novel ensemble neuro-fuzzy forecasting approach for the wholesale price index (WPI) of textile commodities (a total of twenty-five items) of the present Indian WPI series. The offered technique used two soft-computing methods – an extreme learning machine (ELM) neural network and an Abbasov-Mamedova (AM) fuzzy time-series (TS) model. The proposed ELM-AM uniquely fused the outcomes acquired from both elements (i.e., ELM and AM models) through a weighted averaging strategy to construct the final ensemble output. The present work employs two accuracy metrics, i.e., forecast-MAPE and forecast-RMSE, and multiple (five) forecast horizons, i.e., three, six, nine, twelve, and eighteen months horizons, to assess the proposed ELM-AM's forecasting ability. The proposed ELM-AM exhibited high accuracy for all the twenty-five items' WPIs across the first four forecast horizons, with high accuracy observed in twenty-two out of twenty-five, i.e., 88% of the cases in the remaining horizon. The proposed ELM-AM outmatched twenty-four diverse approaches (i.e., both component models, four automatic soft-computing techniques, six commonly used automated TS forecasting approaches, six state-of-art hybrid techniques, and six contemporary ANFIS models) and, thus, found to be a fit contender for forecasting the WPI of textile items in India.

Keywords: Abbasov Mamedova Model, Extreme Learning Machine, Neuro-Fuzzy Model, Wholesale Price Index.

Introduction

Economic forecasting assists in future planning and it is widely acknowledged. It helps not only businesses but also individuals in informed decisions. It provides a view of potential economic slowdowns, recessions, risks, and uncertainties. It also furnishes insights into possible expansions and growths and, in essence, offers cognition of the country's overall economic health. Governments craft effective policies based on these data. These forecasts help in various areas of strategic planning, e.g., pricing, marketing, optimization, finance, supply chain, and demand. Price indices, e.g., Consumer Price Index (CPI), Wholesale Price Index (WPI), and Producer Price Index (PPI), are important economic indicators. The stock market – a leading indicator, can also reveal the economy's condition. Price index forecasting helps to predict inflation and identify potential recession. It assists in managing expenses and costs, forecasting revenue and profits, and understanding market trends and dynamics. It further helps to uncover promising prospects and to make well-informed choices in strategies and policies. In recent times, many researchers utilized varied time-series (TS) forecasting approaches for forecasting different indices, e.g., CPI, WPI and stock market (1-3).

Motivation

India is a global player in the textile sector. This sector contributes significantly to the national economy. In employment and revenue generation, it's an important facet. With a strong national presence, manifold value chains, and robust associations with other industries, e.g., agriculture, chemical, fashion, packaging, retail, and transport, this sector substantially impacts the overall national socio-economic evolution through rural development, women empowerment, and the advancement of small and medium enterprises. Multilayer-perceptron (MLP), Autoregressive Integrated Moving Average (ARIMA), and Holt-Winters techniques were employed to forecast all the WPIs of textile commodities in India. A dataset comprising 60 months of data, from April 2012 to March 2017, was utilized. High accuracy was achieved for the majority of the WPIs. To the best of available knowledge, exclusive research on forecasting WPI of textiles in India has been conducted in this context (4).

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The present study was motivated by this prior work, leading to the use of a larger and more recent dataset of textile WPIs in India, along with the application of multiple time series forecasting approaches to assess their effectiveness. The objectives of this study are as follows: to develop a soft-computing approach-based ensemble TS forecast approach for the WPI of individual textile commodities of the Indian WPI series; to evaluate the forecast performances of the proposed approach on different forecast horizons and test the statistical significance of the results obtained; to contrast, the forecast accuracies of the proposed approach with diverse automatic TS forecast approach, both soft-computing based and commonly used techniques; and to identify whether the proposed approach performs better than the other contemporary state-of-art hybrid TS forecast approaches.

Background and Prior Research

The ARIMA (5), various exponential smoothing (ES) techniques, e.g., Simple Exponential Smoothing, i.e., SES (6), Double Exponential Smoothing, i.e., DES (7), and Triple Exponential Smoothing, i.e., TES (8), Time-Series Linear Model, i.e., TSLM (9), and Error-Trend-Seasonality, i.e., ETS (10) are some widely recognized and standard approaches for attaining successful outcomes in TS forecasting.

Numerous researchers utilized soft-computing strategies, e.g., Feed forward Neural Networks, i.e., FFNN (11), Generalized Regression Neural Networks, i.e., GRNN (12), MLP (13), Extreme Learning Machine Neural Networks, i.e., ELM (14), Support Vector Regression, i.e., SVR (15), and Abbasov-Mamedova, i.e., AM fuzzy time series (16), to forecast various TS data.

Utilization of hybrid approaches in TS forecasting is also common, where two TS forecast techniques are combined to obtain the final results, e.g., ARIMA-ETS (17), ETS-ANN (17), and ARIMA-ANN (18). Similarly, the combination of data-adaptive and multiresolution approaches like Empirical Mode Decomposition (EMD) or Ensemble Empirical Mode Decomposition (EEMD) with other techniques, e.g., ARIMA and Time Delay Neural Network (TDNN) also furnished several hybrid approaches - for example: EMD-ARIMA (19), EEMD-ARIMA (20), and EMD-TDNN (21).

Recent works illustrated the use of the neuro-fuzzy approach in various forecasting tasks encompassing price and index forecasts, e.g., stock index (22-25) and a variety of item prices (26-28). In one study, a wavelet-based neuro-fuzzy method was used to forecast stock prices of SBI, TCS, Wipro, and Tata Steel (22). In one study, an ensemble neuro-fuzzy technique was proposed that used multi-dimensional Gaussian functions and applied it to forecast the stock index of Cisco, Alcoa, American Express, and Disney (23). A neuro-fuzzy model employing grid partitioning, Gaussian membership functions, and Takagi-Sugeno rules was utilized to forecast stock indices of SAX, PX, WIG, and BUX (24). Another study implemented a neuro-fuzzy model trained using both binary and continuous genetic algorithms for forecasting the NASDAQ stock index (25). For bitcoin price forecasting, a model comprising two adaptive neuro-fuzzy sub-systems - an inverse-learning-based controller and a process modelling unit - was introduced (26). A genetic algorithm-based neuro-fuzzy technique forecasted copper price volatility, where the offered approach used Takagi–Sugeno–Kang model (fuzzy model) and operated the genetic algorithms to estimate the model parameters (27). A salp swarm and genetic algorithm-based neuro-fuzzy approach was proposed in another work for forecasting crude oil prices and superior performance was observed in comparison to other techniques such as genetic, salp swarm, particle swarm, and grey wolf optimization-based methods (28).

Originality

The proposed ELM-AM approach presents a novel ensemble neuro-fuzzy TS forecasting technique for the WPI of individual textile commodities of the current Indian WPI series. The authors in this current work outline the novelties of the proposed ELM-AM approach as follows:

- It is the first attempt to develop an ensemble neuro-fuzzy forecast approach for the WPIs of the individual commodities of the 'Manufacture of Textiles' group in India using the monthly data of one hundred thirty-eight months spanning from April 2011 to September 2022.
- The proposed approach uniquely performs an ensemble of two well-known soft-computing techniques – an ELM network and an AM fuzzy-time-series (FTS) method. The proposed ELM-AM uses weighted averaging to produce the final ensemble forecasts.

- The proposed system accepts the univariate time series as input, delivers automatic multi-step ahead forecasts, and initiates a new direction toward an ensemble neuro-fuzzy TS forecast technique development involving the ELM and AM methods.
- The component ELM network of the proposed ELM-AM approach automatically executes the following: using the auto correlated lags (determined in the feature engineering of the proposed ELM-AM) as input to the ELM network, model training, tuning hyper-parameters employing a tailored search space, obtaining the optimized ELM, and using it (optimized-ELM) to compute the out-of-sample forecasts.
- Another component of the proposed approach, i.e., the AM FTS model, automatically performs hyper parameter tuning using a custom search space, achieves model optimization, and figures out the out-of-sample forecasts using the optimized AM.
- The ELM-AM outperforms twenty-four TS forecasting approaches, i.e., both the components, four automatic soft-computing techniques, six commonly employed automated TS forecast approaches, six state-of-art hybrid forecast techniques, and six neuron-fuzzy strategies.

Methodology

Data Collection and Preparation

The Indian WPI series (base 2011-12 = 100) lists twenty-five individual commodities under its 'Manufacture of Textiles' group. This work collected the monthly index data of all these twenty-five items. The dataset contains data from April 2011 to September 2022, i.e., data of one hundred thirty-eight months, collected from the 'data [dot] gov [dot] in' platform (29). The data is monthly, and there is no missing value. We split the dataset for model training and model testing. For each item, this work split the one hundred thirty-eight months of WPI data into one hundred twenty months of training and eighteen months of the test set. The researchers used the training set for hyper-parameter tuning, model training, and final model development, and the test set for forecast accuracy calculation of the models.

Proposed Methodology Overview

Figure 1 presents the methodology adopted in this work wherein the researchers collected the data, split data into training and test set, and applied the training set for model training and test set for accuracy computation.

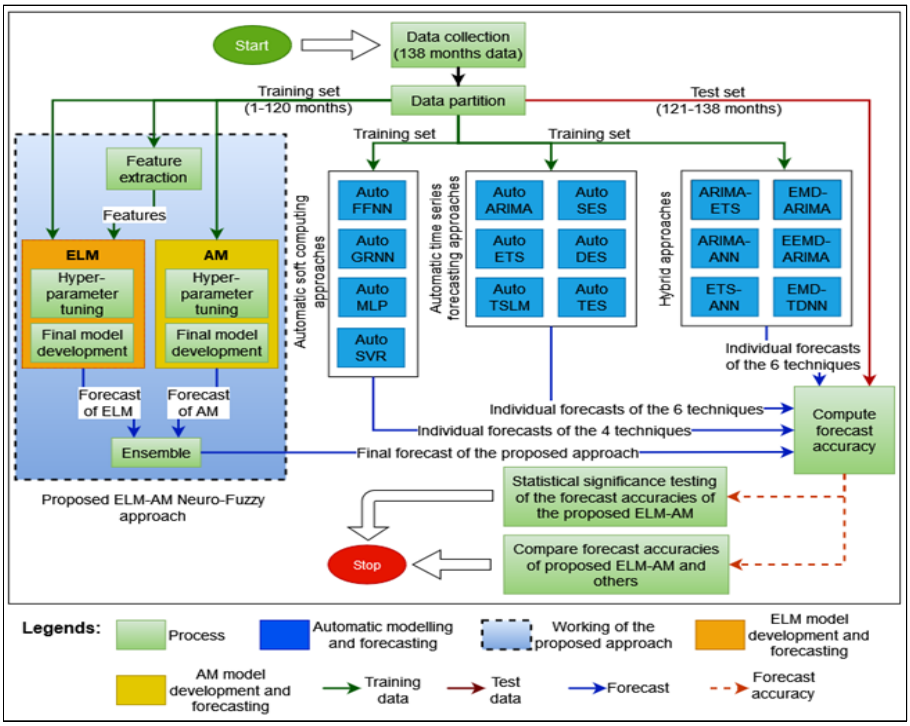

Figure 1: Methodology Overview

This work proposed a novel ensemble neuro-fuzzy TS forecast approach and utilized it to forecast the WPIs of the twenty-five textile items. The proposed neuro-fuzzy technique used the forecasts of an ELM neural network and an AM FTS forecast model to produce the final ensemble output (forecast). The researchers in this paper evaluated the forecast performance of the proposed ELM-AM to identify its efficient applicability in these cases and tested the statistical significance of the results obtained.

Competing Forecasting Techniques

The current work evaluated the proposed approach's performance on this dataset by contrasting it with sixteen other TS forecast approaches. This work applied the following four automatic soft-computing techniques: Auto FFNN (30), Auto GRNN (31), Auto MLP (32), and Auto SVR (33). It further utilized six commonly employed automated TS forecast approaches, namely the followings: Auto ARIMA (34), Auto ETS (35), Auto TSLM (36), Auto SES (37), Auto DES (37), and Auto TES (37). In addition, the researchers in this work compared the proposed ELM-AM with six state-of-art hybrid forecast techniques which are as follows: ARIMA-ETS (17), ETS-ANN (17), ARIMA-ANN (38), EMD-ARIMA (19), EEMD-ARIMA (19), and EMD-TDNN (39).

Forecasting Strategy and Evaluation Setup

For each approach, the work generated eighteen months of out-of-sample forecasts for each of the twenty-five item's WPI. This paper evaluated the proposed ELM-AM's performance on five forecast horizons - three, six, nine, twelve, and eighteen months horizons.

Accuracy Metrics and Statistical Testing

The current work used the following two accuracy metrics: Mean Absolute Percentage Error, i.e., MAPE (40) and Root Mean Squared Error, i.e., RMSE (41). A model has high accuracy if its MAPE ≤ 10 (42). This paper counted the cases when the proposed ELM-AM achieved high accuracy and used this data to analyze its (ELM-AM's) forecasting ability. It utilized the one-sample 'Wilcoxon Signed Rank' test (43) to check the statistical significance of the forecast MAPE of the proposed ELM-AM. Further, it compared the forecast RMSE and MAPE of the ELM-AM with various other models to evaluate its performance.

Software and Packages Used

This work employed various packages of the R software (version 4.2.2) to generate both the hyper parameter-tuned optimized and automatic (auto) models. It used the following packages: 'AnalyzeTS' (44) for the AM fuzzy time series models; 'nnfor' (45) for the ELM and auto-MLP models; 'tsfgrnn' (46) for the auto-GRNN models; 'TSSVM' (33) for the auto-SVR models; 'forecast' (47, 48) for the auto-FFNN, auto-ETS, and auto-TSLM models; 'stats' (49) for the auto-SES, auto-DES, and auto-TES models; 'forecast Hybrid' (50) for the ARIMA-ETS, ETS-ANN, and ARIMA-ANN models; 'decomposedPSF' (51) for the EMD-ARIMA and EEMD-ARIMA models; 'eemdTDNN' for the EMD-TDNN models (52). It used 'tsfeatures' for feature extraction (53).

Architecture of the Proposed Approach

Figure 2 displays the functioning of the proposed ELM-AM neuro-fuzzy approach. It contains two components – an ELM neural network and an AM FTS model. The ELM is, essentially, an FFNN with a quicker convergence rate than traditional ANNs (54). It primarily uses one hidden layer, operates 'Moore-Penrose generalized inverse' to randomly assign the weights, and doesn't use back propagation (55). It is simple, efficient, and offers quick learning. This work extracted the TS features, determined the auto correlated lags, employed them as input to the ELM, and tuned the hyper-parameters to get the optimal ELM.

The other component is an FTS model. The FTS approaches are advantageous due to their readability and simplicity and uncertainty handle capacity (56, 57). In the current work, the researchers employed the AM FTS technique in their proposed neuro-fuzzy approach. The edge of the AM FTS approach over other FTS techniques is its capability to predict out-of-sample values, i.e., values beyond the min-max range (58).

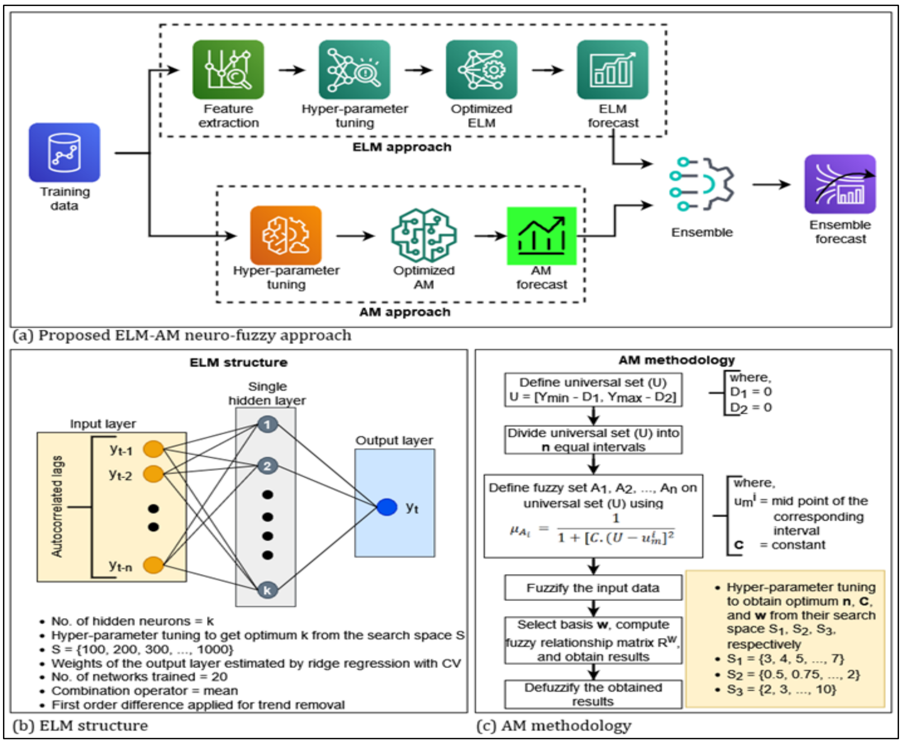

Figure 2: Proposed ELM-AM Neuro-Fuzzy Approach

For the component ELM network, the proposed system considered the training set data and extracted its features; fed the auto correlated lags identified from the feature extraction step to the ELM as input; tuned the hyper-parameters utilizing a custom search space to get the optimized number of hidden neurons and obtained the optimal ELM. Further, for the component AM model, the researchers fed the training set data to it; performed hyper-parameter tuning using a tailored search space to get its optimized version. This work utilized both these optimized models to provide their respective forecasts.

Finally, the proposed ELM-AM neuro-fuzzy approach employed in-sample error based weighted averaging to produce the ensemble output (forecast). The work operated the in-sample RMSE for weight computation.

Table 1 presents the hyper-parameter tuning approaches for the ELM and AM methods. Through hyper-parameter tuning, this work identified the optimum no. of hidden nodes from its search space for the ELM. Similarly, it employed hyper-parameter tuning to determine the optimum values of n, C, and w parameters from their respective search spaces for the AM FTS model.

Figure 2 depicts the architecture of the ELM and AM models employed in the present study, and Table 1 describes the model hyper parameters tuning procedure. In the case of the ELM, the only hyper parameter is the number of hidden nodes (k) contained in the unique hidden layer, optimized from a search space (starting value: 100). Among the hyper parameters of the AM fuzzy time series model n (staring value: 3), C (staring value: 0.5) and w (staring value: 2) play an important role. These parameters were optimized. Finally, the optimal values were applied in the ELM-AM ensemble to provide robust forecasting performance.

Table 1: Hyper-Parameter Tuning

Algorithm 1 Hyper-Parameter Tuning of ELM Model	**Algorithm 2 Hyper-Parameter Tuning of AM FTS Model**
Input: A training data set	**Input**: A training data set
Output: Optimum number of hidden nodes for which RMSE is minimum	**Output:** Optimum values of n, C, and w for which RMSE is minimum
Initialize the search space of no. of hidden nodes, S = {100, 200, 300, ..., 1000};	Initialize the search space of n, S_1 = {3, 4, 5, 6, 7};

```
Initialize min_rmse = ∞;
Initialize optimum_k = 0;
for each value s in S do
  Train ELM using parameter s;
  rmse_s = Calculated RMSE;
  if rmse_s < min_rmse then
    min_rmse = rmse_s;
    optimum_k = s;
  end if
end for
Return optimum_k;
```

```
Initialize the search space of C, S2 = {0.5, 0.75, 1, ..., 2};
Initialize the search space of w, S3 = {2, 3, 4, ..., 10};
Initialize min_rmse = ∞;
Initialize optimum_n = 0, optimum_C = 0, optimum_w = 0;
for each value s1 in S1 do
  for each value s2 in S2 do
    for each value s3 in S3 do
      Develop AM FTS model using s1, s2, and s3;
      rmse_s = Calculated RMSE;
      if rmse_s < min_rmse then
        min_rmse = rmse_s;
        optimum_n = s1;
        optimum_C = s2;
        optimum_w = s3;
      end if
    end for
  end for
end for
Return optimum_n, optimum_C, optimum_w;
```

Results

We noted the WPIs exhibited unalike patterns. Twenty-one WPIs displayed positive linearity, and four showed negative linearity. On the other hand, six WPIs revealed positive curvature, and nineteen demonstrated negative curvature. Therefore, the WPIs exhibited different characteristics.

Optimized ELM and AM Models

Table 2 exhibits the structure of the optimized ELM and n, C, and w parameters of the optimized AM model. It also lists their corresponding in-sample errors and the weights applied for ensemble forecasting. This work computed the weights using the in-sample RMSE.

Table 2: Optimized ELM and AM Models and Their Corresponding in-Sample RMSE and Weights

Index	Optimized ELM	Optimized AM n	C	w	Optimized ELM In-sample RMSE (weight)	Optimized AM In-sample RMSE (weight)
WPI1	[9-1000-1]	6	0.75	9	1.51 (0.48)	1.42 (0.52)
WPI2	[11-700-1]	3	1.25	7	1.57 (0.47)	1.38 (0.53)
WPI3	[13-100-1]	4	0.5	2	1.74 (0.54)	2.04 (0.46)
WPI4	[14-100-1]	3	0.5	10	1.8 (0.54)	2.13 (0.46)
WPI5	[12-1000-1]	3	0.5	3	1.9 (0.48)	1.76 (0.52)
WPI6	[18-1000-1]	3	2	2	2.11 (0.54)	2.46 (0.46)
WPI7	[22-100-1]	3	0.5	2	1.58 (0.56)	2.01 (0.44)
WPI8	[19-100-1]	4	0.75	2	1.22 (0.52)	1.35 (0.48)
WPI9	[24-100-1]	4	0.5	3	1.23 (0.5)	1.23 (0.5)
WPI10	[11-100-1]	3	0.5	4	1.8 (0.5)	1.8 (0.5)
WPI11	[11-100-1]	4	0.5	2	2.53 (0.53)	2.8 (0.47)
WPI12	[32-100-1]	6	0.5	4	1.94 (0.45)	1.58 (0.55)
WPI13	[13-100-1]	4	0.5	3	1.15 (0.53)	1.3 (0.47)
WPI14	[17-100-1]	4	0.5	2	1.69 (0.53)	1.88 (0.47)
WPI15	[32-1000-1]	6	0.5	2	1.02 (0.53)	1.14 (0.47)

WPI16	[30-100-1]	3	0.5	3	2.21 (0.55)	2.72 (0.45)
WPI17	[19-100-1]	4	0.5	2	3.77 (0.58)	5.28 (0.42)
WPI18	[31-100-1]	3	0.5	3	1.26 (0.56)	1.6 (0.44)
WPI19	[30-100-1]	4	0.5	3	2.98 (0.51)	3.06 (0.49)
WPI20	[19-200-1]	3	0.5	2	1.79 (0.54)	2.09 (0.46)
WPI21	[32-100-1]	4	0.5	2	3.93 (0.53)	4.42 (0.47)
WPI22	[12-100-1]	3	0.5	2	1.63 (0.52)	1.79 (0.48)
WPI23	[26-100-1]	6	0.5	2	1.98 (0.5)	2.01 (0.5)
WPI24	[17-100-1]	3	0.5	2	1.67 (0.49)	1.64 (0.51)
WPI25	[32-100-1]	3	0.5	2	1.79 (0.53)	2.05 (0.47)

Forecast Performance Evaluation of the Proposed ELM-AM Approach

Figure 3 portrays the forecast performances of the ELM-AM approach. In three, six, nine, and twelve months ahead of forecasts, the ELM-AM approach obtained high accuracies, i.e., MAPE ≤ 10, for each WPI. For a forecast horizon of eighteen months, the proposed ELM-AM attained high accuracy in eighty-eight per cent of cases, i.e., twenty-two out of twenty-five WPIs. The mean and median forecast-MAPE of the ELM-AM models for three, six, nine, and twelve months ahead of forecasts are well below 5 shows in Table 3. The mean and median forecast-MAPE for a forecast horizon of eighteen months is 6 and 5.62, respectively, Table 3. This paper observed that the proposed ELM-AM performed nicely up to the twelve-month forecast horizon (horizon of 3, 6, 9, and 12 months) with 100% high accuracy cases. It obtained a maximum mean MAPE value of 4.15 (12 months horizon) and a maximum median MAPE value of 3.70 (12 months horizon). It also functioned sufficiently well for the eighteen-month horizon.

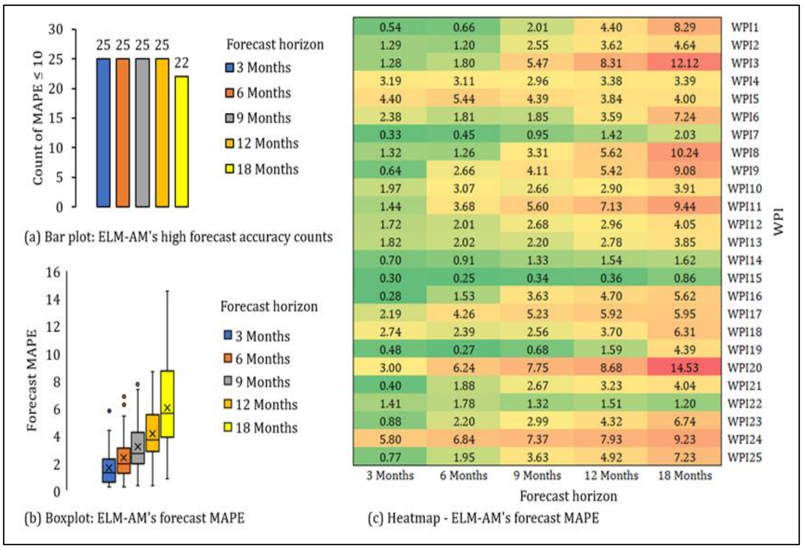

Figure 3: Forecast Performance of the Proposed ELM-AM Approach

Table 3: Summary Statistics of Forecast Performance of the ELM-AM Approach

Forecast MAPE	**Forecast Horizon (Months)**				
	3	**6**	**9**	**12**	**18**
Min	0.28	0.25	0.34	0.36	0.86
Max	5.80	6.84	7.75	8.68	14.53
Mean	1.65	2.39	3.21	4.15	6.00
Median	1.32	1.95	2.68	3.70	5.62

This work employed the one-sample 'Wilcoxon Signed Rank Test' to test the statistical significance of the forecast accuracies of the ELM-AM approach in different forecast horizons. Table 4 lists the test results. It revealed that in all the cases, the p-values are more than the significance level (alpha) = .05. Thus, this work retained the null hypotheses for all five horizons.

Table 4: Summary Statistics of Forecast Performance of the ELM-AM Approach

Forecast horizon	Null hypothesis	p-value	Remarks
3 months	H_{01}: Median (MAPE) ≤ 2.50	0.999	
6 months	H_{02}: Median (MAPE) ≤ 2.50	0.868	
9 months	H_{03}: Median (MAPE) ≤ 2.50	0.074	Accept Null Hypothesis
12 months	H_{04}: Median (MAPE) ≤ 5.00	0.972	
18 months	H_{05}: Median (MAPE) ≤ 5.00	0.126	

Table 5: Comparison of Forecast Performance of the ELM-AM Approach with Component ELM and AM Approaches

Criteria	Model	Forecast Horizons (Months)				
		3	6	9	12	18
Maximum (MAPE)	ELM-AM	$5.80^{*\$}$	$6.84^{*\$}$	$7.75^{*\$}$	$8.68^{*\$}$	$14.53^{*\$}$
	ELM	8.05	10.16	11.43	12.56	14.80
	AM	6.28	8.15	8.64	9.49	15.03
Mean (MAPE)	ELM-AM	$1.65^{*\$}$	$2.39^{*\$}$	$3.21^{*\$}$	$4.15^{*\$}$	$6.00^{*\$}$
	ELM	1.73	2.41	3.43	4.44	6.31
	AM	1.86	2.77	3.55	4.46	6.40
Median (MAPE)	ELM-AM	$1.32^{*\$}$	$1.95^{\$}$	$2.68^{*\$}$	$3.70^{*\$}$	$5.62^{*\$}$
	ELM	1.50	1.74	2.95	4.24	6.03
	AM	1.34	2.41	3.06	3.89	6.58

* ELM-AM outperformed ELM; \$ ELM-AM outperformed AM

Performance Comparison of the Proposed ELM-AM Approach with Component Models

Table 5 exhibits a comparative analysis between the proposed ELM-AM and its component models, i.e., the ELM and AM. The ELM-AM outperformed the ELM in fourteen out of fifteen (i.e., 93.3%) comparisons. The ELM-AM outdid the AM in all fifteen (i.e., 100%) assessments.

Performance Comparison of the Proposed ELM-AM with Automatic TS Forecasting Approaches

Figure 4 illustrates a comparative analysis between the proposed ELM-AM with ten automatic TS forecast approaches.

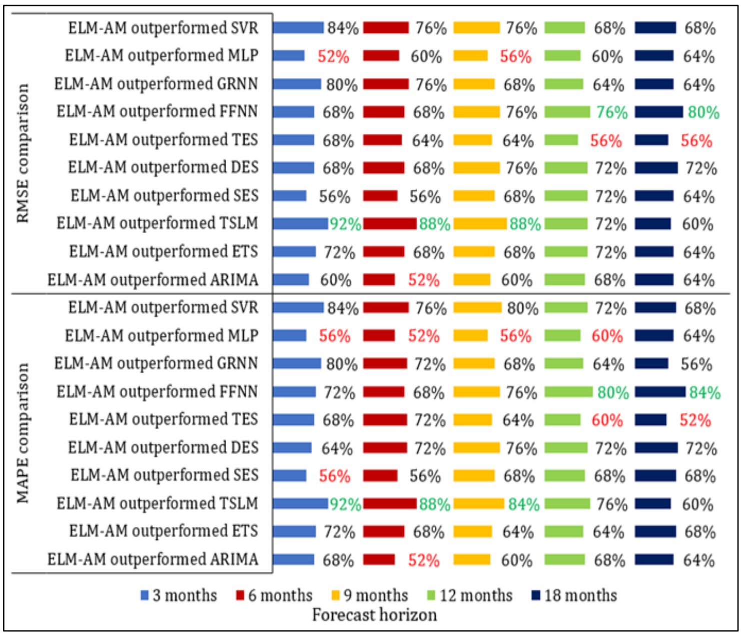

Figure 4: Comparison of Forecast Performance of the ELM-AM Approach with Ten Automatic TS Forecast Approaches

In this work, the researchers computed the number (percentage) of cases when the ELM-AM outperformed the other, i.e., ELM-AM obtained lower values of forecast accuracies (MAPE and RMSE) than the other. In all the comparisons, the ELM-AM surpassed the others for the majority, i.e., more than 50% of the cases.

Performance Comparison of the Proposed ELM-AM with Hybrid TS Forecasting Approaches

This paper contrasted the forecast accuracies (MAPE and RMSE) of the proposed ELM-AM with six contemporary state-of-art hybrid TS forecast approaches. The techniques are as follows: ARIMA-ETS (17), ETS-ANN (17), ARIMA-ANN (38), EMD-ARIMA (19), EEMD-ARIMA (19, 20), and EMD-TDNN (39). The researchers in this paper computed the number (percentage) of cases when the ELM-AM got lower forecast-MAPE and forecast-RMSE than the other. For each forecast horizon, the ELM-AM outperformed the other in more than 50% of the cases shows in Figure 5.

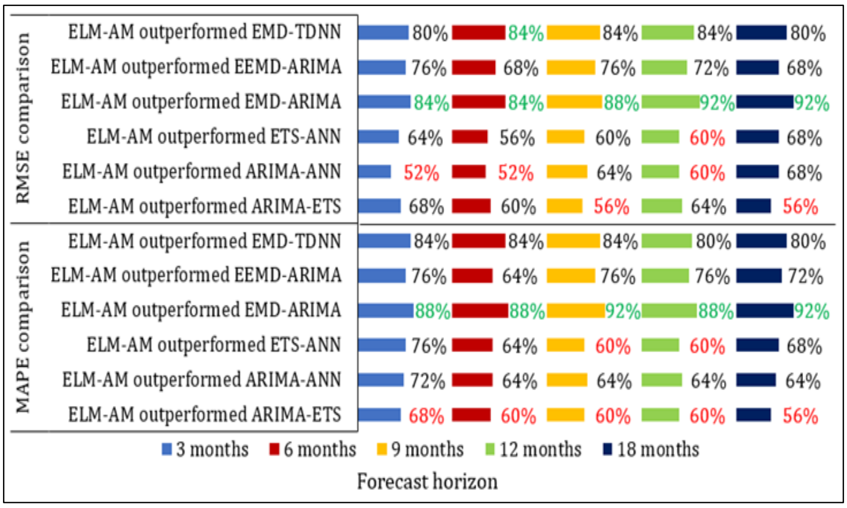

Figure 5: Comparison of Forecast Performance of the ELM-AM Approach with Ten Automatic TS Forecast Approaches

Proposed ELM-AM and other Neuro-Fuzzy Approaches

For assessing the quality of the proposed ELM-AM, Table 6 lists a comparative analysis of the offered ELM-AM with some adaptive neuro-fuzzy inference system (ANFIS) models employed by others (59, 60). The proposed ELM-AM outperformed six out of six compared models, and, therefore, the authors observed that the proposed ELM-AM is competitive with these state-of-art techniques. Utilizing all of these neuro-fuzzy approaches on the current work's dataset for evaluating them is one of the prospective dimensions of this work.

Table 6: Forecast Performance of the Proposed ELM-AM and other Neuro-Fuzzy Approaches

Sl.No.	Model	Data	MAPE
1	ANFIS with Gaussian membership function	COVID19 confirmed cases in Bangladesh (59)	8.96
	ANFIS with Generalized Bell-shaped membership function		8.95
	Proposed ELM-AM		6.71
2	ANFIS with Gaussian membership function	COVID19 confirmed cases in India (60)	24.53
	Genetic Algorithm based ANFIS		22.78
	Differential Evolution based ANFIS		18.58
	Teaching-Learning-based-Optimization based ANFIS		15.53
	Proposed ELM-AM		13.49

Discussion

This work proposed a novel ensemble TS forecast approach that employs two soft-computing strategies – an ELM network and an AM FTS forecast model. The proposed ELM-AM provides ensemble forecasts for the WPI of individual textile commodities (twenty-five items) of the present Indian WPI series. The functions of the proposed ELM-AM are as follows: accepting the univariate series as input, automatically performing feature engineering, tuning hyper parameters of both ELM and AM using their respective search spaces, obtaining the optimized models for both components, computing the final results, and providing multi-step ahead forecasts. This work utilized the monthly WPI data of all the twenty-five individual commodities from the 'Manufacture of Textiles' group of the current Indian WPI series. The data spans one hundred thirty-eight months, i.e., from April 2011 to September 2022. The proposed ELM-AM method initiates a new pathway to deliver out-of-sample values for these WPIs. This work is the first attempt to develop an ensemble neuro-fuzzy forecast approach for this dataset.

The present study is a significant contribution to the WPI forecasting literature as it introduces a new ensemble neuro-fuzzy forecasting model that integrates an ELM neural network and an AM fuzzy time series model. Different from past studies that mainly apply traditional or independent machine learning methods and that also feature smaller datasets – such as a 60 months data used in earlier research - this study draws on a significantly larger and more recent dataset containing 138 months of WPI data of 25 textile commodities (4). To the best of our knowledge, it is the first attempt to use an ensemble soft-computing approach based on the combination of ELM and AM for WPI prediction specifically in the field of textiles. In addition, several hybrid methods, time series models, state-of-the-art models and ANFIS-based techniques are among the 24 competing models against which the proposed method is tested. Statistical validation is also performed by means of the Wilcoxon Signed Rank Test in order to assess the strength of the model across multiple forecast windows of 3, 6, 9, 12, and 18 months. The novelty of this work is also in the experimental setup and methodology used, which are different from previous research and that could support the development of new forecasting methods for economic indices like the WPI.

The proposed ELM-AM obtained high forecast accuracies (MAPE ≤ 10) in 100% of cases for each three, six, nine, and twelve months forecast horizon. It achieved high accuracy in 88% of cases for eighteen months horizon. The results attained are statistically significant.

Both constituent approaches of the proposed ELM-AM method, i.e., the ELM network and the AM FTS technique, are contemporary, state-of-art techniques and good at TS forecasting tasks. These two components also provided good forecast performances in the present work. The current work exhibited that the proposed ELM-AM achieved better forecast accuracy than both components. Thus, it offered a more efficient technique than both the components for this dataset.

One important advantage of the proposed ELM-AM model in relation to traditional econometric forecasting methods, such as ARIMA, ETS and other exponential smoothing methods, is its capacity to accommodate complex non-linear structures, which are frequently found in economic and price time series. They also depend on linear assumption and the seasonality, trend, and error structure must be pre-specified. Instead, the ELM-AM ensemble combines the advantages of the ELM neural network in accommodating nonlinear patterns, and the capabilities of AM fuzzy time series model of accounting for vagueness and uncertainty in the price behaviour. It allows for a better generalization of the ensemble at different forecasting horizons. The empirical results presented in this work, for example in Figure 4, show that the ELM- AM consistently beats traditional models in terms of lower forecast errors MAPE, and RMSE, especially in longer forecast horizons. These results suggest that, although baseline accuracy could be obtained from simple models, the proposed soft-computing ensemble model represents a stronger and more flexible approach for predicting WPI in the textile industry.

To provide a fair context of the performance obtained using the proposed ELM-AM model, its forecast accuracy was contrasted against that of some widely used methods from the literature. These include traditional statistical models such as ARIMA, ETS, and TSLM; soft-computing techniques such as FFNN, GRNN, MLP, and SVR; and hybrid models including ARIMA-ETS (17), ETS-ANN (17), ARIMA-ANN (38), EMD-ARIMA (19), EEMD-ARIMA (19, 20), and EMD-TDNN (39). Plus, the ELM-AM was also compared with six of the latest ANFIS architectures (59, 60). In every test, the ELM-AM either outperformed or was competitive, and this was especially true in the case of multi-step forecasting. The results presented here provide evidence that the approach described is a methodological step forward that produces real improvements over existing models in the literature.

The findings from this study have immediate relevance to praxis in areas such as production scheduling, competitive trade, and inflation. With regard to production planning and scheduling, multi-horizon WPI predictions help textile industries determine appropriate purchasing plans for raw materials, stocking materials accordingly, and establishing production cycles, assist in controlling costs and effectively using available resources. In terms of trade competitiveness, having foresight of textile commodity prices allows exporters and others in the industry to set prices, insulate themselves from international market risks, and plan strategically. As textile goods are one of the major components of the manufacturing industry within the Indian WPI basket, such accurate predictions could help policy makers and regulators keep track of prices, predict inflationary pressures, and implement timely macroeconomic measures. Such forecasts can also help small and medium enterprises (SME) that are even more vulnerable to price fluctuations, as the process provides data to help these businesses to have a basis for budgets and financial planning. This pertains particularly to the decision-making process at various levels of the textile industry and the larger economy by offering this ELM-AM model as a way that improves forecasting.

Limitations and Future Scope

The researchers in this work applied the proposed ELM-AM on a specific dataset (WPI of textile commodities of the current Indian WPI series) and have not tested it on other datasets from this domain, i.e., other macroeconomic indices of India and other countries. This paper has not tested its scalability also. Performance examination of the model using a much wider hyper parameter search space is another limitation of the current work. Addressing these limitations will open new research directions in the future.

Conclusion

The authors in this current work applied the proposed ELM-AM and sixteen diverse TS forecasting techniques to the WPI of textiles dataset (i.e., WPI of textile commodities of the current Indian WPI series). The proposed ELM-AM outperformed them in multiple horizons (3, 6, 9, 12, and 18 months forecast horizons) using multiple accuracy criteria (forecast-MAPE and forecast RMSE). In addition, the authors compared the performance of the proposed ELM-AM approach with several other contemporary ANFIS models. For this, the current work employed the ELM-AM on two distinct datasets (COVID-19 datasets). The proposed ELM-AM outdid six of these ANFIS models. Therefore, this work exhibited that the proposed ELM-AM is an efficient forecasting technique for the WPIs of individual textile commodities in India. It offered better performance than several other contemporary approaches. Thus, this paper concludes that the ELM-AM is skilled in predicting the out-of-sample values of the WPIs of individual textile items in India and is a suitable alternative to forecast them.

Abbreviations

AM: Abbasov–Mamedova, ANFIS: Adaptive Neuro-Fuzzy Inference System, ANN: Artificial Neural Network, ARIMA: Autoregressive Integrated Moving Average, CPI: Consumer Price Index, DES: Double Exponential Smoothing, EEMD: Ensemble Empirical Mode Decomposition, ELM: Extreme Learning Machine, EMD: Empirical Mode Decomposition, ES: Exponential Smoothing, ETS: Error-Trend-Seasonality, FFNN: Feed forward Neural Network, FTS: Fuzzy Time Series, GRNN: Generalized Regression Neural Network, MAPE: Mean Absolute Percentage Error, MLP: Multilayer Perceptron, PPI: Producer Price Index, RMSE: Root Mean Squared Error, SES: Simple Exponential Smoothing, SVR: Support Vector Regression, TDNN: Time Delay Neural Network, TES: Triple Exponential Smoothing, TS: Time Series, TSLM: Time Series Linear Model, WPI: Wholesale Price Index.

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Author Contributions

The author, being the sole contributor, was responsible for all aspects of the current work.

Conflict of Interest

The authors declare no conflict of interest.

Ethics Approval

Not applicable.

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