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Time series analysis of electric energy consumption using autoregressive integrated moving average model and Holt Winters model

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ABSTRACT

With the increasing demand of energy, the energy production is not that much sufficient and that's why it has become an important issue to make accurate prediction of energy consumption for efficient management of energy. Hence appropriate demand side forecasting has a great economical worth. Objective of our paper is to render representations of a suitable time series forecasting model using autoregressive integrated moving average (ARIMA) and Holt Winters model for the energy consumption of Ohio/Kentucky and also predict the accuracy considering different periods (daily, weekly, monthly). We apply these two models and observe that Holt Winters model outperforms ARIMA model in each (daily, weekly and monthly observations) of the cases. We also make a comparison among few other existing analyses of time series forecasting and find out that the mean absolute percentage error (MASE) of Holt Winters model is least considering the monthly data.

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1. INTRODUCTION

The prediction of energy is vital for electricity traders who buy and sell electricity, change loads, organize maintenance and unit commitment to balance their purchase of electricity, as well as to supply their consumers with optimal price products. The need of electricity is increasing so rapidly and the impact of this is so crucial and harmful for our environment. Use of electricity in the USA in 2018 was 16 times greater than that of in 1950 [1]. According to the energy information administration data, the consumption of electricity can be 79% greater through 2050 [2]. That's why proper prediction of electrical energy consumption is really needed to control the excessive use or to reduce waste of energy to minimize its harmful effect on the environment. Saving of electricity does not require a lot of cash. It needs a proper way of consuming electricity in the most efficient way [3]. Most of the proposed prediction models usually use statistical method as a tool for forecasting future data [4]. The suitable prediction models are recognized from some factor like prediction period, prediction interval, the duration of the time series, characteristics of time series [5]. In this paper a comparative study is presented for statistical prediction of two commonly used linear demand models for energy consumption in Ohio/Kentucky. The models are a trendy time series linear model named autoregressive integrated moving average (ARIMA) [6] model and Holt-Winters model. These models have exceptional adaptive capacity to deal with the linearity in problem solving [7]. We applied ARIMA and Holt Winters models for several reasons. ARIMA is a very strong time series model where a series past data is used as an independent variable. ARIMA forecast data are generally more reliable and accurate [8]. Holt Winters model is easier to apply, provides accurate forecast and recent observations are given significance here [9].

The comparison is made by considering the lowest root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and the highest value of mean absolute percentage accuracy (MAPA) for time series predictions. Our main contribution is to represent the best suitable and accurate technique among two powerful time series model- ARIMA and Holt Winters model. Our work is done for daily, weekly and monthly electricity consumption from 2012 to 2018 of Duke Energy Ohio/Kentucky [10]. In this paper the section 2 presents some existing works related to time series data and other models. Section 3 represents theoretical explanation of our work and models. Section 4 explains the methodology. Section 5 shows the analysis of the result and section 6 concludes our work.

2. RELATED WORKS

Different researches have been done so far with time series data. Ma *et al.* [11] applied support vector machines (SVM) to forecast energy consumption in buildings of China. Their analysis showed that SVM method can forecast energy consumption with quite a good accuracy. They didn't use other models in their paper or didn't show any comparative result. Nie *et al.* [12] used an ARIMA and SVM hybrid technique for load forecasting. They used this hybrid model to achieve a better accuracy. But the hybrid model was not clearly mathematically explained. Fard and Zadeh [13] presented a hybrid technique for short time load forecasting which is based on wavelet transform, Artificial Neural network and ARIMA. This hybrid model can increase the complexity in many cases. In [14] several time series models have been used to predict the consumption of electricity of University Tun Hussein Onn Malaysia (UTHM). The models they used are simple moving average (SMA), weighted moving average (WMA), Holt-Winters (HW), Holt linear trend (HL), simple exponential smoothing (SES) and centered moving average (CMA). From their analysis they found that HW gives the smallest MAE and MAPE.

Pan [15] showed for Airline passenger data that prediction of Holt-Winters technique is more accurate compared to ARIMA model. In their case they could have experimented with data of different periods by re-sampling the data. Chujai *et al.* [16] presented a suitable model and period among weekly, daily, quarterly or monthly for forecasting household energy consumption. They used ARMA model and ARIMA model for data analysis. They used the lowest value of AIC to figure out the most appropriate model and the least value of RMSE to find the appropriate period. They didn't use other metrics like MAPE, and MAE to analyze the result.

Bouktif *et al.* [17] used long short term memory based model to forecast electricity consumption. By selecting the best base line, choosing the appropriate features and applying genetic algorithm, they found an optimal model prediction. In [18] support vector regression has been applied on the data of energy consumption of different buildings. This data is hourly observation of different buildings. They didn't use different models and different periods of data for better analysis. Vinagre *et al.* [19] proposed a forecast method of energy consumption based on artificial neural network for an office building using the data from October 2014 to April 2015. Their average MAPE based on the best network was 13.6%. This percentage is quite moderate and can be better using other models or hybrid models.

Yoo and Myriam [20] proposed a model based on neural network to predict the residential electricity consumption in Seoul using the historical data from January 1996 to July 2016. They found out some interesting characteristics which have direct impact on the data. The MAPE of the total dataset was 4.85%. Bilal Şişman [21] made a comparison between ARIMA and Grey Model by forecasting the electricity consumption in Turkey where it has been found that the MAPE of ARIMA and Grey Model were 4.9% and 5.6% respectively. They also analyzed that both are quite better than MAED model which has MAPE of 14.8%. This study can further be applied to other fields of forecasting along with other models to increase its accuracy and efficiency.

In [22] 4 different models based on multi objective genetic algorithm have been applied to predict the power consumption using the data from 1 September 2010 to 29 February 2012 of a building in Spain. They compared these models with existing perceptron model [23] and a naïve autoregressive baseline (NAB) [24] model. The MAPE of the NAB model showed the worst performance. An auto-encoder using deep learning model has been proposed in [25] by the researchers for predicting electric energy consumption. They used household power consumption of five years and obtained mean squared error of 0.384 but they haven't mentioned any percentage of error. This work also can be extended using several household data or the data of a whole area to make it more applicapble. Kim and Cho [26] proposed CNN-LSTM neural network which can predict the energy consumption of the housing effectively and achieved RMSE of 61.14%.

In [27] the researchers proposed LSTM and GRU to predict the traffic flow. It has been shown that MSE of two RNN is smaller than ARIMA and GRU gives better performance than LSTM in 84% of total time series. Tso and Yau [28] presented three techniques- regression analysis, neural network and decision tree for the prediction of energy consumption. They compared the three-model based on their RASE. They found out that the RASE of the three models are quite similar. Others performance metrics could be used besides RASE to have a better comparison among the models.

3. THEORETICAL FRAMEWORK

Time series analysis is on historical data which is taken collectively for continuous period which can be of different periods- hourly, daily, weekly, monthly, quarterly, and yearly depending on the usage and scope of users. We are using ARIMA as well as Holt Winters model for analyzing the time series data of energy consumption for Duke Energy Ohio/Kentucky [10]. Figure 1 shows the general flow diagram of our work. Here the hourly observations of energy consumption are used and later resampled to daily, weekly and monthly data. Further the ARIMA and Holt Winters model are applied on these data separately.

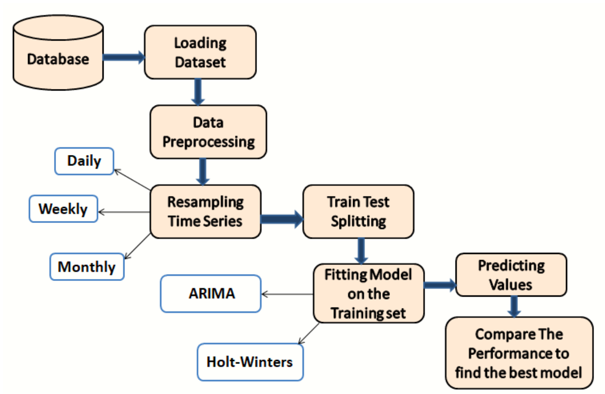


Figure 1. Work flow of analysing time series

3.1. ARIMA model

ARIMA is a technique that analyzes autocorrelation in the time series by modeling it directly. It is the combination of autoregressive (AR) process, moving average (MA) process and stationery (I) series [29]. It is an integrated (I) series to become static, it has to be differentiated. The (AR) terms are the Lags of the stationary series. Predictive error lags are, in actual fact, moving averages known as MA terms. It uses Box and Jenkins approach which has been extensively applied in studies of time series forecasting [30]. The ARIMA model consists of three parameters (p, d, q) [31]. Here, p is the autoregressive component's order, d means the amount of dissimilarities required to make the series stationary ARMA (p, q) and q is moving average component's order [32].

3.2. Holt Winters model

Holt-Winters model is a technique to forecast the characteristics of a time series data. It is a very popular forecasting technique for time series data. It works with three features of the time series: a regular/mean value, a cyclical pattern which repeats seasonally and a slope or trend over time. The model combines the effect of these three aspects to predict or guess a present or future data. This model is called triple exponential smoothing as the 3 features of the time series analysis-typical/regular value, slope or trend value, and seasonality are represented as 3 types of exponential smoothing. The model needs some parameters (α, β, γ)- one for each smoothing, the duration of a season, and the amount of periods in a season.

- α (Coefficient of level smoothing or base value): The parameter α determines the weight of the past values [33].
- β (Coefficient of trend smoothing or trend value): The parameter β determines the degree of the recent trend values [33].
- γ (Coefficient of seasonality smoothing or seasonal component): The parameter γ indicates the coefficient for the seasonal smoothing [34].

3.3. Performance metrics

- Mean absolute error (MAE): It is calculated by (1).

MAE = Sum of the absolute error of n observation/ n [35] (1)

– Root mean squared error (RMSE): The square root of the mean squared differences between forecasted and test (actual) observation is calculated by RMSE as shown in (2).

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2} \qquad [36] \tag{2}$$

Here n= number of observations, y_j =true value, $\hat{y}_j$=predicted value.

– Mean absolute percentage error (MAPE): It can be measured by (3).

$$MAPE = \frac{\sum\frac{|A-F|}{A}x100}{N} \qquad [37] \tag{3}$$

N= number of total observations, A=True value, F=Predicted value.

– Mean absolute percentage accuracy (MAPA): Mean absolute percentage accuracy can be measured simply subtracting the MAPE value from 100. This gives us the accuracy in percentage.

4. METHODOLOGY

Our main goal is to apply ARIMA and Holt-Winters model in our data set (Duke Energy Ohio/Kentucky) to forecast some energy consumption values for daily, weekly and monthly data and make a comparison of the results to find the suitable model for forecasting. We worked with python 3 using jupyter notebook. The Workflow of our analysis is given in Figure 1.

4.1. Dataset

The dataset we used is an hourly energy consumption data taken from PJM's website [10]. PJM Interconnection LLC is a regional transmission organization (RTO) in the USA. Figure 2 (a) shows a sample of the dataset we used and Figure 2 (b) shows the specifications of the dataset. The dataset symbolizes the hourly energy consumption (in Mega Watt) of Ohio/Kentucky [10].

4.2. Loading and resampling the data set

The data set contains 57740 observations of hourly energy consumption from 12/31/2012 1:00 AM to 1/2/2018 12:00:00 AM. Firstly, the dataset is loaded in the csv format using panda’s library. Original dataset is provided in Figure 3 where the hourly observations in mega watt are graphically shown. Then we resample the dataset into daily, weekly and monthly observations. After re-sampling into daily, weekly and monthly observations, the datasets are graphically shown in Figure 4, Figure 5 and Figure 6 respectively.

We split our data set into test set and training set. Then we apply the models on the training set to examine the test set. The training and test set are split accordingly:

– Daily observations: First 1800 observation are used as training set and rest of them as test set of total 2407 observations for both ARIMA and Holt Winters model.
– Weekly observations: First 260 observations are used as training set for Holt-Winters model, first 300 observations as training set for ARIMA model and rest of them as test set of total 344 observations.
– Monthly observations: First 60 observations are used as training set and rest of them as test set both ARIMA and Holt Winters model of total 80 observations.

4.3. Building models for prediction

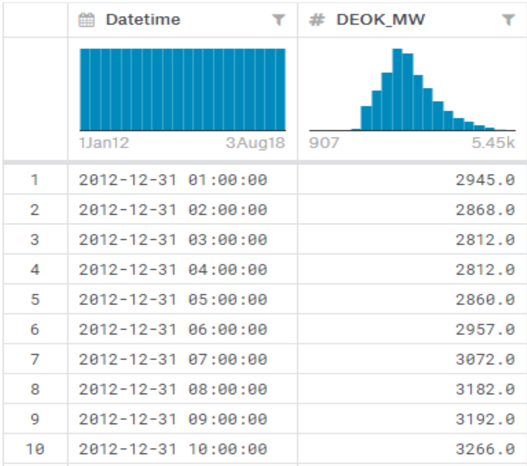
– Autoregressive integrated moving average **(**ARIMA) model

The first thing of building an ARIMA model is to find out the most appropriate order of ARIMA (p, d, q). The function auto_arima () is used which provides best ARIMA model based on Akaike Information Criterion (AIC) value. In our case the most suitable order for daily, weekly and monthly data are (3, 0, 3), (1, 0, 1) and (2, 1) respectively.

– Holt Winters model

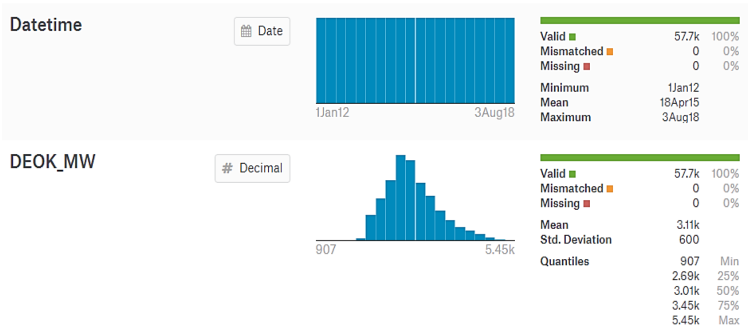
To build the model, the function ExponentialSmoothing () is used. An important part of building the model is to determine the suitable parameters (α, β, γ). The most suitable value for alpha and gamma are determined for our dataset. Here are the coefficient values-

α = 0.85 & γ = 0.15 for daily data
α = 0.23 & γ =0.0 for weekly data
α = 0.56 & γ = 0.0 for monthly data



	Datetime	DEOK_MW
	1Jan12 – 3Aug18	907 – 5.45k
1	2012-12-31 01:00:00	2945.0
2	2012-12-31 02:00:00	2868.0
3	2012-12-31 03:00:00	2812.0
4	2012-12-31 04:00:00	2812.0
5	2012-12-31 05:00:00	2860.0
6	2012-12-31 06:00:00	2957.0
7	2012-12-31 07:00:00	3072.0
8	2012-12-31 08:00:00	3182.0
9	2012-12-31 09:00:00	3192.0
10	2012-12-31 10:00:00	3266.0

(a)



(b)

Figure 2. (a) Sample of the dataset, (b) Specification of the dataset [10]

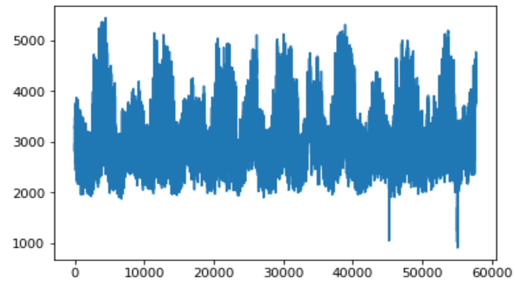


Figure 3. Original dataset (hourly observations)

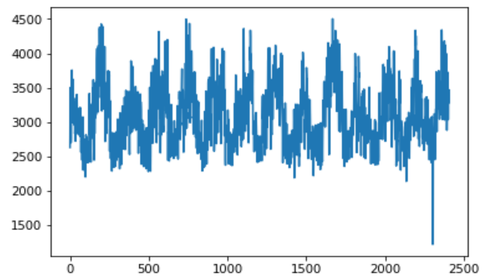


Figure 4. Daily dataset after resampling

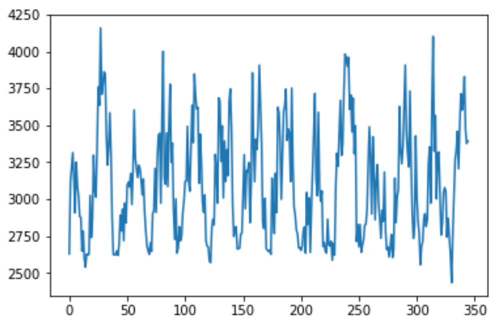


Figure 5. Weekly dataset after resampling

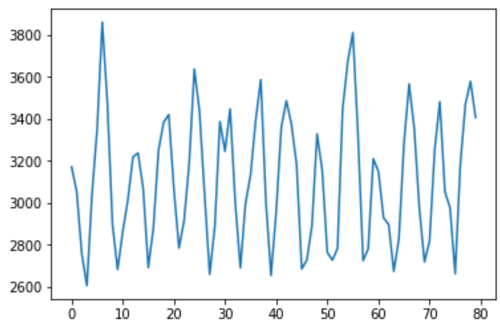


Figure 6. Monthly dataset after resampling

4.4. Predicting values

After applying the models on the test set, obtained results are illustrated in Figures 7-12. Each of the figures represents the original and predicted values. In the Figures 7-12, the comparison of the original and forecasted data is shown using two models (ARIMA and Holt Winters). Here the x axis indicates the time period (day, week or month) and the y axis indicates the energy consumption in Mega Watt.

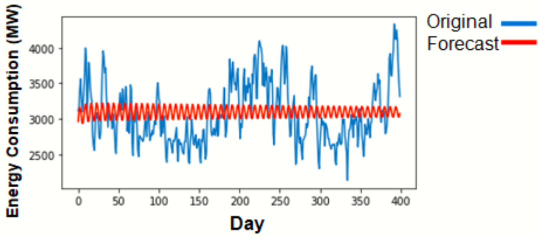


Figure 7. ARIMA on daily datasett

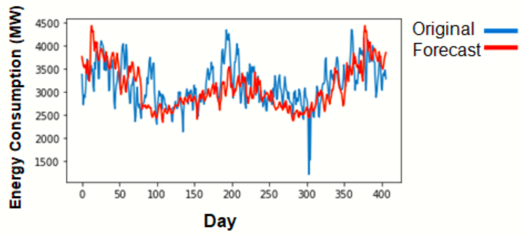


Figure 8. Holt-Winters on daily dataset

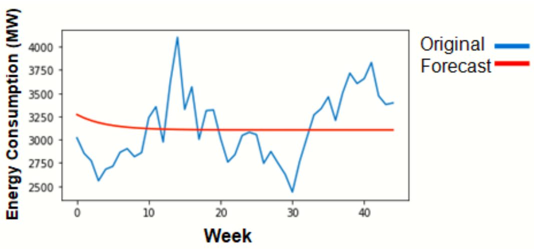


Figure 9. ARIMA on weekly dataset

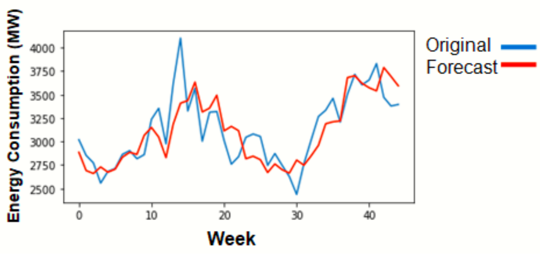


Figure 10. Holt-Winters on weekly dataset

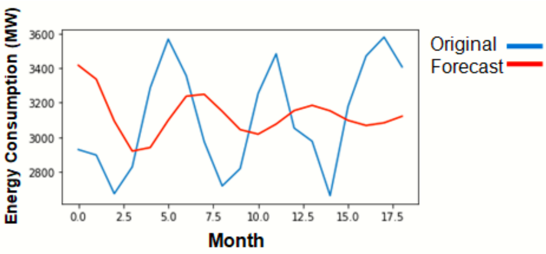


Figure 11. ARIMA on monthly dataset

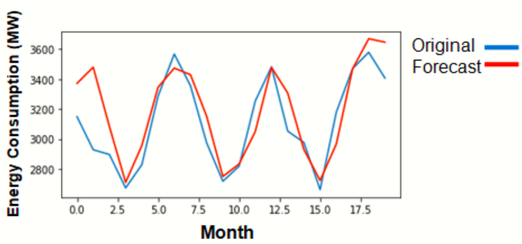


Figure 12. Holt-Winters on monthly dataset

5. RESULT ANALYSIS AND DISCUSSION

5.1. Analysis from the output graph

Figures 7 and 8 represent the output of daily observations of energy consumption using ARIMA and Holt Winters model respectively. It shows that the ARIMA model doesn't follow the original values as the Holt Winters model does. Figures 9 and 10 represent the output of weekly observations of energy consumption using ARIMA and Holt Winters model respectively. Here we see that Holt Winters Model follows the original values but ARIMA model gives almost a linear output. Figures 11 and 12 represent the output of monthly observations of energy consumption using ARIMA and Holt Winters model respectively. Like the previous two datasets also here Holt Winters model follows the original values more precisely than ARIMA model. It gives us an intuition that Holt Winters model outperforms ARIMA model in each case.

5.2. Analysis using evaluation metrics

After obtaining the results of the two models for daily, weekly and monthly data, the results are compared using the MAE, RMSE, MAPE and MAPA values. These are shown in Table 1. From the Table 1, we observe that for daily, weekly and monthly, in all cases the error values (MAE, RMSE and MAPE) are less for Holt Winters model. The Accuracy (MAPA) is greater for Holt Winters model for each case. For ARIMA model the accuracy in daily, weekly and monthly data are 88.51%, 89.814% and 90.85% respectively. For Holt Winters model the accuracy in daily, weekly and monthly data are 89.74%, 94.589% and 95.64% respectively.

And we also determine that the greater the period, the more accurate is the result. We get the best accuracy for monthly data using Holt Winters model that is 95.64%.

5.3. Comparison with other existing works

Finally, we compare our two models with few other models. The comparison is based on the mean absolute percentage error (MAPE). There exist many other analyses of the prediction models for predicting the electric energy consumption. Table 2 gives us the idea of other analyses and our analysis. We can see from Table 2 that Holt winters model has the minimum MAPE (incase of monthly observations) than all other models. Our obtained MAPE value is 4.36% for monthly observations using Holt Winters model. Thus, we can use this model for predication of energy consumption with a view to making a proper plan of electricity supply and minimizing the energy waste for sustainable development. This model also can be used in other time series prediction for proper management and decision making.

Table 1. Comparison of Two models based on different evaluation metrics

Period	Evaluation metrics	ARIMA	Holt Winters
Daily Observation	MAE	343.41	313.81
	RMSE	426.09	407.63
	MAPE	11.49%	10.26%
	MAPA	88.51%	89.74%
Weekly Observation	MAE	303.48	171.58
	RMSE	357.18	222.02
	MAPE	10.186%	5.411%
	MAPA	89.814%	94.589%
Monthly Observation	MAE	316.21	134.44
	RMSE	347.18	184.12
	MAPE	9.15%	4.36%
	MAPA	90.85%	95.64%

Table 2. Comparison of our obtained MAPE with other existing analysis

Model References	Data Set	Method Used	MAPE (%)
Eugénia Vinagre, Luis Gomes, Zita [19]	Oct 2014-Apr 2015 (Energy consumption for an office building)	ANN	13.6
Sang Guun Yooa, Myriam Hernández-Álvarez[20]	Jan 1996- Jul 2016 (Residential electricity consumption of Seoul)	Neural Network	4.85
Bilal ŞİŞMAN[21]	1970-2013 (Turkish Statistical Institute and Electricity distribution and consumption statistics of Turkey)	ARIMA	4.9
		Grey Model	5.6
Khosravani, Castilla, Berenguel, Ruano, Ferreira[22]	1 Sep 2010-29 Feb 2012 (Solar energy research centre bioclimatic building, University of Almeria, Spain)	Multi Objective Genetic Algorithm (MOGA)	5.04 (Average of the best models)
Models we used to analyze	12 Dec 2012-1 Feb-2018 Energy consumption of Ohio/Kentucky from PJM's Website [10]	ARIMA (for monthly data)	9.15
		Holt Winters (for monthly data)	4.36

6. CONCLUSION

One of our important concerns today is the appropriate management of energy and hence an accurate predicting model for forecasting energy consumption is required. We tried to apply the ARIMA and Holt Winters model in the energy consumption data of Ohio/Kentucky from PJM's website [10] and made a comparative analysis of the results. The main aim of our study was to find the suitable model among the two models for daily, weekly and monthly data for appropriate prediction. We determined the best suited model based on the minimum value of MAE, RMSE and MAPE. From our analysis it was observed that Holt Winters model provided more accuracy for the data sets in each case (daily, weekly, monthly).

Later we compared few other existing models with our two models which also reflect that the Holt Winters model that we used has greater accuracy for the monthly observations. So, we can conclude that for this kind of long-term forecasting, our proposed Holt Winters model can work efficiently for proper energy management. Further studies can be done with the similar dataset considering other parameters and environmental factors which has a greater impact on the data. We can also work using some other hybrid models or models like ANN and genetic algorithm to be able to have better result on short term load forecasting.

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