Nature Inspired Load forecasting model based on Neural Network and Cuckoo Search Optimization

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Abstract

In the last few years, predicting electricity consumption has become one of the most essential sectors for both electric utility centers and customers. Anticipating power usage is critical for effective management decisions and company strategies. This research presents an effective and highly accurate hybrid electricity consumption prediction model in which Discrete Wavelet Transform (DWT), Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN), and Cuckoo Search (CS) optimization technique is utilized. The reduction in errors generated in electricity consumption predictions and an increase in its accuracy is the primary aim of the suggested approach. The proposed work decomposed the data belonging to Punjab State Power Corporation Limited (PSPCL) using the DWT approach in two levels; these levels signify the lowest and the highest level of energy consumption. After this, ARIMA model implementation was performed on the entire decomposed data for attaining data of Time Series. Further, the data is combined using the Inverse Discrete Wavelet Transform (IDWT), which is improved as well with the use of a nature-inspired CSA approach. The developed model is trained with the implementation of the ANN technique that aids in estimating future electricity utilization using input layers to fed them with the enhanced data. MATLAB software was utilized for validating the performance of the developed approach. The outcomes obtained showcased our hybrid approach is outperforming other similar models in terms of MAP, MAPE, and accuracy.

Keywords: Load forecasting, Electricity Consumption, ARIMA, Cuckoo search Optimization, DWT, ANN

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Introduction

Energy is considered one of the crucial factors in modern civilization and energy usage has long been a problem for humanity. Globally, rising energy consumption is increasingly bringing attention to energy saving challenges. It is widely called that electricity, especially in big amounts, cannot be stored properly and hence should be utilized as soon as it is produced. As a result, it's critical not to use much more energy than is needed [1-2]. The transmission branch places orders for energy with the production branch, which subsequently distributes the power to the clients. Overproduction, which is regarded as a dead loss for the corporation, occurs when energy is created but not dispersed. Surplus electricity generation is a complex job, and excess power preservation is complex and challenging as well. In this regard, the development of a system that can precisely estimate energy needs while minimizing electricity output and retention is required. Those systems can aid in optimizing electricity production and utilization. Moreover, with the assistance of enhanced production planning and energy purchasing in advance, every household's power usage expenditures are reduced [3]. Predicting electricity consumption is a major technical strategy for managing electricity needs. An effective power forecast method is necessary to logically organize the planning of power distribution in the power system so that the energy supply wastage, which is critical for the development of an energy-saving society is avoided [4]. While evaluating and predicting the need for energy in advance, the operational tactics, management of energy storage systems, and upcoming power plant activities can be strengthened.

Energy prediction models are tailored to a country or utility based on current market circumstances. Every nation does have its consuming model tailored to its specific circumstances. In order to effectively estimate power use, a few key factors are taken into consideration. Initially, the factors determining the nation's electricity usage should be well established. In most cases, the system must include historical information as well as independent factors that are thought to influence consumption. The next factor to take into account is selecting a technique that is appropriate for the modelling framework [5]. Power usage is influenced by socioeconomic and environmental elements in particular. Environmental elements comprise geographical and climate data [6-7], whereas socio-economic factors comprise industry and residential data. Identifying the fundamental relationship between various elements related to energy consumption might provide instructions for energy authorities management to facilitate effective planning and initiatives. Despite the importance of predicting power consumption depending on generic variables, we feel that a good outcome may be achieved if we address the exact characteristics of the people and the area wherein energy is utilized. This research offers the forecast of home power consumption in Punjab State, by using a real dataset with unique characteristics for the given location in order to validate this hypothesis. In the last few years, Punjab has established itself as a state of development and capitalization. There has been a lot of technical progress, as well as a lot of capitalization and commercialization. Electricity consumption has increased considerably as a result of greater technological and economic growth. The Punjab government has set up an entity called "Punjab State Power Corporation Limited" to analyze power demand and use in the province. PSPCL has multiple places to monitor, as well as tehsils. Many cities use more electricity, making it more difficult to manage and distribute electricity to villages simultaneously. Over the past few years, a substantial number of electricity consumption prediction models like ANN [8], Grey Models [9], Support Vector Machine [10], and others have been proposed by various researchers. However, the electricity consumption in these techniques is entirely based on the Time-Series data. Moreover, although these models have faster execution time still the prediction accuracy is much lower in these techniques. With the view to boostingthe accuracy rate of these techniques, authors in [11], proposed an effective Bi-LSTM based approach to predict the consumption of electricity in residential houses and showcased better outcomes.

With the view to increase the prediction accuracy, this research presented a hybrid framework in which ARIMA, DWT, Cuckoo Search (CS) optimization algorithm, and ANN is used to enhance power consumption prediction performance. Also, for predicting thesucceeding energyconsumption, the ARIMA technique is applied. The last year's data based on electricity was used to determination of the lowest and highest energy usage by using DWT which is a decomposition technique. Moreover, for optimization and classification of data neural network as well as the cuckoo search optimization algorithm was performed. The major aims of the study work are given below:

1. Use of ARIMA for modeling time series data

and forecasting the succeeding outcomes

2. The elucidation of ARIMA modeling issues by observing the transformation of discrete wavelet
3. Development of ARIMA hybrid model along with wavelet transform.
4. Analysis of the performance as well as accuracy rate of the suggested technique.

The following are the remaining sections of this paper. Section 2 examines the relevant publications. Section 3 describes the suggested prediction system, experimental database, and assessment procedure. The obtained measurements and some statistical findings are described in Section 4. Ultimately, Section 5 summarizes the paper's accomplishments and concludes.

Literature Review

Over the years, a substantial number of approaches have been developed that can be used for forecasting electricity consumption. Some of the renowned publications have been discussed briefly in this section. The development of electricity utilizationprediction techniques in which different learning techniques are used along withstatistical analysis possesses several major issues. **Goude et al. [12], based on** standardized regression process theory, proposed asemi-parametric solution to model energy utilization of approximately greater than 2200 French distribution system stations utilized in both the medium and short term. **Minaye, E et al. [13],** focused on the development of Jimma City Electric Power Load models and proposed an experimental technique that could act as a reference for the aforementioned development. For the function of load features and increased accuracy, acompound growth approach was used along with thequadratic &linear regression andtrending statistical analysis methodology. **Salvó, G et al. [14],** with the purpose to estimate thespatial growing electricity demand, proposed a new methodology. This new point of focus added a significant value but was not able to replace the conventional tools which were available for utilities. The research study generated two multi-fractals by dividing the consumer need analysis. Various properties like constant frontier dimensionality, stability, etc. were shown by the attained outcomes.**Al-Hamadi, H. M. [15],** usedfuzzy logic as a classification approach for load forecasting of long-term prices. The authors considered various factors which included, load data from prior years, size of the population, and annual growth factors for the linear regression fuzzy model. Through experimental results, less than 3.68% of absolute error increasedinthe projected average daily load of the original load was confirmed during the whole year. **AlRashidi, M. R et al. [16],** attempted to introduce a new yearly peak load prediction method for energy supply systems in which they utilized Particle Swarm Optimization (PSO) algorithm to reduce the errors which were related to the estimated system parameters. The recent data records taken from Egyptian and Kuwaiti networks were utilized for the completion of the study work. **Dong et al. [17],** for prediction of future residential energy allotment by taking just two steps, presented a hybrid approach. Initially, the prediction was conducted based onnon-AC energy consumption with the use of available data. in the second phase of the suggested model, the authors fed unpredictable weather conditions as input to the thermal DAE network along with the internal heat gain to mimic zone temperature. **Davidetal.[18],** used the popular integration of two linear models namely GARCH (Generalized Auto-RegressiveConditionalHeteroskedasticitymodel) and ARMA for evaluation of their econometric quality to provide probabilisticsolarirradiance forecasts. **Al-Musaylh et al. [19],** attempted to adopt G-data for each half, one- and 24-hours predictionhorizons while focusing upon the data-driven technology for a limited duration viz. hourly forecasting. Thealgorithms used by the authors of this model include MARS, SVM, andARIMA. The simulating results revealed that MARS outperforms standard SVM and ARIMA models in short term forecasting. **Khandelwal et al. [20],** in order to develop a new forecasting method, separated the dataset of

Time Series with the help of DWT and resulted into two major parts, namely non-linear and linear. ARIMA and ANN, the models of the Time series, were used for the identification and prediction of these two parts, like approximate and detailed parts were individually rebuilt, respectively. The proposed method achieved the best possible prediction outcomes for every sequence which was clearly shown by the attained results.

Problem Statement

After analyzing the literature study, it is observed that several techniques based on regression analysis, exponential smoothing, ARIMA, and others have already been proposed by different researchers in order to forecast electricity consumption prediction. These approaches were basic and easy to apply, however when dealing with nonlinear and unpredictable electricity consumption data, the forecasting outcomes were less accurate and susceptible to a variety of issues. Moreover, the impact of distributed energy on user-side power requirements and load profile varies. Simultaneously, in the open retailing industry for electricity sales, the prediction of energy usage is confronted with the power requirements of small-scale customers, which is more susceptible to random influences than a standard load forecast. In addition to this, due to the complexity of the available datasets and the absence of general applicability of forecasting outcomes, the intricacy of the conventional energy consumption prediction models was increased which makes them inefficient. Inspired by these findings, the need for developing a new and effective electricity consumption prediction model arises with low complexity and high accuracy. In this regard, a novel and a unique hybrid approach is proposed in this paper that can determine energy consumption for longer periods.

Proposed Work

In order to overcome the limitations of the traditional electricity consumption predictions, a new and effective hybrid electric energy utilization prediction model has been developed in this paper, that has used popular methods belonging to distinct classes namely, Artificial Neural Network (ANN), Cuckoo Search (CS), ARIMAand DWT.

The major aim of the proposed approach is the development of an effective prediction model that is capable of providing an accurate forecast of powerusagein Punjab State with high accuracy. In the proposed work, ARIMAtechnique has been used for predicting the electricity consumption in Punjab state. ARIMA (p, d, q) is the classical notation that has been used for ARIMAwherein, the observed values for lag belonging to the prediction model are represented by p, d depicts the time duration gained followed by the difference between raw views and is often called as “degree of variation” and q represents the dimensions of moving window and is called as “degree of moving average”. ARIMA was particularly utilized for stationary time series data and it is the enhanced version of ARMA model. The ARIMA model was developed by integrating AR and MA procedures. It can be expressed mathematically as equation 1.

$$z_t = K + \vartheta_1 z_{t-1} + \vartheta_2 z_{t-2} + \cdots + \vartheta_m z_{t-m} + n_t ----(1)$$

Where, ϑ_1, ϑ_2......ϑ_m represents the intercept terms at the 1st, 2nd, and final location accordingly. K represents the constant and n_t represents White Gaussian noise.

The values obtained from equation (1) are frequently utilized to forecast future data. Nonetheless, the MA model can be expressed mathematically as equation 2.

$$z_t = K + n_t + \varphi_1 n_{t-1} + \varphi_2 n_{t-2} + \cdots + \varphi_r n_{t-r} ----(2)$$

Regression is denoted by MA, which further specifies the lagged error value.

Additionally, for the purpose for determination of the lowest and the highest energy usage for last year's data of electricity, the decomposition mechanism i.e., Discrete Wavelet Transform (DWT) which is a lossless transformation technique is applied. The main motive of using DWT in the proposed work is to decompose a signal into specific orthogonal functions with different frequencies. The original form of the given input signal can be retrieved anytime just by employing the reverse DWT. The DWT divides the signal into two distinct frequency sub bands, notably higher rate, and lower rate frequency. The high-frequency regions contain information from the edge portions, while the low-frequency regions decompose into higher and lower frequencies. At the beginning of decomposition, four sub-bands namely, LL, HL, LH, and HH were included. Moreover, for providing input to every succeeding decomposition level, the preceding level's LL sub-band is being used. This resulted in overall ten sub-bands.The Wavelet transform is used to de-noise and compress images that enable a multi-resolution analysis of a large number of datasets to extract meaningful data.

Moreover, with the view to enhance the efficacy of the suggested work, we have also implemented Cuckoo Search (CS) optimization algorithm along with the Neural Network for optimizing the data and classifying it. CS is a nature inspired optimization algorithm that forages the behavior of a Cuckoo bird that lays its eggs in anotherbird'snest. A solution is represented by a nest egg, while the achieved solution is represented by a cuckoo egg. The better and fresh solutions (cuckoos) are then used to shift the worst-case solution inside the nests, which is the fundamental goal of this method. The Cuckoo Search algorithm is given below:

Algorithm:Pseudo code for CuckooSearch(CS)

```
Initialization of Population of 'N'Nests.
Find Nests.
        While (Termination condition is not satisfied)
Generate new solutions randomly S_i from Best Nest.
Choose nest randomly S_j from Population.
                   If S_i is best than S_j
Replace S_j with S_i
Eliminate Worse Nests,
Replace with Randomly Generated Nests.
```

Artificial Neural Networks are the penultimate method employed to hybridize the suggested algorithm. ANN has proved to be an effective and helpful substitute to ARIMA systems for forecasting time series relationships with discrete attributes. The strategy aids in improving the specified model's prediction accuracy. This work utilizes a single hidden layer ANN in addition to a single output. The outcome ofANNis given by equation 3;

$$Z_t = \emptyset_o + \sum_{j=1}^{n} \emptyset_o h\left(\varphi_{oj} + \sum_{i=1}^{m} \varphi_{ij} Z_{t-i}\right) + \varepsilon_t - - - - - (3)$$

Where, $\emptyset_o$ and φ_{ij} represents the weights whose values range from (j=0,1,2,3, 4……n) and (i= 0,1,2,3, 4,..m) respectively. $\emptyset_o$and$\emptyset_{oj}$ represents the Bias value, ε_t represents the White Noise and h represents the hidden layer activation function. The ANN algorithm is represented below. Also, the following steps are the significant steps for training the network.

Algorithm:Pseudo code for ANN

```
Begin
Initialize ANN and definea fundamental feature as input/training data
Target (TR) and Neurons (N)
Fix, Model-Net = Newff (T-Data, TR, N)
Model -Net.TrainParam.Epoch = 1000
Model -Net.Ratio.Training = 70%
Model -Net.Ratio.Testing  = 15%
Model -Net.Ratio.Validation = 15%
Model -Net = Train (Model -Net, T-Data, TR)
Current Data = Feature of real-time data
Prediction = simulate (Model -Net, Current Data)
If Prediction = True
Results = Show predicted data
 End
Return: results in terms of prediction
End
```

Therefore, by using several benefits of ARIMA, DWT, and Cuckoo search algorithm along with the ANN, the electricity consumption for the Punjab state is predicted by the model effectively. The detailed and step by step working of the suggested hybrid approach is discussed in the next section of this paper.

Methodology

The current work is conducted in the following steps in order to predict future electricity use. The sample for this research was gathered from PSPCL in India. The flowchart of the hybrid model is shown in Figure 1, along with its work methodology which is explained in the following steps.

Step 1: The first and foremost step is to collect necessary information from the sources. In the proposed work, Punjab State Power CorporationLimited(PSPCL) has been used. PSPCL is the government of Punjab's energy generation and distribution corporation that was established in the year 2010 with the mission of operating and maintaining the state's power plants and distribution infrastructure.

Step 2: The second step makes use of DWTwhich is Continuous Wavelet Transform which accounts for breaking up of time seriesdata and results into data samples in the form ofan integernumber.

Step 3: Further the entire electric energy utilization is decomposed into four different categories featured with distinct ranges with the decomposition of DWT. These distinct ranges are i.e., $L_{min}\ to\ L_{max}(LL),\ L_{max}\ to\ L_{min}(LH),\ H_{min}\ to\ H_{max}(HH),\ L_{max}\ to\ H_{max}(LH)$.According to PSPCL datasets, these deconstructed aspects are useful in determining the highest and lowest electricity usage in Punjab. The job of LPF and HPF is to decompose the data.

Low Pass Filter (LPF): it can be defined as the filter that decomposes the entire range of frequency into smaller frequencies. LPF is used to attenuate signals with frequencies higher in comparison to the cut-off frequency while permitting lower frequencies for continuous flow through.

High Pass Filter (HPF): Likewise, an HPF is used for filtering out the frequencies whose values are less than the threshold frequency.

Figure 1. Flowchart of Proposed Hybrid Model

Step 4: After this, the implementation of the ARIMA model is done separately on each decomposed frequency i.e. minimum and maximum, for attaining Time series data. . LL, LH, HL, and HH are the attained frequencies.

Step 5: Once the ARIMA model is implemented individually, the next step is to integrate Moving Average and Autoregressive techniques by utilizingthe Integrated (I) element that aids to provide the suggested model training.

Step 6: In the next step of the proposed hybrid model, the output attained from these different four ARIMAmodelsis fed to Inverse (I) DWT to aggregate them. It results in the development of a well-defined record which is beneficial to providing thetraining of the proposed approach.

Step 7: The ANN demands more particularity and precise data for training during the classification stage. Therefore, to enhance the classification accuracy rate of the ANN classifier, the Cuckoo Search optimization technique with a novel fitness function is used to obtain the supreme record of the preceding month's electric energy usage.

Step 8: The training of the method gets easier and faster as the uniqueness of the data record increases. In the classification phase that is, ANN receives the exceptional data record which is attained from CS optimization and is fed to the training dataset as input. Finally, the suggested model is trained using ANN, which makes it useful for forecasting the future month based on electricity usage.

Step 9: In the last step of the proposed hybrid electricity consumption forecasting model, the analysis of performance is conducted in terms of various performance measures that are discussed in the followed-up section of this work.

Results Obtained

The reliability and efficacy of the proposed hybrid model are examined and validated by comparing its performance with similar models in MATLAB software. The performance results were examined in terms of MAPE, MAP, and Accuracy (%). Every simulating parameter is defined below.

- **MeanAbsolutePercentage Error (MAPE):** MAPE can be defined as the parameter that measures the dependent series quantity which changes from itslevel of the predicted model. Theperformance in the error percentage is demonstrated by MAPE. Mathematically, it is represented as,

$$MAPE = \frac{\sum \left(Y_{obs,1} - Y_{model,i}\right) / \left(Y_{obs,i}\right) \vee}{P} \times 100\left(Y_{obs,i} \neq 0\right) ----(4)$$

Where, $Y_{obs,i}$ depicts the actual sequence, $Y_{model,i}$ represents the predicted electric energy values and P denotes the total count sample.

- **Mean Average Precision:**The appearance of more than two measurement values that exist nearby each other is referred to as parameter precision. And the average precision scores mean evaluated to each corresponding data with the use of several methods are defined as MAP.Mathematically, MAP can be calculated as;

$$MAP = \frac{\sum_{Q=1}^{n} AvgPr\ (Q)}{N} ------(5)$$

Where N and n represent the number of desired samples and retrievedsamples respectively, AvgPr depicts theprecision average at level$Q$.

- **Accuracy (%):** The system's method of measuring accurate value determines how near the calculated value is to the genuine value. The accuracy calculation is performed by using a small reading, which reduces the inaccuracy. The accuracy can be mathematically stated as follows.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} ------(6)$$

Performance Evaluation

The efficacy and reliability of the suggested hybrid model are firstly examined and then performed the comparison with the standard ARIMA with the DWT model in terms of electricity consumption prediction. Figure 2, illustrates the comparison graph for the standard and proposed hybrid model from 2013 to 2017. The blue bars in the given graph denote the original electricity consumption in the Punjab state from 2013 to 2017 and the red and green bars depict the predicted values of standard ARIMA along with the DWT model and suggested hybrid approach. after analyzing the graph closely, the observations were made that no significant distinction between original and predicted consumption values exists. The average computed value of the electricity consumption predicted by standard ARIMA,ARIMAwithDWT models came out to be 3464988567,3557198158, while it came out to be 3455724556 in the suggestedhybridmodel. Therefore, a 3% averagedifference i s attained across values predicted actually and ARIMA + DWT model, that is 0.39% in our approach. H ence, the proposed hybrid approach is providing more effective and accurate results than standard models.

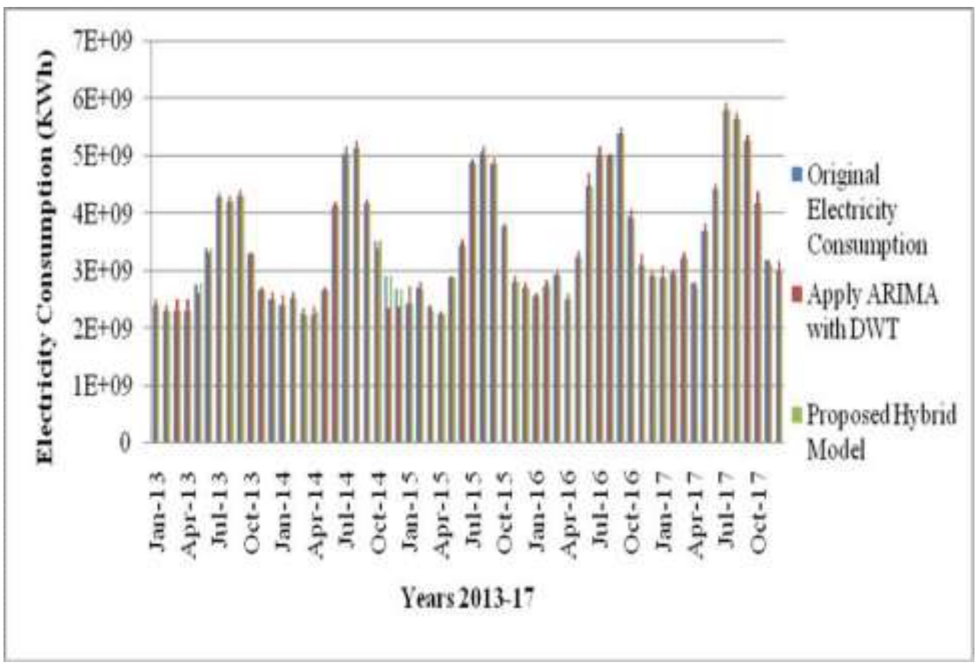

Figure 2.Electricity usage (KWh) in standard and proposed model

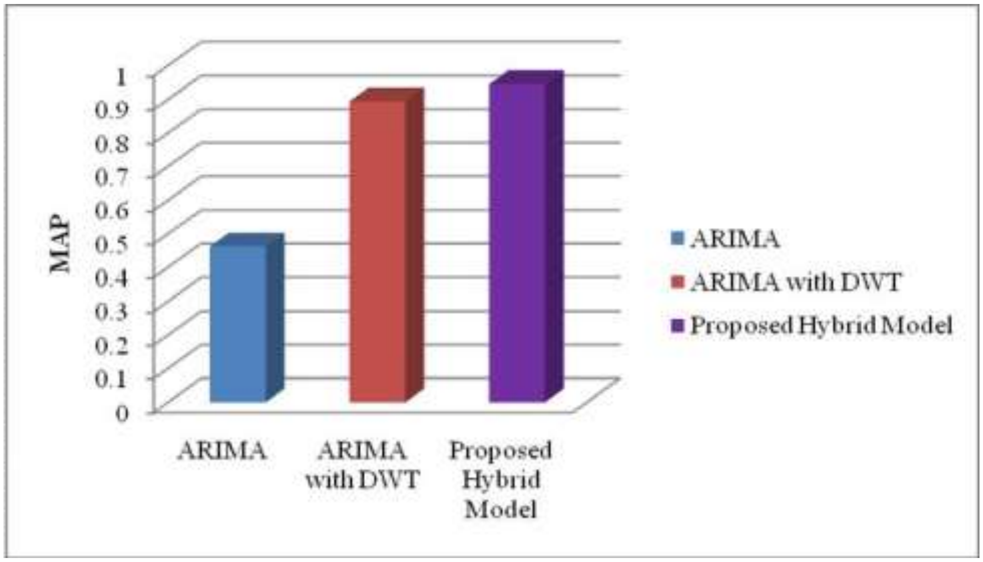

Figure 3. Comparison graph for MAP

Moreover, the efficiency of the suggested hybrid approach is also verified by performing a comparison of its performance with the standard ARIMA, and ARIMA with DWT models in terms of MAP. Figure 3, shows the comparison graph for the same. After analyzing the figure closely, it is observed that the value of MAP in standard MAP came out to be only 0.4623940, while it came out to be 0.894494 in standard ARIMA with the DWT model. On the other hand, the value of MAP in the proposed hybrid model came out to be highest at 0.94521, to signify its supremacy. The exact values obtained in each model are depicted in table 1.

Table 1: Specific values of MAP in standard and proposed model

MODEL	**MAP value**
ARIMA	0.4623940
ARIMAwith DWT	0.894494
ProposedHybrid Model	0.94521

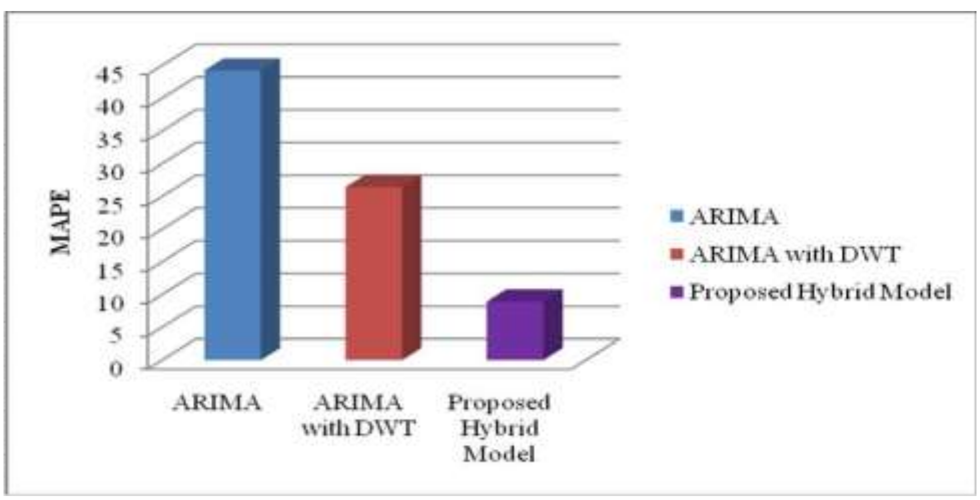

Figure 4. Comparison graph for MAPE

Likewise, the efficacy of the suggested model is analyzed and examined with conventional ARIMA and ARIMA with DWT models in terms of MAPE, and the graph obtained is shown in figure 4. From the given graph, it is observed that the value of MAPE came out to be the highest I standard ARIMA model with 44.239359, followed by ARIMA with DWT with 26.438503. However, the value of MAPE came out to be least in the proposed hybrid model with just 8.944945. The values attained are also recorded in tabular form and are shown in table 2.

Table 2: Values for MAPE in standard and Proposed model

MODEL	MAPE values
ARIMA	44.239359
ARIMAwith DWT	26.438503
ProposedHybrid Model	8.944945

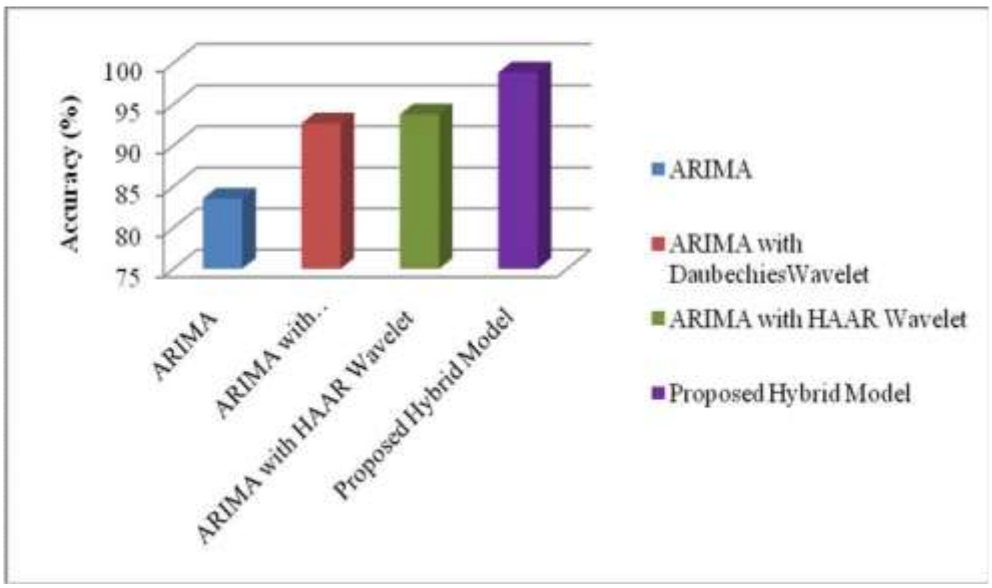

Figure 5. Comparison graph for Accuracy

In addition to this, the effectiveness of the suggested hybrid approach is validated by equating it with standard models in terms of their accuracy. Figure 5 represents the comparison graph attained. After examining the given graph, it is observed that the value of accuracy came out to be least in the conventional ARIMA model with only 83.53%, followed by standard ARIMAwithDaubechies Wavelet and ARIMAwithHAARWavelet with 92.76% and 93.76% respectively. While as, when the performance of the proposed hybrid model is analyzed in terms of accuracy rate, it came out to be 98.86% respectively. The accuracy values are depicted in table 3.

Table 3: Accuracy attained in standard and Proposed Hybrid-Model

Usedtechniques	Accuracy(%)
ARIMA	83.53
ARIMAwithDaubechiesWavelet	92.67
ARIMAwithHAARWavelet	93.76

ProposedHybridModel	98.86

From the above given graphs and tables, it is calculated that the proposed hybrid model proves its effectiveness by showing excellent results and is outperforming traditional models in terms of MAP, MAPE and accuracy as well to prove its dominance.

Conclusion

In this paper, an effective and highly accurate electricity consumption hybrid forecasting model is proposed wherein ARIMA, DWT, CS, and ANN are used. The efficacy of the suggested hybrid forecasting approach is examined and validated by equating its performance with a few promising methods in MATLAB software. The proposed hybrid model predicts the electricity consumption in the Punjab state by using the stochastic process. The outcomes attained revealed that power usage values which are predicted by the suggested hybrid model are closely related to the original electricity consumption values. In addition to this, the proposed hybrid prediction model showed its effectiveness ina few traditional modelsregarding MAP, MAPE, and accuracy as well to demonstrate its effectiveness. The results revealed that the value of MAP in traditional ARIMA and ARIMA with DWT was mounted at just 0.4623940 and 0.894494, whereas, the value of MAP in the proposed hybrid model is 0.94521. Likewise, the value of MAPE came out to be least in the proposed hybrid model with only 8.944945, while as, it was 44.239359 and 26.438503 in conventional ARIMA and ARIMA with DWT model. Furthermore, the suggested hybrid model outperforms other similar approaches in accuracy as well. The results revealed that there is an increase of 10.23% in accuracy when compared to the standard ARIMA model.

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