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# Forecasting Techniques for Estimation of Per Capita Energy Consumption in the Electric Grid

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***Abstract:-*** This study presents a thorough analysis of per capita load forecasting techniques used to predict electrical energy consumption on a per capita basis. Further, examines the historical time series data on per capita energy consumption to develop models that predict future energy demand with considerable accuracy. Statistical forecasting techniques as well as the Machine Learning techniques were used to analyze the time series data of per capita electricity consumption and subsequently predict the future trends. The dataset used for the forecasting of per capita electricity consumption is obtained from the Website of Central Electricity Authority, Ministry of Power, Government of India. Statistical time series analysis techniques used in this research are Auto-Regressive Integrated Moving Average and HoltWinters Smoothing also known as Triple Exponential Smoothing. Machine Learning model that was used to examine the per capita electricity consumption is Long-Short Term Memory based Recurrent Neural Network. An additive regression model known as Facebook Prophet is implemented for forecasting the per capita load demand. Finally, the performance of each of these techniques is evaluated by factor MAPE i.e. mean absolute percentage error. Thus, analyses the performance of each of the four techniques on the per capita consumption data for various states. Based on the performance of the implemented models, two of the best models were utilized for the implementation regional and national energy forecasting. In view of the accuracy of the forecasts, the Facebook Prophet and Holt-Winters Smoothing techniques are quite suitable for estimation of per captia energy consumption.

***Keywords***: *Forecasting, Per capita energy, Machine learning, Artificial intelligence, load demand.*

## 1. Introduction

Generally, the electricity is vital input for development of advanced industrialization of every economy. Despite the labour-intensive and expensive process for production, transmission, and distribution of electrical energy, the demand and utilization of electricity is increasing exponentially across the globe [1]. Thus, the per capita consumption (PCC) of electrical energy is a significant parameter to visualize the quantity of electricity utilized by an individual in a given time frame i.e. a year. Further, the PCC is directly proportional to overall economic health of the country [2].

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The per capita consumption (PCC) of developed nations is at higher level due to advanced industrialization and urbanization. Moreover, PCC of electrical energy is to be enhanced for adoption of technological advancements in the developing nations [5]. Thus, the forecasting of PCC is significant for the country like India since the scope for economic growth is relatively high in the immediate future. Further, the forecasted information of PCC is instrumental in configuration of restructured power system with sufficient balance between forecasted demand and growing electric power production [1].

The basic role of forecasting is to predict the future outcomes based on available historical time series data trends and other associated information. Usually, the forecasting tools cannot predict possible outcomes accurately due to uncertain future events e.g. integration of electric vehicles, drifts in country economy [4]. The unavailability of quality data is another concern to retain the accuracy of forecasted information. One of the major challenges associated with the prediction of per capita consumption of electrical energy is the time horizon of the forecast. The deterioration of predicted patterns in long term forecasting is serious concern due to consideration of limited historical time series data without uncertainties. Thus, the accuracy of long term forecasting e.g. PCC prediction mainly depends on tools/methods which can resolve the above discussed concerns/issues [6].

In literature, several techniques have been implemented for the forecasting of future electricity demand but most of the suggested methods are essentially restricted to the prediction of the total electricity consumption of a country or a region instead of the per capita consumption. Broadly, load demand prediction methods are constructed based on statistical techniques and the machine learning (ML) algorithms [10]. The statistical technique includes the analysis of time series data through statistical operations e.g. moving averages, exponential smoothing and auto regressive integrated moving average (ARIMA) to forecast the future trends. Whereas, ML algorithms e.g. artificial neural networks (ANN), support vector machines (SVM) construct the artificial intelligence (AI) to predict the future patterns through training and learning of available time series data [3]. Usually, ML techniques are superior than the statistical techniques in terms of the accuracy and the nature of predictions. The ML techniques demand large volume of data to train the model and test its accuracy of constructed AI for prediction purposes.

According to the time horizon, the load/per capita consumption (PCC) forecasting can be executed at short-term, medium term and long-term levels [10]. Short term forecasting (i.e. hours to week) is applied in management of the daily technical operations of the power system [7]. The medium-term load forecasting (i.e. several months) of the electric power system is crucial in electricity market operations [8]. Long term forecast (i.e. a year to ten years) is relatively beneficial to enhance economic policies of the region, per capita growth, etc., [9]. Thus, the authors have explored the prediction tools suitable to forecast the per

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capita consumption (PCC) of electrical energy at state, regional and national levels of Indian electric grid in this paper.

In this paper, the per capita consumption (PCC) of electrical energy is predicted by various suitable forecasting techniques through training and testing the proposed models with the available PCC historical data. The performance of proposed models is validated on different PCC data sets of Indian electric grid through mean absolute percentage error (MAPE).

The remaining paper is organized as: Section 2 describes the proposed long-term forecasting techniques to predict the behaviour of per capita electricity consumption. The performance of proposed forecasting methods on Indian electric gird at various levels are explained in Section 3 and Section 4 concludes the proposed research work.

## 2. Forecasting Methodology

Various studies have been carried to develop methodologies for demand/load forecasting of the complex interconnected power system. Load forecasting methods are classified based on the degree of mathematical model and constraints i.e. qualitative and quantitative methods. Generally, forecasting techniques are build on historical data which may be insufficient to predict accurate outcomes [11]. In above scenarios, the qualitative forecasting techniques, such as the curve fitting, Delphi method, etc., are typically used for accurate forecasts.

However, the accuracy of prediction based on qualitative methods is very sensitive to choice of forecasting models and experts opinions. Thus, quantitative methods e.g. exponential smoothing, regression analysis, decomposition methods, BoxJenkins, machine learning/artificial intelligence approaches are widely adopted to predict the future outcomes with limited historical data [13]. Hence, the authors have explored the quantitative methods such as autoregressive integrated moving average (ARIMA), long short-term memory based recurrent neural network (LSTM-RNN), Holt-Winters smoothing (HWS), Facebook Prophet (FBP) and the respective methodologies are described in the subsequent sections.

### *A. ARIMA prediction model*

Autoregressive integrated moving average (ARIMA) is a member of a class of models that uses its own past values i.e. its own lags and lagged forecast errors, to extract the trends of a given time series data for prediction purposes. ARIMA model is quite suitable for non-seasonal time series data with low random noise [20]. An ARIMA model is one where the time series is differenced at least one time in order to ensure the given time series data is stationary. Thereafter, the auto regression (AR) and moving average (MA) operations are executed together i.e. ARIMA on given time series data.

The performance of ARIMA is very sensitive to following three parameters i.e. *'p'* and *'q'* which signifies the order of auto regression and moving average respectively, *'d'* specifies

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the order of differencing required to transform non-stationary to respective stationary time series data. Usually, $d$ is considered as zero for stationary time series data [25].

The concept of ARIMA is applied in this paper to predict the per capita consumption (PCC) of electrical energy and its mathematical function with respect to time is expressed as

$$PCC_t = c + \sum_{i=1}^{p} \lambda_i PCC_{t-i} + \sum_{j=1}^{q} \delta_j \, \Omega_{t-j} + \epsilon_t \qquad (1)$$

where,

• $c$ is intercept constant based on confidence interval of prediction i.e. $(1 - c)$ and generally the value of $c$ is considered as 5% and same is chosen in the paper also.

• $\lambda_i$ is estimated coefficient of $PCC_{t-i}$ by the AR model.

• $PCC_{t-i}$ is past lag value at time $t - i$.

• $\delta_j$ is estimated coefficient corresponding to forecast lagged error i.e. $\Omega_{t-j}$ by the MA model.

• $\Omega_{t-j}$ is forecast lagged error and is mathematically defined as $\Omega_{t-j} = PCC_{t-j}^{predicted} - PCC_{t-j}^{actual}$

• $\epsilon_t$ is a random white noise with mean zero at time t to replicate the actual noise in the time series data.

The major challenge with ARIMA is to incorporate the seasonality behaviour during prediction of time series data. The seasonality trend can be adopted and modelled through artificial intelligence techniques e.g. Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) feature.

### *B. LSTM-RNN prediction model*

In the present study, the recurrent neural network with long short-term memory (LSTM-RNN) technique is adopted for prediction of per capita consumption (PCC) of electrical energy. The LSTM-RNN model is an improved recurrent neural network (RNN). The RNN is a type of artificial neural network with variable length sequence input by hidden state which is activated each time based on the past data. Longterm dependencies are not effectively recognized by the RNN due to hidden layer short-term dependencies. To overcome the above issue, long short-term memory (LSTM) cell network is introduced as shown in Fig.1. The schematic representation of a standard LSTM-RNN cell is shown in Fig.2. Unlike traditional RNN, LSTM has memory blocks which are connected through successive layers each block handle its state and the output with the help of gates.

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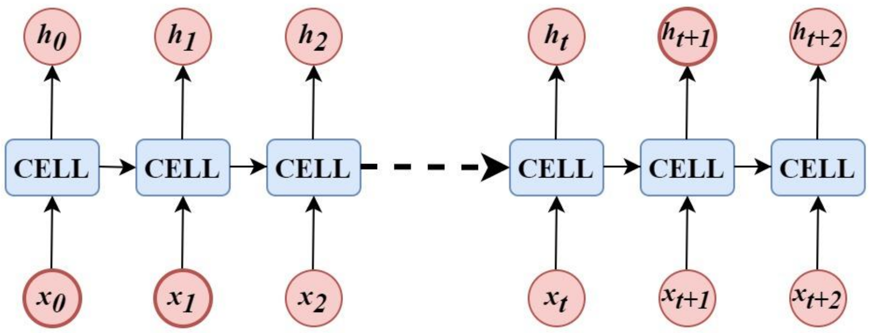


*Fig.1: LSTM Network*

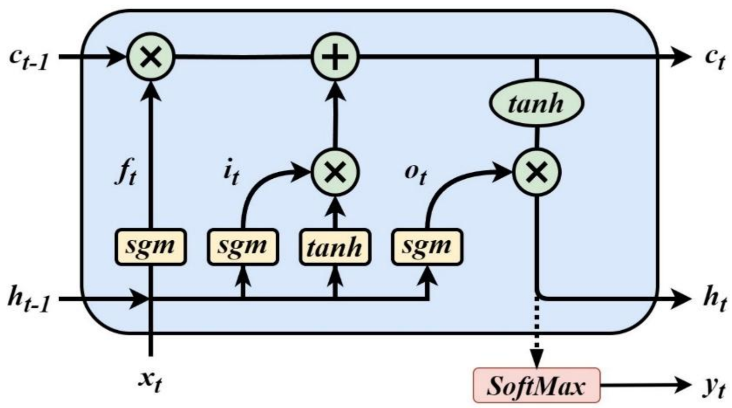


*Fig.2: LSTM Model Architecture*

The capability to remember past information is achieved by adding memory state cells i.e. $c_t$ to the implicit layer, and three gate units are introduced to control the use of historical sequence information [18]. Mathematically, the state of memory cell is computed as

$$c_t = (f_t c_{t-1} + i_t \eta_t) \tag{2}$$

where, $c_{t-1}$ is the previous state of memory cell at time $(t-1)$. Generally, the initial state of memory cells is empty i.e. zero.

$f_t$ is forget gate function which controls retention of past data and mathematically expressed as shown below:

$$f_t = sgm(A_f x_t + B_f h_{t-1} + \mu_f) \tag{3}$$

where, $sgm$ is sigmoid activation function, $x_t$ is input given at time $t$, $h_{t-1}$ is the value of hidden state at time $(t-1)$, $A$ and $B$ are weight matrices for the input and hidden layers respectively and $\mu$ is bias vector of associated forget gate, input gate, data controller and output gate. The associated values of $A$ and $B$ matrices, $\mu$ vector are updated by using back-propagation through time strategy [27].

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$i_t$ is input gate which is responsible to control the input data and mathematically expressed as

$$i_t = sgm(A_i x_t + B_i h_{t-1} + \mu_i) \tag{4}$$

$\eta_t$ is data controller to add and remove the input data i.e. $i_t$ from the respective memory cell and mathematically expressed as

$$\eta_t = tanh(A_c x_t + B_c h_{t-1} + \mu_c) \tag{5}$$

The value of $\eta_t$ ranges between –1 to 1. The negative value of $\eta_t$ signifies that the input data is to be deducted from the cell state, otherwise added to the respective cell state.

Further, the output of each hidden layer cell i.e. $h_t$ can be computed as

$$h_t = o_t * tanh(c_t) \tag{6}$$

where, $o_t$ is intermediate output gate and controls the input to next successive hidden layer and mathematically expressed as

$$o_t = sgm(A_o x_t + B_o h_{t-1} + \mu_o) \tag{7}$$

Thus, the output of hidden state layer i.e. $h_t$ on current output i.e. $o_t$ as well as the long-term memory i.e. $c_t$ [24]. Moreover, the memory cell output at given time i.e. $y_t$ can be extracted by utilizing SoftMax activation function [28] i.e.,

$$y_t = SoftMax(h_t) \tag{8}$$

The major limitation with LSTM-RNN is requirement of high volume of training data-set to achieve the acceptable accuracy during long-term prediction scenarios. The forecasting models with limited training data-set for long-term prediction can be achieved with advanced statistical techniques e.g. Holt-Winters Smoothing model.

### *C. HWS prediction model*

Basically, Holt-Winters smoothing (HWS) is a statistical forecasting technique for time series data to predict future information based on weighted average of past observations. The key feature of HWS is triple exponential smoothing i.e. smoothing of data variations, trend and its seasonality. In this paper, two types of time series seasonality are considered e.g. multiplicative and additive [24].

The mathematical model to predict the future data in reference to multiplicative seasonality is described below:

Assume a time series data i.e. $x_t$ that begins at time $t = 0$ with a seasonal change cycle of length T. The smoothing phenomena to predict the best estimates of data variations ($z_t$), trend extraction ($e_t$) and seasonality correction factor ($r_t$) are computed as [26]

$$z_t = M_z + (1 - \alpha)(z_{t-1} + e_{t-1}) \tag{9}$$

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where, $M_z = \alpha \frac{x_t}{r_{t-1}}$

$$e_t = \beta(z_t - z_{t-1}) + (1-\beta)e_{t-1} \quad (10)$$

$$r_t = M_r + (1-\gamma)(r_{t-T}) \quad (11)$$

where, $M_r = \gamma \frac{x_t}{z_t}$, α, β and γ are data, trend and seasonal change smoothing factors respectively with a range of [0, 1]; $z_0 = x_0$.

The initial trend estimate $e_0$ based on limited time series data is determined as

$$e_0 = \frac{1}{T}\sum_{i=1}^{T} \frac{x_{T+i} - x_i}{T} \quad (12)$$

The seasonal correction factor expression (11) is valid only when $t \geq T$ and $r_t$ can be computed during t < T as

$$r_i = \frac{1}{N}\sum_{i=1}^{N} \frac{x_{T(k-1)+i}}{U_k}, \quad \forall\, i \in [1, T] \quad (13)$$

where, $U_k$ is the average value of the $x$ in the k$^{th}$ cycle of the data and can be expressed as

$$U_k = \frac{1}{T}\sum_{i=1}^{T} x_{T(k-1)+i}, \quad \forall\, k \in [1, N] \quad (14)$$

where, $N$ is number of complete cycles present in the time series data.

The above discussed HWS concept is adopted to predict the per capita consumption (PCC) of electrical energy and its mathematical function to forecast upto $m^{th}$ period can be computed as

$$PCC_{t+m} = (z_t + \mathrm{m}e_t)r_{t-T+(m-1)mod\,T} \quad (15)$$

Furthermore, the mathematical model to predict the future data in reference to additive seasonality is similar to that of multiplicative with changes in $M_z$, $M_r$ and $PCC_{t+m}$. The associated values of $M_z$, $M_r$ and $PCC_{t+m}$ and with respect to additive seasonality can be calculated as

$$M_z = \alpha(x_t - r_{t-T}) \quad (16)$$

$$M_r = \gamma(x_t - z_{t-1} - e_{t-1}) \quad (17)$$

$$PCC_{t+m} = (z_t + \mathrm{m}e_t) + r_{t-T+(m-1)mod\,T} \quad (18)$$

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The Holt-Winters smoothing (HWS) model is quite effective in long-term prediction of per capita consumption (PCC) of electrical energy. However, HWS involves high volume of computation due to triple exponential smoothing phenomena. The above raised issue can be resolved by a specialized time series library model i.e. FaceBook Prophet (FBP).

### *D. FBP prediction model*

The FaceBook Prophet (FBP) is specialized time series library for forecasting of information with strong seasonal effects [22], [23]. FBP is a procedure to forecast time series data, based on additive model where yearly, weekly, and daily seasonality is fitted with non-linear trends along with holiday effects. The FBP can be represented as a non-linear regression model to predict the per capita consumption (PCC) of electrical energy and expressed as [25]

$$PCC_t = g(t) + s(t) + d(t) + \epsilon_t \tag{19}$$

where, $\epsilon_t$ is a random white noise with mean zero at time *t* to replicate the actual noise in the time series data.

*g(t)* is the logistic growth function or piecewise-linear trend, mathematically defined as

$$g(t) = \frac{x(t)}{1 + e^{-\rho(t-\varphi)}} \tag{20}$$

where, *x(t)* is the input at time *t*, $\rho$ and $\phi$ are the growth rate and an offset parameter respectively.

*s(t)* represents the seasonal patterns and can be effectively modelled through Fourier series. The arbitrary smooth seasonal effects i.e. *s(t)* can be approximated with a standard Fourier series and mathematically expressed as

$$s(t) = \sum_{n=1}^{N} \left( a_n cos\left(\frac{2\pi nt}{T}\right) + b_n sin\left(\frac{2\pi nt}{T}\right) \right) \tag{21}$$

where, $T$ is periodicity of time series data e.g. $T = 365.25$ for yearly data-set, $a_n$ and $b_n$ are Fourier coefficients with respect to given time series data which are randomly initiated with zero mean and variance of $\sigma^2$.

Further, the approximated Fourier series (21) is truncated to $N = 10$ which works effectively for most of time series data. *d(t)* is a function to extract/model the holiday effects in the time series data, mathematically expressed as

$$d(t) = x(t)\vartheta \tag{22}$$

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where, $\vartheta$ is holiday bias vector which is randomly initiated based on available past data-set of holidays with zero mean and variance of $\tau^2$.

### 3. Simulation Results

The proposed forecasting techniques such as autoregressive integrated moving average (ARIMA), long short-term memory based recurrent neural network (LSTM-RNN), Holt-Winters smoothing (HWS), Facebook Prophet (FBP) are implemented on Google Colaboratory. The validation of above prediction methods is performed on prediction of per capita consumption (PCC) of electrical energy upto 08 years from available data-sets spanning 20 years through Central Electricity Authority operated by Ministry of Power, Government of India. The efficacy of forecasting techniques is measured through a performance factor known as mean absolute percentage error (MAPE) which is defined as

$$MAPE = \frac{1}{V}\sum_{i=1}^{V}\left|1 - \frac{PCC_i^{predicted}}{PCC_i^{actual}}\right| \times 100 \quad (23)$$

Further, the efficacy of proposed prediction methods is depicted in three phases i.e.

1) *Training phase*: The selected data-sets from available data-sets of PCC are utilized to train the proposed model and it is depicted under yellow shade.

2) *Testing phase*: The remaining data-sets from available data-sets of PCC are utilized to test the proposed model and its response is shown under blue shade.

3) *Prediction phase*: The future trend of PCC based on available data-sets is visualized in the green shade.

Moreover, the robustness of proposed forecasting techniques is validated through prediction of various states (e.g. Bihar, Meghalaya, Tripura), regions (e.g. North Eastern and Southern) and national per capita consumption (PCC) of Indian sub-continent.

#### *A. Performance of state level PCC prediction*

The information of Indian per capita consumption (PCC) of electrical energy is collected for 20 years since 2002 and utilized as data-set to predict the PCC for next 08 years i.e. till 2030 in this paper. An ARIMA model is applied on PCC data-sets of selected states of India i.e. Tripura and Bihar. The utilized ARIMA model is trained with one year data-set and equipped with parameters as tabulated in Table I. Further, the remaining 11 years PCC data-set is validated through ARIMA model as discussed in Section II A.

The framed ARIMA model is successfully tested for 11 years of Tripura and Bihar PCC data-sets with MAPE efficacy of 22.67% and 12.85% respectively as shown in Fig. 3.

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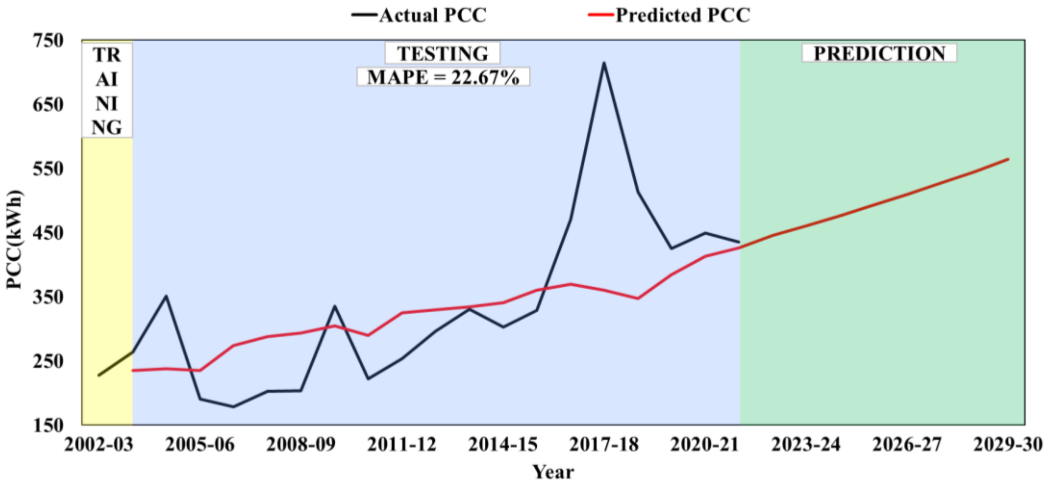
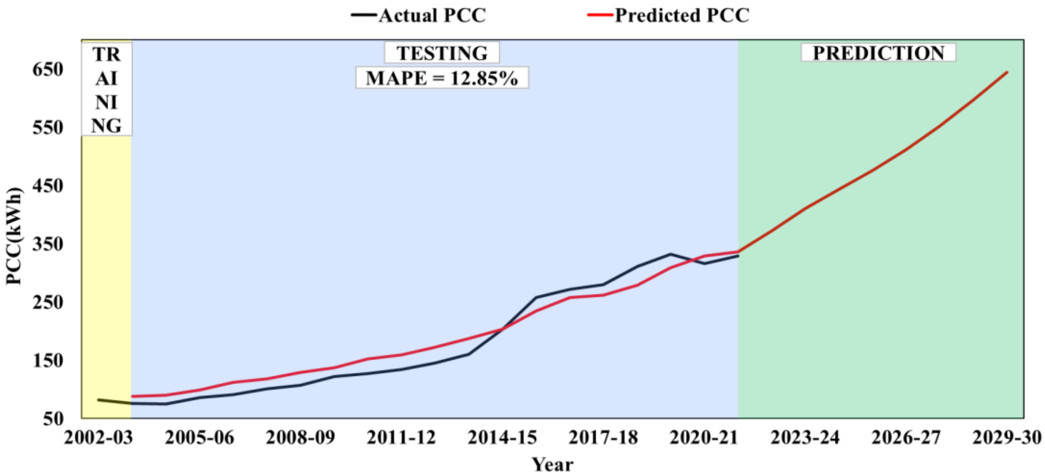
TABLE I: ARIMA PARAMETERS

| Region | P | d | q |
|---|---|---|---|
| Tripura | 2 | 1 | 0 |
| Bihar | 1 | 1 | 0 |




*3(a) For Tripura State*




*3(b) For Bihar State*

***Fig. 3: Response of state level PCC prediction using ARIMA model***

It is observed from Fig. 3a that MAPE is high i.e. 22.67% which leads to capture only trend (linear prediction) behaviour of Tripura state PCC irrespective of dynamics data-set with appreciable seasonality. Whereas, the MAPE of Bihar state is 12.85% with ramp profile of PCC data-sets as depicted in the Fig. 3b. Thus, ARIMA model is best suitable for linear behaviour short term prediction data-sets e.g. Bihar and may not fit for long term prediction of dynamic data-sets with seasonality feature e.g. Tripura. Hence, ARIMA model predicts the linear behaviour prediction of given PCC data-sets with high MAPE.

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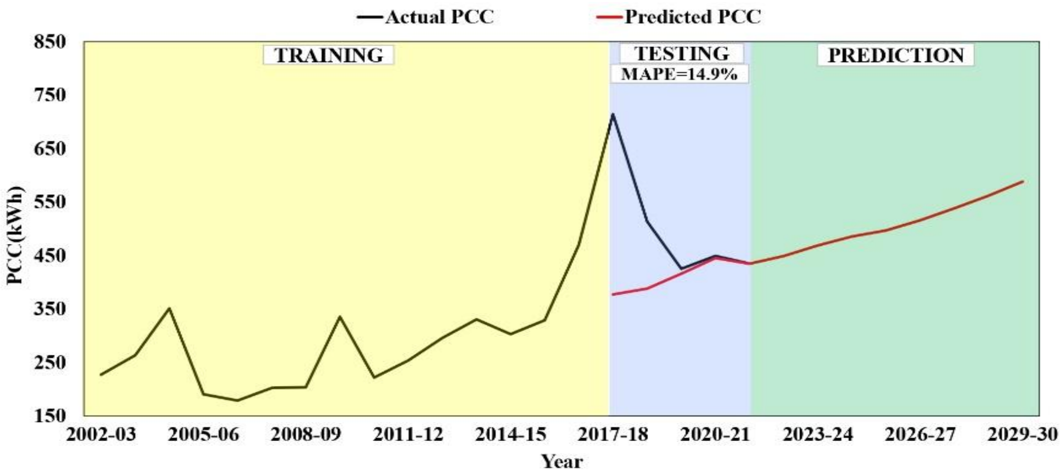
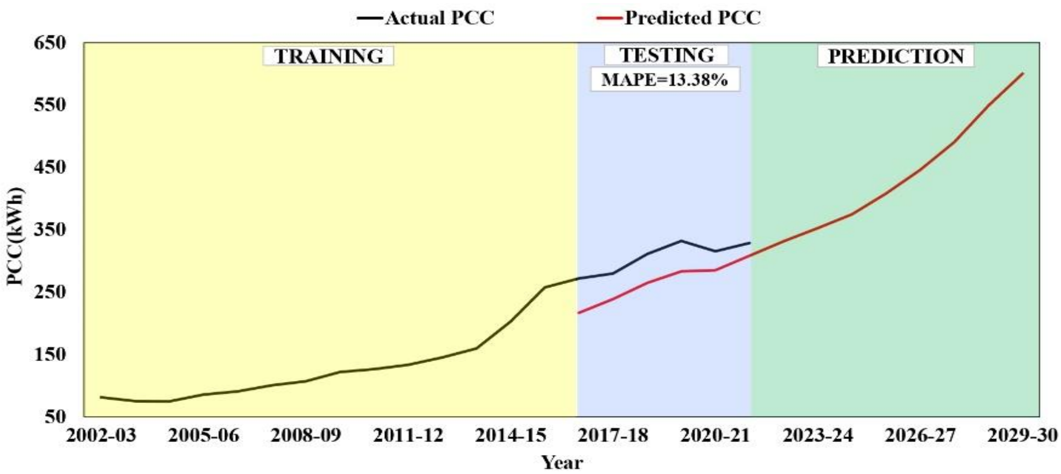
To improve the accuracy of PCC prediction, the long shortterm memory based recurrent neural network (LSTM-RNN) and Holt-Winters smoothing (HWS) forecasting models are trained with 10 years data-sets and tested the performance on 02 years PCC data-set of respective states. The response of LSTM-RNN and HWS on Tripura and Bihar PCC data-sets is shown in Fig. 4 and Fig. 5 respectively.




*4(a) For Tripura State*




*4(b) For Bihar State*

***Fig. 4: Response of state level PCC prediction using LSTM-RNN model***

From Figs. 4a, 4b and Figs. 5a, 5b respectively, the simulation results reveal that the MAPE for Tripura and Bihar states during PCC prediction by LSTM-RNN and HWS are 14.90%, 13.38% and 18.50%, 12.44% respectively.

It is interesting to point that PCC algorithm i.e. LSTM-RNN is ramp profile with low MAPE than that of ARIMA model. Whereas, HWS prediction model showcase the dynamic behavior i.e. seasonality feature with ramp profile trend during long term forecasting of PCC

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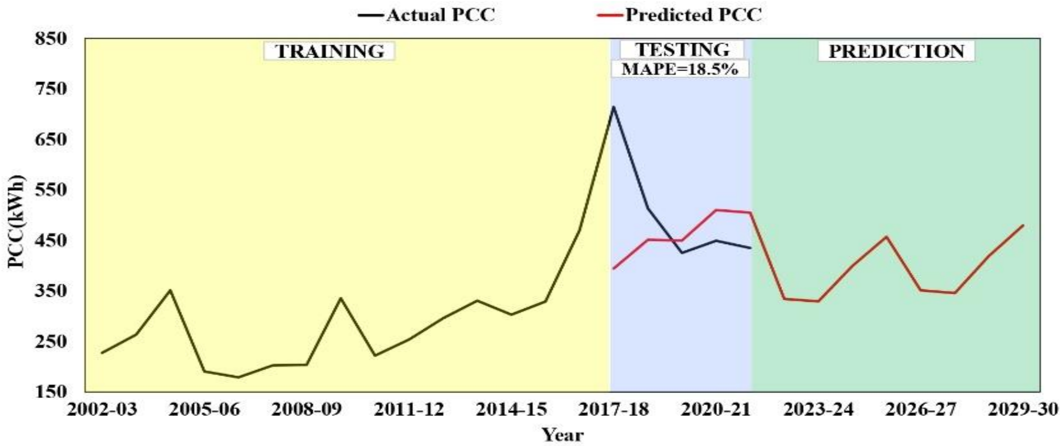
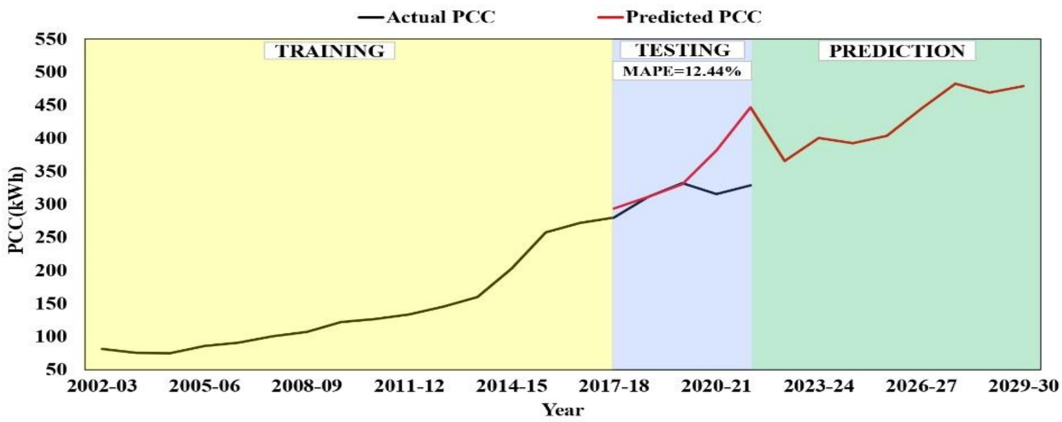
of Tripura and Bihar states with high MAPE than that of LSTM-RNN prediction model. Thus, Holt-Winters smoothing (HWS) model is quite suitable for long term forecasting of per capita consumption (PCC) of electrical energy. To enhance the accuracy of PCC prediction, Facebook Prophet (FBP) model as discussed in Section II D is simulated on Tripura and Bihar data-sets. The FBP prediction model is trained with 08 years data-sets and tested the performance on 04 years PCC data-set of respective states. The developed FBP model is successfully tested for 04

years of Tripura and Bihar PCC data-sets with MAPE efficacy of 15.70% and 12.33% respectively as shown in Fig. 6. The simulation results reveal that the FBP model is also more appropriate for long term forecasting of per capita consumption (PCC) of electrical energy as like as HWS prediction model. The efficacy of proposed forecasting techniques such as autoregressive integrated moving average (ARIMA), long short-term memory based recurrent neural network (LSTM-RNN), Holt-Winters smoothing (HWS), Facebook Prophet (FBP) during state level PCC prediction i.e. Tripura and Bihar states is tabulated in Table II.




*5(a) For Tripura State*




*5(b) For Bihar State*

***Fig. 5: Response of state level PCC prediction using HWS model***

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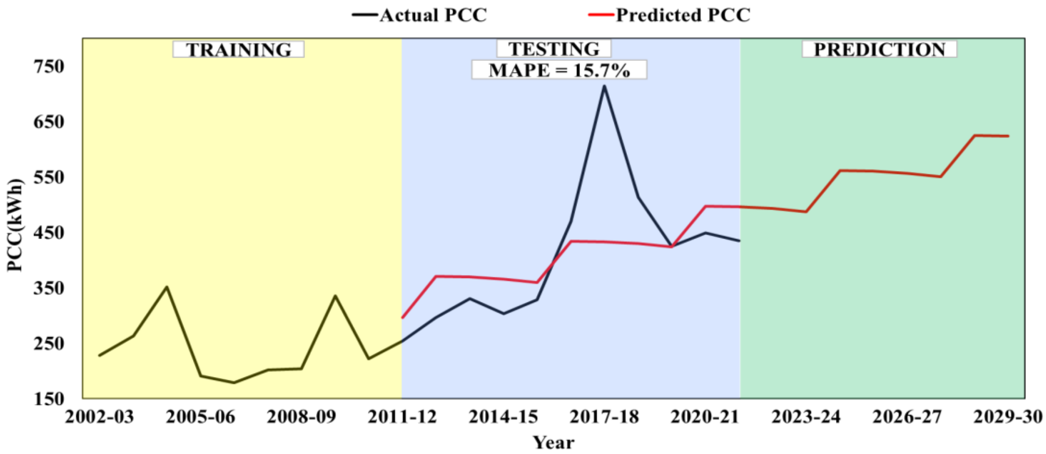
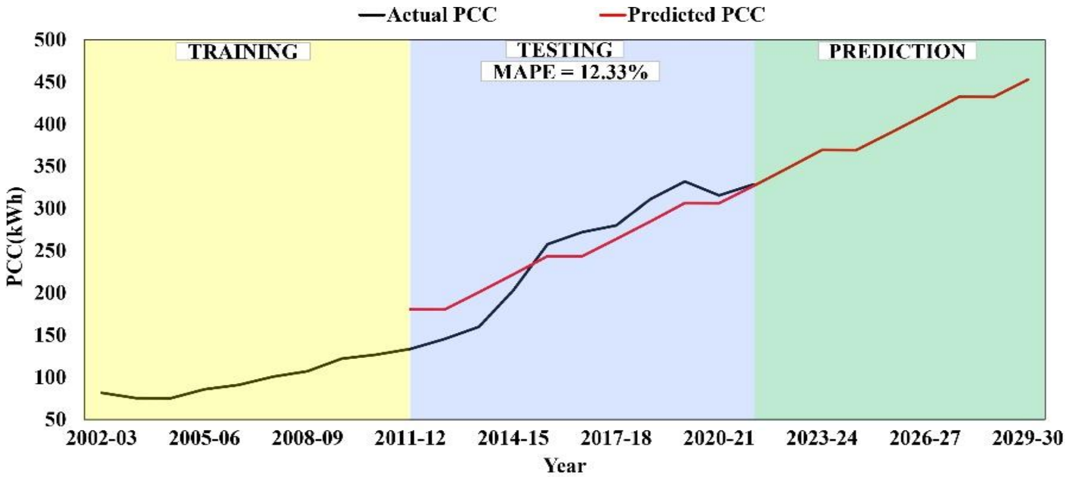
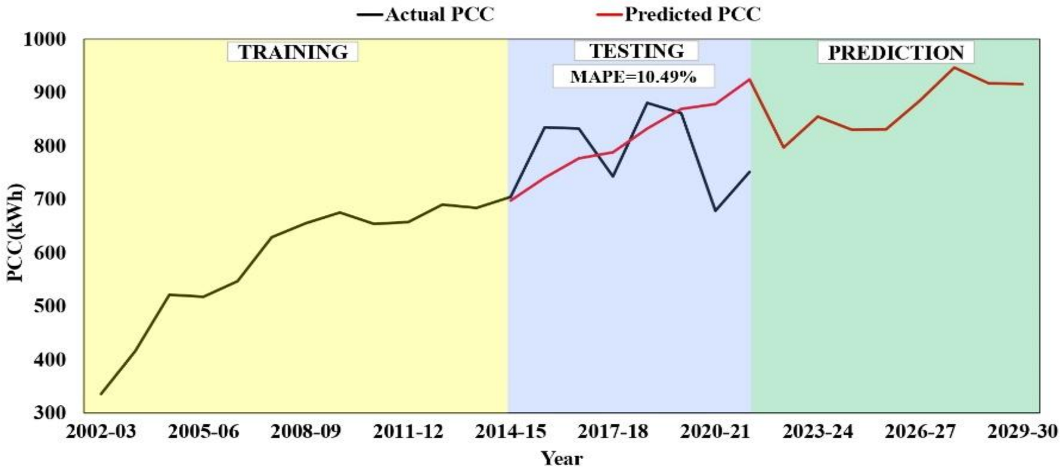



6(a) For Tripura State




6(b) For Bihar State

***Fig. 6: Response of state level PCC prediction using FBP model***




7(a) HWS Prediction

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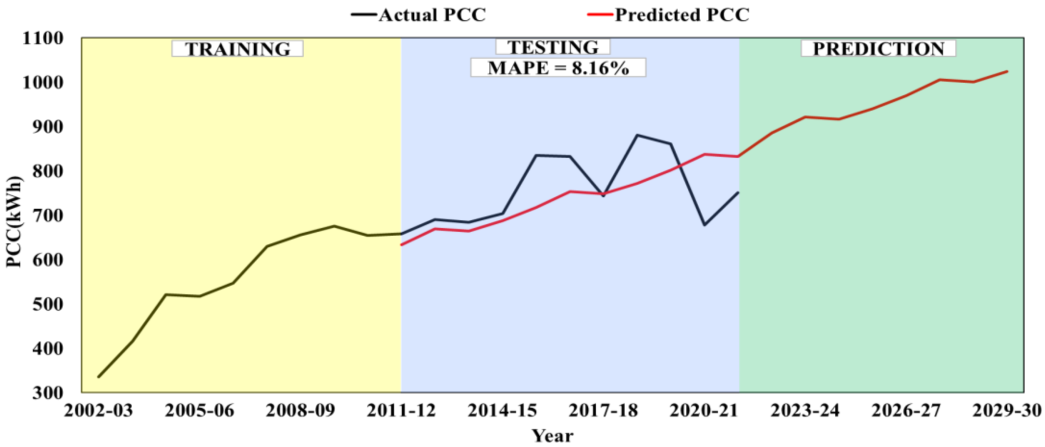


*7(b) FBP Prediction*

***Fig. 7: Response of proposed PCC prediction models for Meghalaya state***

TABLE II: EFFICACY OF PREDICTION METHODS DURING STATE PCC

| Particulars | | FBP | HWS | LSTM-RNN | ARIMA |
|---|---|---|---|---|---|
| MAPE | Tripura | 15.70% | 18.50% | 14.90% | 22.67% |
| | Bihar | 12.33% | 12.44% | 13.38% | 12.85% |
| Train data-sets | | 8 years | 10 years | 10 years | 1 year |
| Test data-sets | | 4 years | 2 years | 2 years | 11 years |
| Prediction Slot | | 8 years | 8 years | 8 years | 8 years |

The proposed forecasting models i.e. FBP and HWS are quite effective i.e. capturing trend with seasonality in long term prediction of per capita consumption (PCC) of electrical energy with acceptable accuracy as shown in Table II. Thus, the above models are applied for a peculiar state of India i.e. Meghalaya to showcase the PCC prediction efficacy. The performance of HWS and FBP models during long prediction of Meghalaya state PCC is depicted in Fig. 7a and Fig. 7b with MAPE accuracy of 10.49% and 8.16% respectively.

Therefore, the proposed models i.e. Holt-Winters smoothing (HWS), Facebook Prophet (FBP) are quite suitable for long term prediction of per capita consumption (PCC) of state level electrical energy in the Indian sub-continent.

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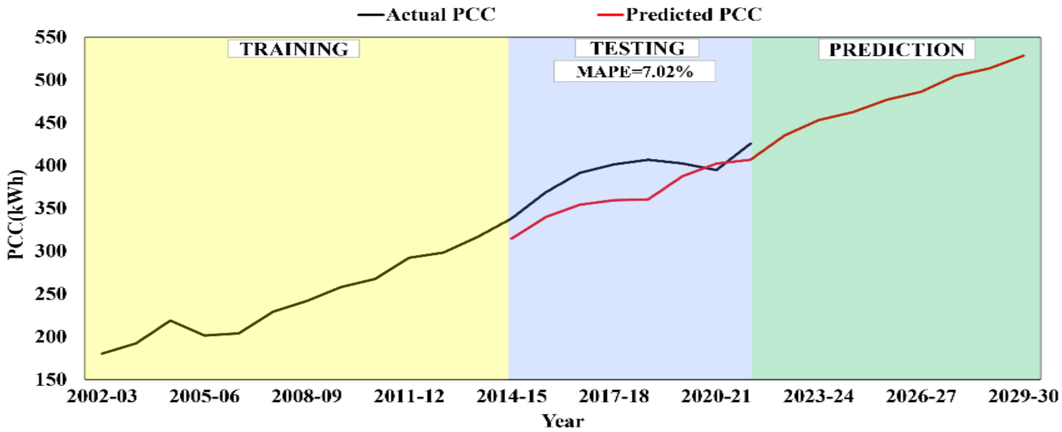
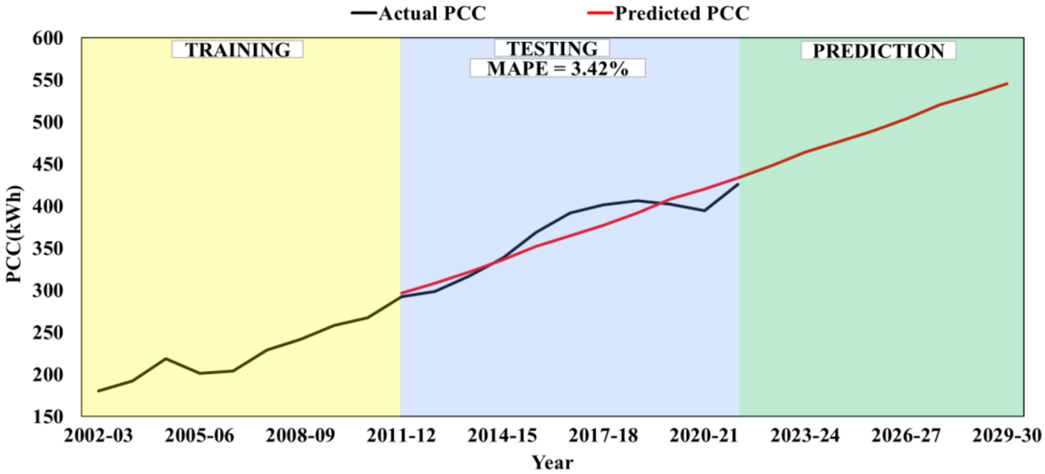
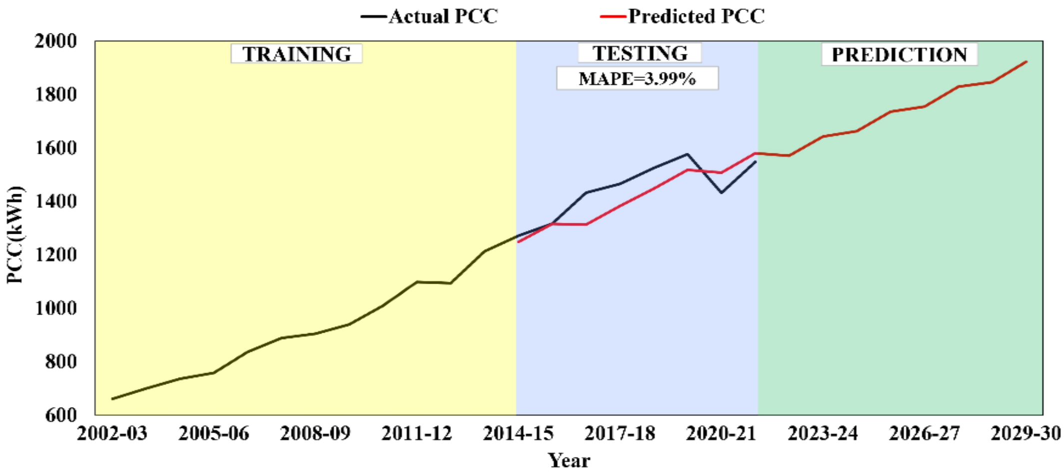



*8(a) HWS Prediction*




*8(b) FBP Prediction*

***Fig. 8: Response of proposed PCC prediction models for North-Eastern region***




*9(a) HWS Prediction*

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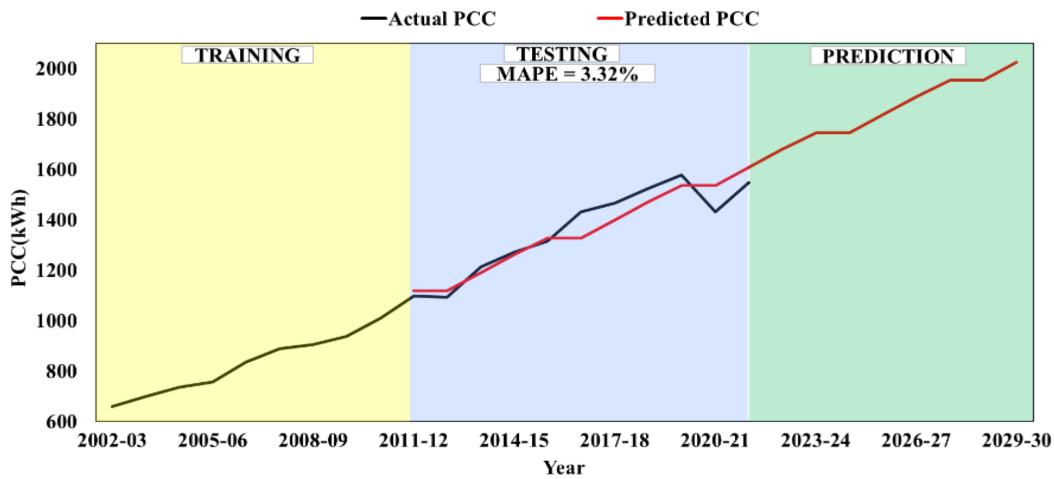
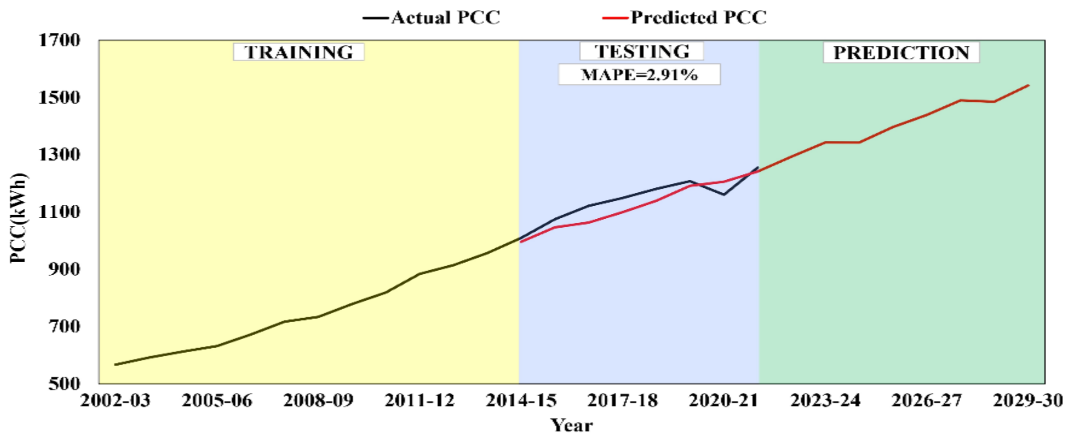
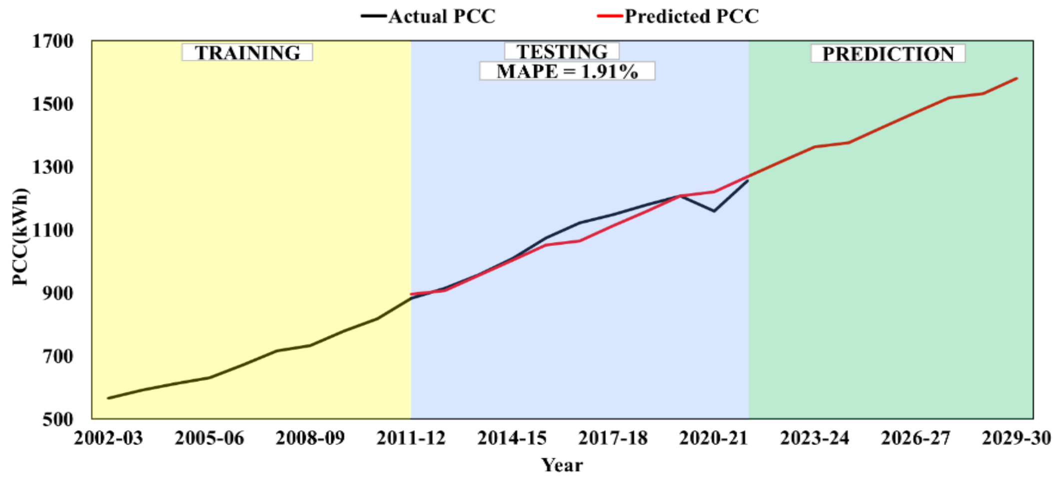



9(b) FBP Prediction

***Fig. 9: Response of proposed PCC prediction models for Southern region***




10(a) HWS Prediction




10(b) FBP Prediction

***Fig. 10: Response of proposed PCC prediction models for Indian Nation***

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### *B. Performance of regional and national PCC prediction*

The electricity grid of India is distributed in five regions i.e. Eastern/Northern/North-Eastern/Southern/Western for effective stability and reliability. The developed and trained Holt-Winters smoothing (HWS) and Facebook Prophet (FBP) as discussed in Section III A are applied on larger scale to predict the per capita consumption (PCC) of regional and national level electrical energy. The performance of proposed HWS and FBP models during long term forecasting of PCC at selected regions i.e. North-Eastern, Southern and national level are shown in Fig. 8, Fig. 9 and Fig. 10 respectively.

From above simulations results, the efficacy i.e. MAPE of proposed Holt-Winters smoothing (HWS) during PCC prediction of North-Eastern and Southern region is 7.02%, 3.99% respectively. Similarly, the MAPE efficiency of proposed Facebook Prophet (FBP) during PCC prediction of North-Eastern and Southern region is 3.42%, 3.32% respectively. Further, the HWS and FBP prediction models are quite effective i.e. MAPE of 2.91% and 1.91% respectively in long term forecasting of Indian PCC of electrical energy.

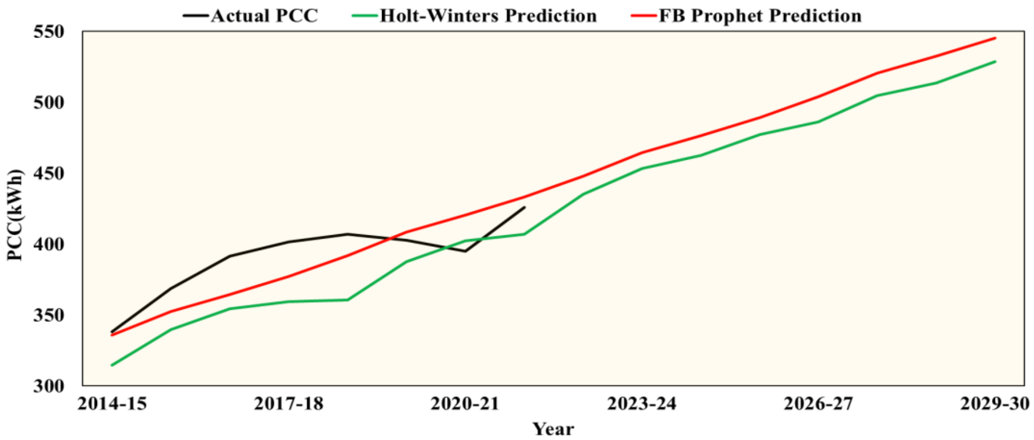


*Fig. 11: Facebook Prophet Result for NER*

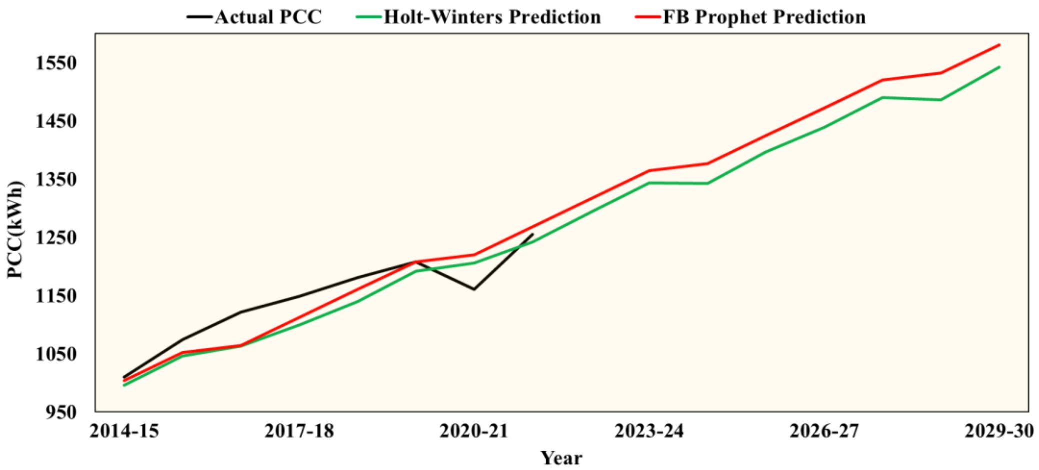


*Fig. 12: Facebook Prophet Result for India*

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### C. Comparative performance of proposed prediction methods

Moreover, the efficacy of proposed Holt-Winters smoothing (HWS) and Facebook Prophet (FBP) during long term prediction of PCC of North-Eastern region and Indian country electrical energy consumption is shown in Fig. 11 and Fig. 12 respectively. The simulation results reveal that the HWS and FBP are competitively captured the trend and seasonality during long term prediction of per capita consumption (PCC) of electrical energy. Furthermore, the performance of Facebook Prophet (FBP) prediction model is more accurate i.e. lower MAPE than that of Holt-Winters smoothing (HWS) model.

Therefore, the proposed Facebook Prophet (FBP) model is quite effective and suitable during long term forecasting of per capita consumption (PCC) of electrical energy at various state, regional and national levels.

## 4. Conclusion

In this paper, various forecasting models such as autoregressive integrated moving average (ARIMA), long shortterm memory based recurrent neural network (LSTM-RNN), Holt-Winters smoothing (HWS), Facebook Prophet (FBP) are developed for estimation of per capita consumption (PCC) of electrical energy. The proposed prediction models are validated through long term forecasting of PCC at different states, regions and national levels. The simulation results reveal that the HWS and FBP are competitively captured the trend and seasonality during long term prediction of per capita consumption (PCC) of electrical energy. Furthermore, the performance of Facebook Prophet (FBP) prediction model is more accurate i.e. lower MAPE than that of Holt-Winters smoothing (HWS) model. It is highlighed that the proposed Facebook Prophet (FBP) model is quite effective and suitable during long term forecasting of per capita consumption (PCC) of electrical energy at various state, regional and national levels. Thus, the proposed work can be utilized by the grid operators/researchers to better manage their energy resources, reduce costs, and improve customer satisfaction. Lastly, extensive research can be explored for improved accuracy and reliability of forecasting models in the context of dynamic energy markets and consumer behaviours.

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