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Multiple Novel Decomposition Techniques for Time Series Forecasting: Application to Monthly Forecasting of Electricity Consumption in Pakistan

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Abstract: In today's modern world, monthly forecasts of electricity consumption are vital in planning the generation and distribution of energy utilities. However, the properties of these time series are so complex that they are difficult to model directly. Thus, this study provides a comprehensive analysis of forecasting monthly electricity consumption by comparing several decomposition techniques followed by various time series models. To this end, first, we decompose the electricity consumption time series into three new subseries: the long-term trend series, the seasonal series, and the stochastic series, using the three different proposed decomposition methods. Second, to forecast each subseries with various popular time series models, all their possible combinations are considered. Finally, the forecast results of each subseries are summed up to obtain the final forecast results. The proposed modeling and forecasting framework is applied to data on Pakistan's monthly electricity consumption from January 1990 to June 2020. The one-month-ahead out-of-sample forecast results (descriptive, statistical test, and graphical analysis) for the considered data suggest that the proposed methodology gives a highly accurate and efficient gain. It is also shown that the proposed decomposition methods outperform the benchmark ones and increase the performance of final model forecasts. In addition, the final forecasting models produce the lowest mean error, performing significantly better than those reported in the literature. Finally, we believe that the framework proposed for modeling and forecasting can also be used to solve other forecasting problems in the real world that have similar features.

Keywords: electricity consumption; monthly forecasting; decomposition methods; times series models

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1. Introduction

Human society is currently facing, and will continue to face, serious problems such as resource shortages and global climate change. Avoiding this dilemma requires two changes to the world's energy mix: a clean energy alternative on the power supply side and an electric energy alternative on the energy consumption side. This work is about electricity consumption. According to local and global statistics, energy consumption follows a rising trend, with electricity accounting for nearly 21% of total energy consumption in 2021 [1].

As the world becomes more dependent on electricity, planning for power generation is critical. Additionally, electric energy may be stored, while electricity may not. On the other hand, electricity is typically utilized shortly after it is generated. This increases the need for energy suppliers to plan their power delivery. Central planning specifications are reliable predictions of future power consumption. In particular, medium- to long-term forecast accuracy of electricity consumption is vital for energy system programming and planning. However, inaccurate prediction of power consumption can be a disadvantage.

Overestimation will lead to the wastage of valuable energy resources, large capital expenditures, and long construction periods. Underestimation has far-reaching negative consequences, such as blackouts. Of course, if beneficial early warnings based on high power consumption prediction accuracy are provided, some precautions can be taken to avoid adverse consequences. Additionally, the time series of electricity consumption is uncertain, complex, and nonlinear, dependent on the political situation, economics, human activities, population behavior, climatic factors, and other external factors that affect the accuracy of electricity consumption forecasts [2–6].

It is well known that electricity consumption/demand time series display distinct characteristics. The monthly consumption time series may exhibit an annual cyclic pattern and a linear or nonlinear long-term trend. Weather and societal variables have a significant impact on electricity usage, which is shown in the consumption time series. Additionally, economic variables frequently impact the trajectory of the consumption time series, while climatic variations inject a periodic behavior into the series [7]. For instance, Figure 1A displays Pakistan's electricity consumption time series for the period from January 1990 to June 2020 with superimposed linear (black line) and nonlinear (red curve) trends. The plots in Figure 1 depict a rising nonlinear trend (Figure 1A), different seasonal effects (Figure 1B), a yearly periodicity (Figure 1C), and the variation of electricity consumption in different years (Figure 1D).

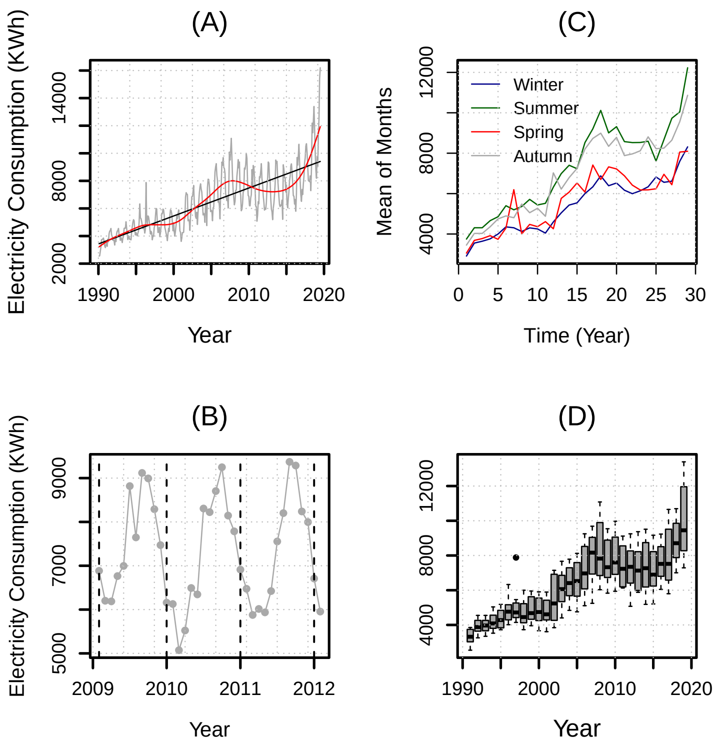

Figure 1. Specific characteristics of the electricity consumption time series (kWh): (**A**) electricity consumption time series for the period from January 1990 to June 2020 (original time series–gray; linear curve–black; nonlinear curve–red); (**B**) annual periodicity for the period from January 2009 to December 2012; (**C**) seasonal plot for the period from January 1990 to June 2020 (winter–blue; summer–dark green; spring–red; autumn–gray), and (**D**) box-plots for yearly observation for the period from January 1990 to December 2020.

In the electricity consumption literature, many techniques have been used to forecast electric power consumption over the last thirty years. Generally, these forecasting methods can be grouped into three categories: statistical methods, models of artificial intelligence, and hybrid system approaches [8]. Examples of statistical models include ARIMA-based models, exponential smoothing models [9], and parametric and nonparametric regression methods. Compared with artificial neural network models, these methods are simple mathematical structures and are easy to implement. In addition, these models are widely used for power consumption forecasting [10–14]. For example, Ref. [15] provides a component-based estimation method to forecast electricity consumption in Pakistan one month in advance using various regression models and time series. To do this, the electricity consumption data are divided into two main components: deterministic and stochastic. To estimate the deterministic component, the authors use parametric and nonparametric regression models. The stochastic part is modeled using four different univariate time series models. Pakistan's electric consumption data from January 1990 to December 2015 were used to evaluate the performance of the proposed method. Their results showed that parametric and nonparametric regression models have the highest accuracy with the combined ARMA model. Another study, Ref. [16], predicts the hourly power consumption for Belgium and German industrial firms by applying Markov's switching model with time-varying transition probabilities. The model consists of a heterogeneous Markov chain and an autoregressive moving average (ARMA) process with a seasonal pattern. The authors use the continuous ranking probability score (CRPS) to estimate the goodness of fit and compare probabilistic models using benchmark models from four different companies. The results show that the proposed model outperforms the traditional additive time series approach and that the Markov switching model performs well. In contrast, artificial intelligence models are more commonly used to address nonlinear load forecasting problems compared with linear time series approaches [17–21]. For example, Ref. [22] proposed a pooling-based Deep Recurrent Neural Network (PDRNN) method for forecasting household demand to address the problem of overfitting. The authors used a dataset from the smart metering electricity customer behavior trials (CBT) conducted in Ireland from 1 July 2009, to 31 December 2010. They validate the performance of the proposed method using a support vector machine (SVR), autoregressive integrated moving average (ARIMA), and three-layer deep Recurrent Neural Networks (RNN). The performance of the model was evaluated using the Root Mean Square Error (RMSE) criterion, and the results showed that the proposed model is 19.5%, 13.1%, and 6.5% more efficient than ARIMA concerning RMSE, SVR, and RNN. On the other hand, Ref. [23] proposed an SVM model for medium-term load forecasting using the EUNITE load competition dataset. The results show that the proposed model is useful for medium-term electric demand forecasting. In another study, two-level short-term load forecasting (STLF) using Q-Learning-based dynamic model selection (QMS), developed by [24] using the electricity demand dataset, found that the proposed technique produced the best results. Aiming at improving forecast electric power consumption, various researchers have combined the features of two or more models to build new models, commonly known as hybrid models [25–31]. For example, Ref. [32] proposed a hybrid model that combines features of machine learning tools (kernels) and vector regression models. The results show that the proposed hybrid model is useful for power demand forecasting. In [33], the authors proposed an ensemble hybrid forecasting model, the ARIMA-ANFIS model, whereby they combined an ARIMA model with an adaptive neurofuzzy inference system (ANFIS). They extended the ARIMA-ANFIS model to three different patterns and applied a hybrid ensemble model to the Iranian dataset to predict energy consumption. The ARIMA model was used for the linear part, and ANFIS for the nonlinear. All the patterns were compared using different methods to check model accuracy. Their results show that the proposed methodology is more efficient and highly accurate. On the other hand, Ref. [34] proposed an ensemble model combining a deep learning belief network (DBN) and a support vector regression (SVR) model for power load forecasting. On another topic, some authors study the effects of different environmental and globalization trends [35,36]. For instance, Ref. [36] used panel estimation methods to study the impact of environmental technologies on energy demand and energy efficiency. The results of the research show that energy consumption decreases as environmental technology improves. In addition, environmental technology plays a vital role in reducing energy intensity and improving energy efficiency. However, generally, each model has its own functional and structural form, and predictive performance varies from market to market [37–40].

In contrast to the methods introduced above, another methodology that can improve performance is to preprocess the dataset to provide a more easily predicted, modified version of the time series [41,42]. An ordinary option when forecasting energy-related time series is to decompose the original dataset into multiple subseries that can be separately predicted and summed to provide a real-time time series forecast. The goal is to obtain a new time series that has a more or less periodic behavior and is, therefore, easy to forecast. This assumption is based on the fact that energy-related quantities are closely related and influenced by climatic and social factors that show a specific periodic behavior. Therefore, this paper proposes a new decomposition and combination methodology that is simple and easy to implement. First, the proposed decomposition methods are Regression Spline Decomposition, Smoothed Spline Decomposition, and Hybrid Decomposition. Second, the three standard time series models considered are linear autoregressive, nonlinear autoregressive, and autoregressive moving averages, to estimate each new subseries. The proposed methodology was used to obtain a one-month-ahead out-of-sample forecast of Pakistan's monthly electricity consumption data. The individual results for the forecasting models are summed, and the final, one-month-ahead electricity consumption forecast is obtained.

The rest of the paper is designed as follows: Section 2 describes the general procedure of the proposed forecasting methodology. Section 3 provides an empirical application of the proposed modeling framework using the Pakistan monthly electricity consumption data. Section 4 comprises a discussion about the proposed methodologies and some of the best models available in the literature. Finally, Section 5 addresses the concluding remarks and future research directions.

2. The Proposed Forecasting Methodology

This section explains the proposed forecasting methodology for one-month-ahead electricity consumption forecasting. As described in the previous section, the time series of electricity consumption contain specific characteristics, such as linear or nonlinear long-run trends, monthly periodicity, and nonconstant mean and variance. Incorporating these unique characteristics into the model significantly increases forecast accuracy. To do this, the electricity consumption time series is decomposed into three new subseries: the long-term trend series, seasonal series, and stochastic series, using the proposed decomposition methods described in the following subsection.

2.1. The Proposed Decomposition Techniques

This subsection describes the general procedure for decomposing a monthly time series of electricity usage. For this purpose, the consumption time series $(\mathfrak{c}_{\mathfrak{m}})$ is split into three new subseries: long-term trend $(\mathfrak{t}_{\mathfrak{m}})$, seasonal $(\mathfrak{s}_{\mathfrak{m}})$, and stochastic $(\mathfrak{r}_{\mathfrak{m}})$ series. The mathematical representation of the decomposed subsequence is given by

$$\mathfrak{c}_{\mathfrak{m}} = \mathfrak{t}_{\mathfrak{m}} + \mathfrak{s}_{\mathfrak{m}} + \mathfrak{r}_{\mathfrak{m}} \quad (1)$$

Hence, for modeling purposes, the long-term trend $\mathfrak{t}_{\mathfrak{m}}$ is a function of time n, the seasonal $\mathfrak{s}_{\mathfrak{m}}$ cycle is the function of the series $(1, 2, 3, \ldots, 12, 1, 2, 3, \ldots, 12, \ldots)$, and the stochastic subseries, which describes the short-run dependence of consumption series, is obtained by $\mathfrak{r}_{\mathfrak{m}} = \mathfrak{c}_{\mathfrak{m}} - (\mathfrak{t}_{\mathfrak{m}} + \mathfrak{s}_{\mathfrak{m}})$. Therefore, the proposed decomposition methods, including DRS (decomposition based on regression splines), DSS (decomposition based on smoothing splines), and DH (hybrid decomposition), are discussed in the following subsections.

2.1.1. Regression Spline Decomposition Method

A regression spline is a general nonparametric approximation of $\mathfrak{c}_{\mathfrak{m}}$ by a piecewise qth degree polynomial, estimating a subinterval bounded by a series of m points (called knots).

Any spline function $\mathfrak{u}(\mathfrak{c})$ of order q can be defined as a linear combination of functions $\mathfrak{u}_\mathfrak{i}(\mathfrak{c})$ called basis functions, whose formula is given by increase.

$$\mathfrak{u}(\mathfrak{c}) = \sum_{i=1}^{m+q+1} \alpha_i \mathfrak{u}_\mathfrak{i}(\mathfrak{c}) \tag{2}$$

The unknown parameter is α_i, estimated by the ordinary least squares method. The most important choices are the number of nodes and their positions, which define the smoothness of the approximation. In this work, we used cross-validation to estimate these quantities.

2.1.2. Smoothing Splines Decomposition Method

To meet the requirements for resolving knot regions, spline features can be predicted using a least-squares penalty environment to limit the sum of squares. Hence, the equation can be written as

$$\sum_{j=1}^{N} (\mathfrak{c}_\mathfrak{m} - \mathfrak{u}(\mathfrak{c}))^2 + \lambda \int (\mathfrak{u}''(\mathfrak{c}))^2 \mathrm{dm}, \tag{3}$$

where $(\mathfrak{u}''(\mathfrak{c}))$ is the second derivative of $\mathfrak{u}(\mathfrak{c})$. The first term describes the goodness of fit, and the second term penalizes the coarseness of the function by the smoothing parameter λ. Moreover, the selection of smoothing parameters is a difficult task and is performed using cross-validation methods in this work.

In the hybrid decomposition method, we decomposed the long-term series $(\mathfrak{t}_\mathfrak{m})$ with a regression spline and the seasonal series $\mathfrak{s}_\mathfrak{m}$ with a smoothing spline.

2.1.3. Seasonal Trend Decomposition Method

To assess the performance of the three proposed decomposition methods, they are compared with a standard and benchmark decomposition method, the Seasonal Trend Decomposition (DSTL). Cleveland et al. [43] proposed a decomposition method where a seasonal time series is divided into trend, seasonal and stochastic components. DSTL uses LOESS to divide the seasonal time series into trend, seasonal, and stochastic components. In particular, the steps for DSTL are: (i) detrending; (ii) periodic smoothing of subsequences: creating a sequence for each seasonal component and smoothing them separately; (iii) low-pass filtering smoothing of regular substrings: recombining and smoothing substrings; (iv) season series cleanup; (v) detrending the original series using the seasonal component calculated in the previous step; and (vi) smoothing the seasonal sequence to obtain the trend component.

To graphically demonstrate and compare the performance of the three proposed decomposition methods described above and the benchmark DSTL decomposition, the decomposed subseries are shown in Figure 2. In each of the Figure 2a–d, the top panel shows the long-term trend $(\mathfrak{t}_\mathfrak{m})$, the middle panel shows the seasonal component $(\mathfrak{s}_\mathfrak{m})$, and the bottom panel shows the stochastic component $(\mathfrak{r}_\mathfrak{m})$. All of the proposed decomposition methods and the benchmark decomposition method were used to decompose $(\mathfrak{c}_\mathfrak{m})$ to adequately capture the long-term nonlinear trend and monthly periodicity of the power consumption series. Moreover, the proposed decomposition methods accurately compared the extracted features with the benchmark method. In particular, of the proposed decomposition methods, the DH method has extracted the dynamic very well compared with the other methods.

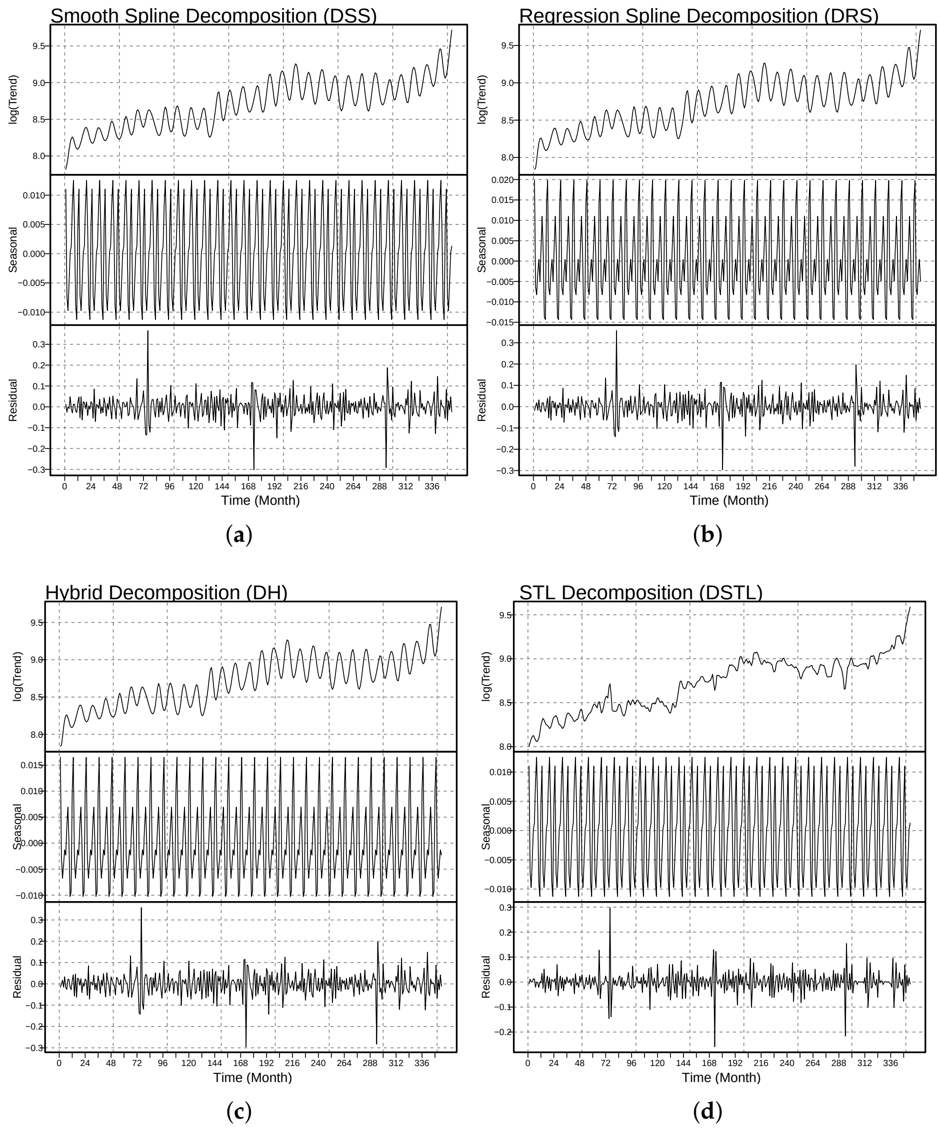

Figure 2. Electricity consumption (kWh) in Pakistan: The monthly electricity consumption series is decomposed by the three proposed decomposition methods: (**a**) DSS, (**b**) DRS, (**c**) DH, and (**d**) the benchmark decomposing method DSTL. In each sub-figure, the top panel shows the long-term trend ($\mathfrak{t}_{\mathfrak{m}}$), the middle panel shows the seasonal ($\mathfrak{s}_{\mathfrak{m}}$) component, and the bottom panel shows the stochastic component ($\mathfrak{r}_{\mathfrak{m}}$).

2.2. Modeling the Decomposed Subseries

Once the subseries are extracted from the monthly electricity consumption time series using the above proposed decomposition methods and benchmark decomposition method, the extracted subseries are fitted using the three considered standard time series models (linear autoregressive, nonlinear autoregressive, and autoregressive moving averages). These three models are explained in the following subsections.

2.2.1. Linear Autoregressive Model

A linear autoregressive (LAR) model uses a linear combination of p past observations of $\mathfrak{c}_{\mathfrak{m}}$ to describe the short-term dynamics of $\mathfrak{c}_{\mathfrak{m}}$, and can be written as

$$\mathfrak{c}_{\mathfrak{m}} = I + \xi_1 \mathfrak{c}_{\mathfrak{m}-1} + \xi_2 \mathfrak{c}_{\mathfrak{m}-2} + \ldots. + \xi_p \mathfrak{c}_{\mathfrak{m}-\mathfrak{p}} + \epsilon_m, \tag{4}$$

where ξ_i $(i = 1, 2, \ldots, r)$ are the AR parameters and ϵ_m is the white noise process. In the current study, parameters are estimated using maximum likelihood estimation. After plotting the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the series, we concluded that lags 1, 2, and 12 were significant and therefore included them in the model.

2.2.2. Nonlinear Autoregressive Model

The nonlinear additive counterpart of LAR is the nonlinear additive model (NLAR), where the relationship between $\mathfrak{c}_\mathfrak{m}$ and its lag values has no specific linear form. The mathematical formulation of this model can be written as

$$\mathfrak{c}_\mathfrak{m} = w_1(\mathfrak{c}_{\mathfrak{m}-1}) + w_2(\mathfrak{c}_{\mathfrak{m}-2}) + \ldots + w_p(\mathfrak{c}_{\mathfrak{m}-\mathfrak{p}}) + \epsilon_m, \quad (5)$$

where w_i is each past value and $\mathfrak{c}_\mathfrak{m}$ is a smoothing function that expresses the relationship between $\mathfrak{c}_\mathfrak{m}$. In this work, the w_i function is represented by a cubic regression spline, and lags 1, 2, and 12 are used for NLAR modeling. To avoid the so-called dimensional curse, a backfitting algorithm was used to estimate the model [44].

2.2.3. Autoregressive Moving Average Model

Autoregressive Moving Average (ARMA) models not only include time series lagged values, but also account for error terms passed into the model. In this study, the decomposed subseries are modeled as a linear combination of p past observations and a delay error term. The equation of the model can be written as

$$\mathfrak{c}_\mathfrak{m} = \mu + \xi_1\mathfrak{c}_{\mathfrak{m}-1} + \xi_2\mathfrak{c}_{\mathfrak{m}-2} + \ldots + \xi_p\mathfrak{c}_{\mathfrak{m}-\mathfrak{p}} + \epsilon_m + \psi_1\epsilon_{m-1} + \psi_2\epsilon_{m-2} + \ldots + \varphi\epsilon_{m-s}, \quad (6)$$

where μ is the intercept, ξ_i $(i = 1, 2, \ldots, p)$ and ψ_j $(j = 1, 2, \ldots, s)$ are the AR and MA parameters, respectively, and $\epsilon_n \sim N(0, \sigma^2_\epsilon)$. In this study, graphical and descriptive analysis shows that the first two lags are significant in the MA part, whereas only lags 1, 2, and 12 are significant in the AR part, that is, a restricted ARMA (12,2) with $\xi_3 = \cdots = \xi_{11} = 0$.

In the comparative study, we denote each combined model with each decomposition method by ${}^{\mathfrak{t}_\mathfrak{m}}\mathrm{DSS}^{\mathfrak{s}_\mathfrak{m}}_{\mathfrak{r}_\mathfrak{m}}$, where the $\mathfrak{t}_\mathfrak{m}$ at top left is associated to the long term component/subseries, the $\mathfrak{s}_\mathfrak{m}$ at top right is associated to the seasonal component/subseries, and the $\mathfrak{r}_\mathfrak{m}$ at bottom right is associated to the stochastic component/subseries. In the forecasting models, we assign a code to each model: "a" for the linear autoregressive, "b" for the nonlinear autoregressive, and "c" for the autoregressive moving average. For example, ${}^{a}\mathrm{DSS}^{c}_{b}$ represents the estimate of the long-term ($\mathfrak{t}$) with the linear autoregressive model, the seasonal series ($\mathfrak{s}$) estimated with the nonlinear autoregressive model, and the stochastics series ($\mathfrak{r}$) estimated using autoregressive moving average models. The individual forecast models are summed to get the final one-month-ahead consumption forecast.

$$\hat{\mathfrak{c}}_{m+1} = (\hat{\mathfrak{t}}_{m+1} + \hat{\mathfrak{s}}_{m+1} + \hat{\mathfrak{r}}_{m+1}) \quad (7)$$

2.3. Accuracy Measures

The Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Correlation Coefficient (CORR) are used to check the performance of all models obtained from the proposed decomposition forecasting methodology. The mathematical equations for MAPE, RMSE, and CORR are given as follows:

$$\mathrm{MAPE} = \frac{1}{N_1}\sum_{i=1}^{N_1}\left(\frac{|\mathfrak{c}_\mathfrak{m} - \hat{\mathfrak{c}}_m|}{|\mathfrak{c}_\mathfrak{m}|}\right) \times 100, \quad (8)$$

$$\mathrm{MAE} = \frac{1}{N_1}\sum_{i=1}^{N_1}(|\mathfrak{c}_\mathfrak{m} - \hat{\mathfrak{c}}_m|), \quad (9)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N_1}\sum_{i=1}^{N_1}(\mathfrak{c}_\mathfrak{m} - \hat{\mathfrak{c}}_m)^2}, \quad (10)$$

$$\text{CORR} = \text{Corr}(\mathfrak{c}_\mathfrak{m}, \hat{\mathfrak{c}}_m), \quad (11)$$

where $\mathfrak{c}_\mathfrak{m}$ is the observed value of the time series, and $\hat{\mathfrak{c}}_m$ is the forecasted electricity consumption value for mth observation (m = 1, 2, . . ., N_1), with N_1 the size of the training set.

3. Case Study Evaluation

This work uses monthly aggregates of Pakistan's electricity consumption (kWh) for the period from January 1990 to June 2020 (a total of 354 months). The dataset was obtained from the Pakistan Bureau of Statistics. For modeling and forecasting purposes, the data were split into two parts: a training part (for model fit) and a testing part (for out-of-sample forecast). The training portion consists of data from January 1990 to December 2013 (274 months), which accounts for about 80% of the total data, and the period from January 2014 to June 2020 (78 months) is used as the out-of-sample (testing) portion.

In order to obtain the forecast for electricity consumption a month ahead, using the proposed forecasting methodology described in Section 2, the following steps have to be followed: first, the proposed decomposition methods and a benchmark decomposition method were used to obtain a long-term trend ($\mathfrak{t}_\mathfrak{m}$), seasonal ($\mathfrak{s}_\mathfrak{m}$), and stochastic ($\mathfrak{r}_\mathfrak{m}$) time subseries. Second, the previously described three well-known times series models were applied to each subseries. Thereby, the models were estimated, and a month-ahead forecast for 78 months was obtained using the rolling window method. Final electricity consumption forecasts were obtained using Equation (7). The accuracy measures MAPE, MAE, RMSE, and CORR were then used to evaluate and compare the performance of the models.

The original time series of electricity consumption ($\mathfrak{c}_\mathfrak{m}$) is divided into a long-term trend ($\mathfrak{t}_\mathfrak{m}$), a seasonal ($\mathfrak{s}_\mathfrak{m}$) and a stochastic subseries ($\mathfrak{r}_\mathfrak{m}$), and three proposed decomposition methods were used in this work. Forecasts for these subseries are obtained using three univariate time series models. Combining the models and subseries forecast, there are ($3^{\mathfrak{t}_\mathfrak{m}} \times 3^{\mathfrak{s}_\mathfrak{m}} \times 3^{\mathfrak{r}_\mathfrak{m}}$ = 27) different combinations for each proposed decomposition method. Thus, there are three proposed decomposition methods, DSS, DRS, and DH, and one benchmark method (STLD), for a total of 108 (4×27) models. For these 108 models, the out-of-sample forecast accuracy measures for one month ahead (MAPE, MAE, RMSE, and CORR) are tabulated in Tables 1–4. The results of the performance measures show that the ${}^{c}\text{DSS}_{c}^{c}$ model produced a better prediction than all other models using the DSS method. The best forecasting model is ${}^{c}\text{DSS}_{c}^{c}$, which produced 2.2382, 181.4303, 241.8992, and 0.9938 for MAPE, MAE, RMSE, and CORR, respectively. However, the ${}^{c}\text{DSS}_{c}^{b}$, ${}^{c}\text{DSS}_{c}^{a}$, and ${}^{a}\text{DSS}_{c}^{c}$ models produced the second, third, and fourth-best results. Using the DRS method, the lowest forecast errors were found by the ${}^{c}\text{DRS}_{c}^{b}$ model, with values of 2.2163, 175.0277, 235.9146, and 0.9940 for MAPE, MAE, RMSE, and CORR, respectively. Notwithstanding, the second, third, and fourth-best results are achieved by the ${}^{a}\text{DRS}_{c}^{b}$, ${}^{c}\text{DRS}_{c}^{c}$ and ${}^{c}\text{DRS}_{c}^{a}$ models, respectively. On the other hand, using the DH method, the lowest prediction errors were found by the model ${}^{c}\text{DH}_{c}^{b}$ model, with values of 1.9718, 157.7533, 199.5219, and 0.9957 for MAPE, MAE, RMSE, and CORR, respectively, whereas the second, third, and fourth-best results are shown in ${}^{c}\text{DH}_{c}^{a}$, ${}^{a}\text{DH}_{c}^{a}$, and ${}^{a}\text{DH}_{c}^{b}$. In contrast, the benchmark decomposition method (DSTL) was outperformed by the proposed methods.

From the proposed decomposition methods and the STL decomposition, the best four models from each combination are selected and compared. The mean of the accuracy measures are listed in Table 5, and it is seen that the ${}^{c}\text{DH}_{c}^{b}$ produced the smallest values (MAPE = 1.9718, MAE = 157.7533, RMSE = 199.5219, and CORR = 0.9957). When comparing the results of this method with the results from some of the models available in the literature (Table 6), we can conclude that the proposed decomposition methods result in more accurate forecasts than the competitors. Among the proposed methods, the DH method proved to provide the highest forecasting accuracy compared.

Table 1. Pakistan's electricity consumption (kWh): out-of-sample one-month-ahead average forecast error for all combined models with the DSS method.

S.No	Models	MAPE	MAE	RMSE	CORR
1	${}^{a}DSS^{a}_{a}$	3.8513	303.1823	395.5292	0.9833
2	${}^{a}DSS^{a}_{b}$	3.7886	299.5319	396.5169	0.9833
3	${}^{a}DSS^{a}_{c}$	2.3521	191.2760	256.6520	0.9930
4	${}^{a}DSS^{b}_{a}$	3.6722	289.3194	394.0852	0.9834
5	${}^{a}DSS^{b}_{b}$	3.6107	285.5530	395.6597	0.9832
6	${}^{a}DSS^{b}_{c}$	2.3908	195.8973	259.4971	0.9929
7	${}^{a}DSS^{c}_{a}$	3.8175	300.6711	397.5553	0.9832
8	${}^{a}DSS^{c}_{b}$	3.7450	296.2238	398.2182	0.9831
9	${}^{a}DSS^{c}_{c}$	2.2939	185.8645	250.0828	0.9934
10	${}^{b}DSS^{a}_{a}$	3.8355	303.7990	400.3169	0.9833
11	${}^{b}DSS^{a}_{b}$	3.7651	299.5174	401.5727	0.9832
12	${}^{b}DSS^{a}_{c}$	2.3829	193.9457	263.4854	0.9928
13	${}^{b}DSS^{b}_{a}$	3.6738	291.3070	399.1517	0.9833
14	${}^{b}DSS^{b}_{b}$	3.6180	288.4040	400.9866	0.9831
15	${}^{b}DSS^{b}_{c}$	2.4173	198.4902	266.6493	0.9926
16	${}^{b}DSS^{c}_{a}$	3.8088	301.8532	402.9203	0.9830
17	${}^{b}DSS^{c}_{b}$	3.7361	297.4499	403.8527	0.9830
18	${}^{b}DSS^{c}_{c}$	2.3342	189.5097	258.0311	0.9931
19	${}^{c}DSS^{a}_{a}$	3.8141	300.0557	396.0669	0.9832
20	${}^{c}DSS^{a}_{b}$	3.7811	298.4973	396.7102	0.9831
21	${}^{c}DSS^{a}_{c}$	2.3239	188.2632	248.0112	0.9935
22	${}^{c}DSS^{b}_{a}$	3.7218	292.1390	395.1023	0.9832
23	${}^{c}DSS^{b}_{b}$	3.6642	288.2662	396.3294	0.9831
24	${}^{c}DSS^{b}_{c}$	2.2911	188.6474	251.7045	0.9933
25	${}^{c}DSS^{c}_{a}$	3.7967	298.9096	398.5101	0.9830
26	${}^{c}DSS^{c}_{b}$	3.7508	296.1589	398.8303	0.9829
27	${}^{c}DSS^{c}_{c}$	2.2382	181.4303	241.8992	0.9938

Table 2. Pakistan's electricity consumption (kWh): out-of-sample one-month-ahead average forecast error for all combined models with the DRS method.

S.No	Models	MAPE	MAE	RMSE	CORR
1	${}^{a}DRS^{a}_{a}$	3.6219	286.1814	385.6078	0.9838
2	${}^{a}DRS^{a}_{b}$	3.5769	283.3066	380.3018	0.9843
3	${}^{a}DRS^{a}_{c}$	2.2938	179.0583	233.9822	0.9941
4	${}^{a}DRS^{b}_{a}$	3.5534	280.5790	379.7724	0.9843
5	${}^{a}DRS^{b}_{b}$	3.4699	275.1287	375.1131	0.9848
6	${}^{a}DRS^{b}_{c}$	2.2535	176.4146	236.3622	0.9939
7	${}^{a}DRS^{c}_{a}$	3.6576	288.3619	389.5358	0.9834
8	${}^{a}DRS^{c}_{b}$	3.6066	284.6170	383.8062	0.9840
9	${}^{a}DRS^{c}_{c}$	2.3016	179.1916	234.8334	0.9940
10	${}^{b}DRS^{a}_{a}$	3.6197	288.3346	388.2273	0.9839
11	${}^{b}DRS^{a}_{b}$	3.5768	286.0483	382.8333	0.9845
12	${}^{b}DRS^{a}_{c}$	2.4216	190.4513	242.9584	0.9937
13	${}^{b}DRS^{b}_{a}$	3.5288	281.4996	383.0212	0.9843
14	${}^{b}DRS^{b}_{b}$	3.4665	278.1669	378.2763	0.9849
15	${}^{b}DRS^{b}_{c}$	2.4007	189.9531	246.1694	0.9935
16	${}^{b}DRS^{c}_{a}$	3.6585	290.9357	392.1562	0.9835
17	${}^{b}DRS^{c}_{b}$	3.6215	288.7784	386.3424	0.9841
18	${}^{b}DRS^{c}_{c}$	2.4383	191.8828	243.8220	0.9937
19	${}^{c}DRS^{a}_{a}$	3.7136	293.0724	391.8557	0.9832
20	${}^{c}DRS^{a}_{b}$	3.6323	287.2605	386.0430	0.9838
21	${}^{c}DRS^{a}_{c}$	2.2916	179.9492	232.3815	0.9941
22	${}^{c}DRS^{b}_{a}$	3.6498	287.2037	386.8070	0.9837
23	${}^{c}DRS^{b}_{b}$	3.5598	280.8756	381.6342	0.9842
24	${}^{c}DRS^{b}_{c}$	2.2163	175.0277	235.9146	0.9940
25	${}^{c}DRS^{c}_{a}$	3.7834	297.8234	396.4955	0.9828
26	${}^{c}DRS^{c}_{b}$	3.6797	289.7838	390.2820	0.9834
27	${}^{c}DRS^{c}_{c}$	2.2904	179.2011	234.5493	0.9940

Table 3. Pakistan's electricity consumption (kWh): out-of-sample one-month-ahead average forecast error for all models combined with the DH method.

S.No	Models	MAPE	MAE	RMSE	CORR
1	${}^{a}DH_{a}^{a}$	3.6829	290.3322	386.3345	0.9837
2	${}^{a}DH_{b}^{a}$	3.6204	286.9580	384.0921	0.9840
3	${}^{a}DH_{c}^{a}$	2.0068	158.7059	199.4186	0.9957
4	${}^{a}DH_{a}^{b}$	3.6247	286.6047	385.6102	0.9838
5	${}^{a}DH_{b}^{b}$	3.5200	280.4262	384.4030	0.9840
6	${}^{a}DH_{c}^{b}$	2.0393	162.0884	204.0827	0.9955
7	${}^{a}DH_{a}^{c}$	3.7206	292.9335	390.9844	0.9833
8	${}^{a}DH_{b}^{c}$	3.6233	286.8009	388.9185	0.9836
9	${}^{a}DH_{c}^{c}$	2.0839	164.6258	206.6300	0.9954
10	${}^{b}DH_{a}^{a}$	3.6624	291.3618	389.4783	0.9838
11	${}^{b}DH_{b}^{a}$	3.6307	290.7418	387.5633	0.9841
12	${}^{b}DH_{c}^{a}$	2.0744	164.3205	211.3162	0.9953
13	${}^{b}DH_{a}^{b}$	3.6016	287.6479	389.0995	0.9838
14	${}^{b}DH_{b}^{b}$	3.5387	284.6500	388.2118	0.9841
15	${}^{b}DH_{c}^{b}$	2.1090	168.4910	216.3346	0.9951
16	${}^{b}DH_{a}^{c}$	3.6959	293.8540	393.9049	0.9834
17	${}^{b}DH_{b}^{c}$	3.6419	291.0633	392.1600	0.9837
18	${}^{b}DH_{c}^{c}$	2.1345	169.5054	217.7980	0.9950
19	${}^{c}DH_{a}^{a}$	3.7636	296.7260	393.3650	0.9831
20	${}^{c}DH_{b}^{a}$	3.6728	290.6076	390.3498	0.9834
21	${}^{c}DH_{c}^{a}$	1.9815	157.0250	194.1687	0.9959
22	${}^{c}DH_{a}^{b}$	3.7257	293.5816	392.9407	0.9831
23	${}^{c}DH_{b}^{b}$	3.6367	287.9581	390.9442	0.9834
24	${}^{c}DH_{c}^{b}$	1.9718	157.7533	199.5219	0.9957
25	${}^{c}DH_{a}^{c}$	3.8181	300.0332	398.4989	0.9826
26	${}^{c}DH_{b}^{c}$	3.7237	293.8677	395.6701	0.9829
27	${}^{c}DH_{c}^{c}$	2.0413	161.5169	202.6835	0.9956

Table 4. Pakistan's electricity consumption (kWh): out-of-sample one-month-ahead average forecast error for all models combined with the DSTL method.

S.No	Models	MAPE	MAE	RMSE	CORR
1	${}^{a}DSTL_{a}^{a}$	11.4390	936.2145	1042.3530	0.8795
2	${}^{a}DSTL_{b}^{a}$	11.4826	940.0003	1048.3239	0.8778
3	${}^{a}DSTL_{c}^{a}$	10.4287	840.1818	954.3405	0.8965
4	${}^{a}DSTL_{a}^{b}$	11.5359	943.3328	1042.6842	0.8794
5	${}^{a}DSTL_{b}^{b}$	11.5795	947.1186	1048.4946	0.8778
6	${}^{a}DSTL_{c}^{b}$	10.5400	847.9374	954.6524	0.8964
7	${}^{a}DSTL_{a}^{c}$	11.4614	936.9204	1040.3136	0.8800
8	${}^{a}DSTL_{b}^{c}$	11.5049	940.7062	1046.2201	0.8783
9	${}^{a}DSTL_{c}^{c}$	10.4823	842.8418	953.5488	0.8966
10	${}^{b}DSTL_{a}^{a}$	11.3617	925.8832	1033.5390	0.8800
11	${}^{b}DSTL_{b}^{a}$	11.4053	929.6691	1039.4770	0.8784
12	${}^{b}DSTL_{c}^{a}$	10.3991	839.0876	954.7580	0.8961
13	${}^{b}DSTL_{a}^{b}$	11.4586	933.0015	1033.5924	0.8801
14	${}^{b}DSTL_{b}^{b}$	11.5021	936.7874	1039.3701	0.8785
15	${}^{b}DSTL_{c}^{b}$	10.5044	845.3495	954.7660	0.8961
16	${}^{b}DSTL_{a}^{c}$	11.3840	926.5891	1031.5245	0.8805
17	${}^{b}DSTL_{b}^{c}$	11.4276	930.3750	1037.3973	0.8790
18	${}^{b}DSTL_{c}^{c}$	10.4620	842.4702	954.0124	0.8963
19	${}^{c}DSTL_{a}^{a}$	11.4204	937.2199	1044.5191	0.8798
20	${}^{c}DSTL_{b}^{a}$	11.4640	941.0057	1050.8107	0.8781
21	${}^{c}DSTL_{c}^{a}$	10.3579	838.3250	951.3494	0.8972
22	${}^{c}DSTL_{a}^{b}$	11.5173	944.3382	1044.6312	0.8799
23	${}^{c}DSTL_{b}^{b}$	11.5609	948.1240	1050.7638	0.8782
24	${}^{c}DSTL_{c}^{b}$	10.4727	846.3646	951.4223	0.8972
25	${}^{c}DSTL_{a}^{c}$	11.4428	937.9258	1042.2494	0.8804
26	${}^{c}DSTL_{b}^{c}$	11.4864	941.7116	1048.4788	0.8787
27	${}^{c}DSTL_{c}^{c}$	10.4041	840.5131	950.2979	0.8974

Once the accuracy measures have been calculated, the next step is to evaluate the dominance of these results. To this end, in the literature, many researchers have performed the Diebold and Mariano test (DM) [45,46]. In this work, to confirm the superiority of the best models listed in Table 5, we performed tests by Diebold and Mariano (DM) on each pair of models [47]. The DM test results (p-values) are shown in Table 7. This table shows that among all the best models, in Table 5, the ${}^{c}DH_{c}^{b}$, ${}^{c}DH_{c}^{a}$, ${}^{a}DH_{c}^{a}$, and ${}^{a}DH_{c}^{b}$ models are statistically superior to the others at the 5% significance level.

Table 5. Pakistan's electricity consumption (kWh): mean forecast error of one-month-ahead post-sample for the best four models with DSS, DRS and DH decompositions.

S.No	Models	MAPE	MAE	RMSE	CORR
1	${}^{c}DSS_{c}^{b}$	2.2382	181.4303	241.8992	0.9938
2	${}^{c}DSS_{c}^{b}$	2.2911	188.6474	251.7045	0.9933
3	${}^{c}DSS_{c}^{a}$	2.3239	188.2632	248.0112	0.9935
4	${}^{a}DSS_{c}^{c}$	2.2939	185.8645	250.0828	0.9934
5	${}^{c}DRS_{c}^{b}$	2.2163	175.0277	235.9146	0.9940
6	${}^{a}DRS_{c}^{b}$	2.2535	176.4146	236.3622	0.9939
7	${}^{c}DRS_{c}^{b}$	2.2904	179.2011	234.5493	0.9940
8	${}^{c}DRS_{c}^{a}$	2.2916	179.9492	232.3815	0.9941
9	${}^{c}DH_{c}^{b}$	1.9718	157.7533	199.5219	0.9957
10	${}^{c}DH_{c}^{a}$	1.9815	157.0250	194.1687	0.9959
11	${}^{a}DH_{c}^{a}$	2.0068	158.7059	199.4186	0.9957
12	${}^{a}DH_{c}^{b}$	2.0393	162.0884	204.0827	0.9955

Table 6. Pakistan's electricity consumption (kWh): mean performance measures of the proposed versus the literature.

S.No	Models	MAPE	MAE	RMSE	CORR
1	${}^{c}DH_{c}^{b}$	1.9718	157.7533	199.5219	0.9957
2	AR	9.7316	841.3092	1116.3690	0.8618
3	NPAR	9.0549	817.5962	1156.6528	0.8598
4	Proposed model [48]	7.6291	665.7315	974.3326	0.9033
5	Proposed model 1 [15]	7.1039	607.8114	860.4425	0.9303
6	Proposed model 2 [15]	6.4823	569.1609	855.5536	0.9386

Graphical representations of the performance measures for all 108 models are shown in Figure 3, for MAPE (top), MAE (center), and RMSE (bottom). From these plots, we can see that the proposed decomposition methods produce the highest accuracy (MAPE, MAE, and RMSE) when compared with the considered benchmark decomposition method. Within the proposed decomposition methods, the DH obtained the highest accuracy. In the same way, the obtained best models for each decomposition method's mean errors are also plotted in Figure 4. It can be seen that ${}^{c}DH_{c}^{b}$, ${}^{c}DH_{c}^{a}$, ${}^{a}DH_{c}^{a}$, and ${}^{a}DH_{c}^{b}$ outperform the others. In addition, the correlation plots of the four best models out of the best 12 models in the first selection are shown in Figure 5. From this figure, we can see that the best model has the highest CORR values and shows a significant correlation between the actual and forecast values. In addition, the original and forecast values for the four best models are shown in Figure 6. Figure 6 shows that the best model's forecasts follow the observed consumption very well. Therefore, from the descriptive statistics, statistical test, and graphical results, we can conclude that the proposed forecasting methodology is highly accurate and efficient for monthly electricity consumption forecasting. Additionally, the proposed decomposition methods have high accuracy and result in efficient forecasts when compared with the considered benchmark method. Within the set of proposed decomposition methods, the DH method produces more precise forecasts when compared with the alternatives.

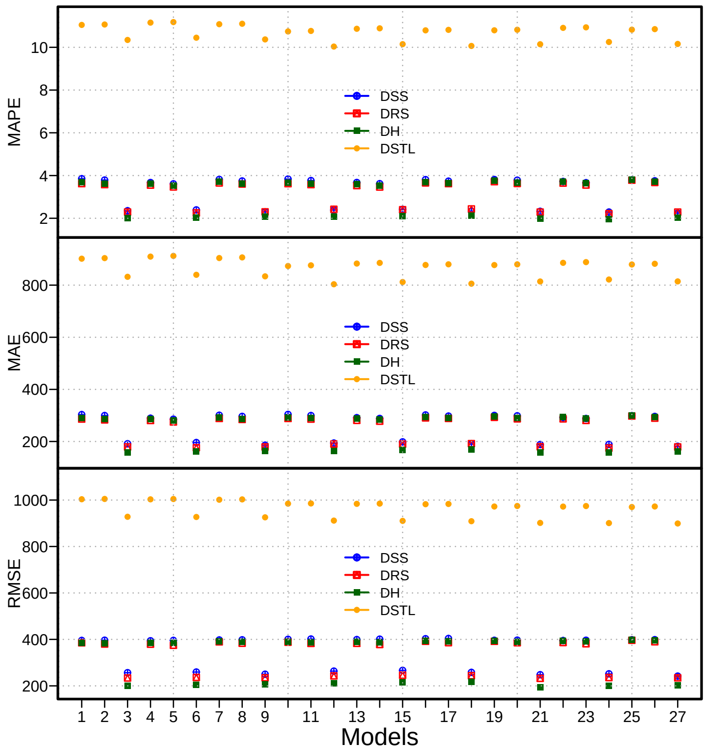

Figure 3. Performance measures: the MAPE (**top**), MAE (**center**), and RMSE (**bottom**) for all combination models using three proposed and the benchmark decomposition methods.

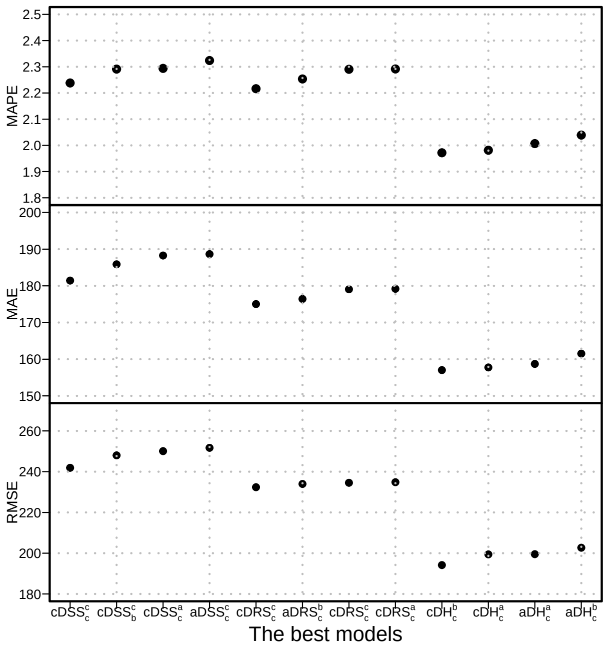

Figure 4. Performance measures: the accuracy measures for the best twelve models: MAPE (**top**), MAE (**center**), and RMSE (**bottom**).

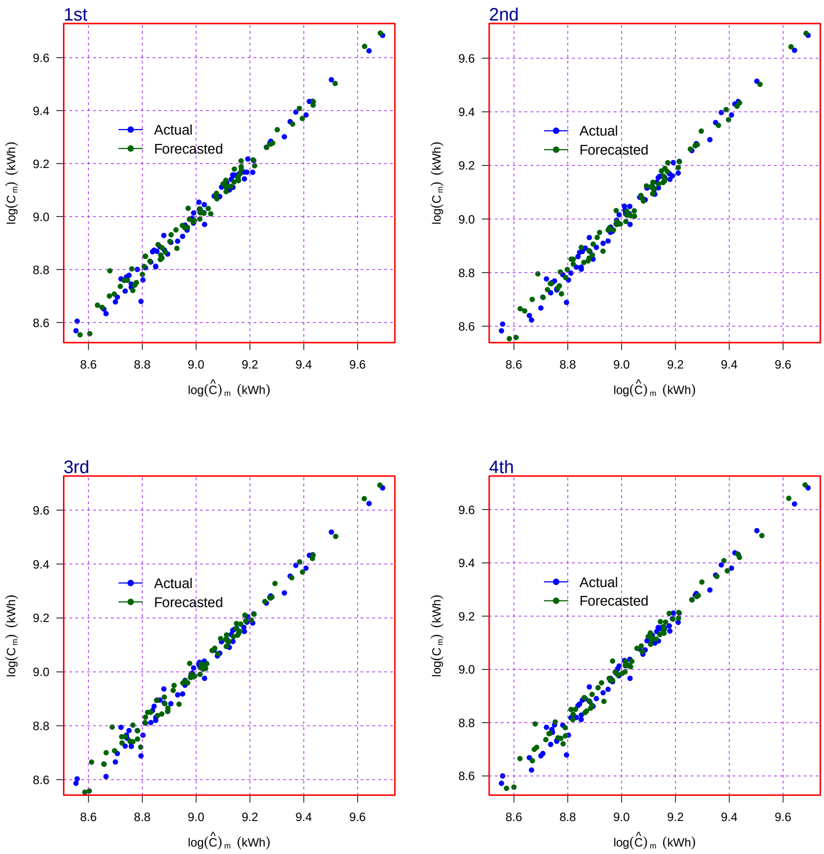

Figure 5. Scatter plot for the electricity consumption forecasting models along with the correlation coefficient (CORR), ${}^{c}\mathrm{DH}_{c}^{b}$ (**1st**), ${}^{c}\mathrm{DH}_{c}^{a}$ (**2nd**), ${}^{a}\mathrm{DH}_{c}^{a}$ (**3rd**), and ${}^{a}\mathrm{DH}_{c}^{b}$ (**4th**).

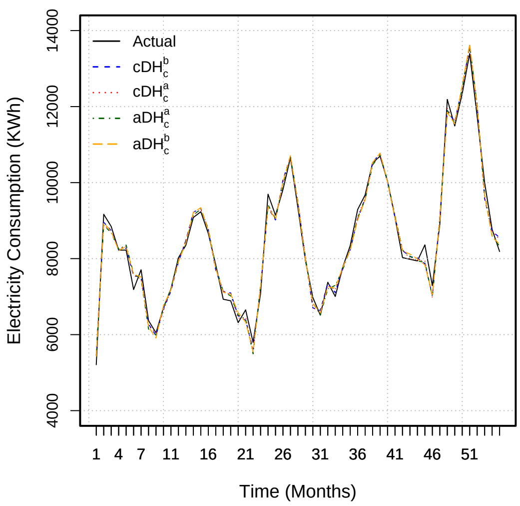

Figure 6. Original and forecasted electricity consumption for four of the best models over five years.

4. Discussion

According to the results (descriptive statistics, statistical test, and graphical analysis), the conclusion is that the final best models for forecasting the monthly electricity consumption are ${}^{c}\mathrm{DH}_{c}^{b}$, ${}^{c}\mathrm{DH}_{c}^{a}$, ${}^{a}\mathrm{DH}_{c}^{a}$, and ${}^{a}\mathrm{DH}_{c}^{b}$. It is important to note that the reported accuracy measures (MAPE, MAE, and RMSE) in this study are relatively lower than those mentioned in other research articles relating to their best models. For instance, an empirical comparison of the best models proposed in this paper with other researchers' proposed models is presented numerically in Table 6 and graphically in Figure 7. As can be seen in both presentations, the proposed final supermodel in this study produces comparatively significantly smaller mean errors. For example, the two best proposed models (NP-ARMA and P-ARMA) of [15] were applied to this work's dataset, and their accuracy measures (MAPE, MAE, and RMSE) were obtained and shown to be significantly higher than those of our best models. In another work, Ref. [48], the best proposed model (ARIMA (3,1,2)) used the current study dataset and obtained accuracy measures (MAPE, MAE, and RMSE) that are also comparatively higher than those of our best models. In the same way, we also compared the results of our best model with two standard time series models: the linear and nonlinear AR models. The results show that the best model proposed in this paper is significantly better than the time series models considered. Additionally, to confirm the superiority of the proposed best model mentioned in Table 6, we performed a statistical test using the DM on each pair of models. The results (p-values) of the DM test are reported in Table 8, showing that the proposed models among all other works and the standard time series (AR and NPAR) models are outperformed by our best model at the 5% significance level. To conclude, based on all of these results, the accuracy of the proposed forecasting methodology is comparatively high and efficient when compared with all considered competitors.

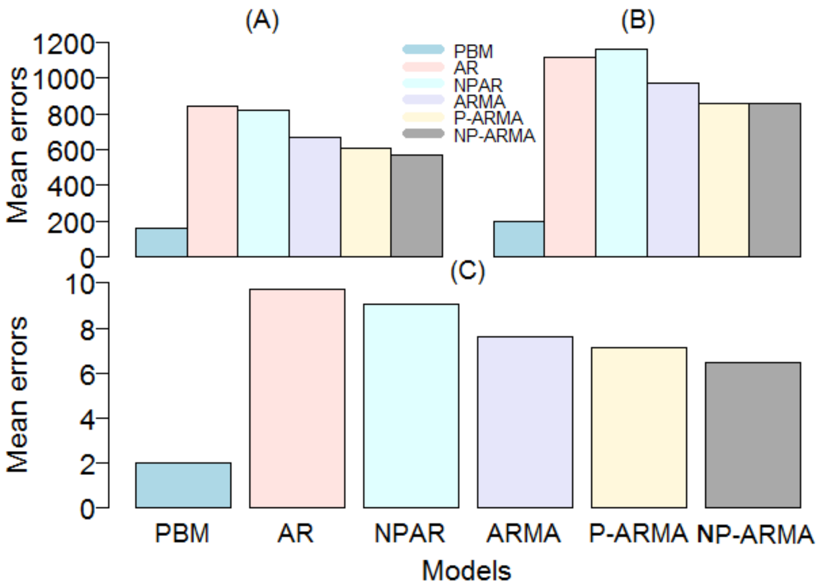

Figure 7. Performance measures: the proposed versus the literature. (**A**) MAE; (**B**) RMSE; and (**C**) MAPE.

Table 7. Pakistan's electricity consumption (kWh): results (p-value) of the DM test for the best twelve models given in Table 5.

Models	^{c}**DSS**$^{b}_{c}$	^{c}**DSS**$^{b}_{c}$	^{c}**DSS**$^{a}_{c}$	^{a}**DSS**$^{c}_{c}$	^{c}**DRS**$^{b}_{c}$	^{a}**DRS**$^{b}_{c}$	^{c}**DRS**$^{b}_{c}$	^{c}**DRS**$^{a}_{c}$	^{c}**DH**$^{a}_{c}$	^{c}**DH**$^{a}_{c}$	^{a}**DH**$^{a}_{c}$	^{a}**DH**$^{b}_{c}$
$^{c}DSS^{b}_{c}$	0.000	0.966	0.977	0.947	0.356	0.345	0.320	0.283	0.002	0.002	0.002	0.002
$^{c}DSS^{b}_{c}$	0.034	0.000	0.289	0.412	0.173	0.148	0.160	0.147	0.001	0.002	0.002	0.001
$^{c}DSS^{a}_{c}$	0.023	0.711	0.000	0.658	0.248	0.225	0.215	0.188	0.002	0.001	0.001	0.001
$^{a}DSS^{c}_{c}$	0.053	0.588	0.343	0.000	0.227	0.187	0.198	0.175	0.003	0.002	0.001	0.001
$^{c}DRS^{b}_{c}$	0.644	0.827	0.752	0.773	0.000	0.527	0.392	0.306	0.004	0.005	0.021	0.019
$^{a}DRS^{b}_{c}$	0.655	0.852	0.775	0.813	0.473	0.000	0.402	0.314	0.004	0.005	0.008	0.006
$^{c}DRS^{b}_{c}$	0.680	0.840	0.785	0.802	0.608	0.598	0.000	0.263	0.004	0.003	0.013	0.018
$^{c}DRS^{a}_{c}$	0.717	0.853	0.812	0.825	0.694	0.686	0.737	0.000	0.010	0.004	0.018	0.029
$^{c}DH^{b}_{c}$	0.998	0.999	0.999	0.997	0.996	0.996	0.996	0.990	0.000	0.185	0.496	0.759
$^{c}DH^{a}_{c}$	0.999	0.998	0.999	0.999	0.995	0.996	0.998	0.996	0.815	0.000	0.783	0.891
$^{a}DH^{a}_{c}$	0.998	0.998	0.999	0.999	0.979	0.992	0.987	0.982	0.504	0.218	0.000	0.773
$^{a}DH^{b}_{c}$	0.998	0.999	0.999	0.999	0.982	0.994	0.982	0.971	0.241	0.109	0.227	0.000

Table 8. Pakistan's electricity consumption (kWh): results (*p*-value) of the DM test for the bestproposed models versus the literature and the benchmark models given in Table 6.

Models	${}^{c}DH_{c}^{b}$	AR	NPAR	ARMA	P-ARMA	NP-ARMA
${}^{c}DH_{c}^{b}$	-	<0.99	<0.99	<0.99	<0.99	<0.99
AR	>0.01	-	0.14	0.99	<0.99	0.94
NPAR	>0.01	0.86	-	<0.99	<0.99	0.98
ARMA	>0.01	0.01	>0.01	-	0.76	0.01
P-ARMA	>0.01	>0.01	>0.01	0.24	-	>0.01
NP-ARMA	>0.01	0.06	0.02	0.99	<0.99	-

5. Conclusions

In this study, we aim to provide accurate and efficient electric power consumption forecasts and propose a novel forecasting methodology based on the decomposition and combination of methods for forecasting monthly electric power consumption. For this purpose, we first decompose the power consumption time series into three new subseries: the long-term trend, the seasonal component, and the stochastic component, using the three proposed decomposition methods. Then, to forecast each subseries, all possible combinations are considered using three standard time series models: the linear autoregressive model, the nonlinear autoregressive model, and the autoregressive moving average model. The proposed methodology was applied to data on electricity consumption in Pakistan for the period from January 1990 to June 2020. Four standard accuracy measures (MAPE, MAE, RMSE, and CORR), statistical tests, and a graphical analysis were performed to assess out-of-sample one-month-ahead predictive accuracy. The results show that the proposed methodology is highly effective in forecasting electrical power consumption. Additionally, it is confirmed that the proposed decomposition method outperforms the benchmark decomposition method DSTL, and among the proposed decomposition methods, the hybrid decomposition (DH) method achieves high accuracy. The final combined model produces the minimum mean forecast errors and is relatively better than those reported in the literature and the standard linear and nonlinear time series models. Finally, we believe that the proposed methodology can also be used to solve other real-world forecasting problems that share similar features.

The present study uses only the electricity composition data from Pakistan; it can be extended to the Brazilian reference framework, using the data that were used in [49]. This will make it possible to broaden the panorama and compare different situations on the subject of energy. Furthermore, the proposed forecasting methodology used only linear and nonlinear time series models; in the future, it will be extended using non-parametric models such as the singular spectrum analysis, machine and deep learning models such as recurrent neural networks, and will support vector regression. This extension will focus on data relating to air pollution in metropolitan Lima, Peru (the same data that was used in [50]).

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