A Comparative Forecasting Analysis of ARIMA Model vs Random Forest Algorithm for A Case Study of Small-Scale Industrial Load

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Abstract - *Ensuring sustainability in electric power grid requires a high-efficiency energy management system with lessened energy depletion. Hence, a smart power grid with an utmost flexible management system alongside an intelligent officiating capability has no alternatives. Predicting the future energy requirement is considered as one of the key features of smart grid. Therefore, the studies of the energy forecasting have started to contribute to the path of efficient energy management for the grid. This paper presents a comparative analysis of forecasting energy demand between a Time series analysis technique (ARIMA model) and a Machine learning technique (Random Forest). A benchmark data set of the small-scale industrial load is taken as consideration for "train and test" both methods. Both techniques are trained and tested on monthly (Short Term Load Forecasting) and yearly (Long-term load forecasting) timespan data. A comparative study depending on the accuracy rate between these two algorithms are is presented for forecasting energy demand.*

Key Words: **Smart Grid; Energy Load Forecasting; Short-Term Load Forecasting (STLF); Long-Term Load Forecasting (LTLF); ARIMA model; Seasonal ARIMA (SARIMA); Random Forest (RF).**

1. INTRODUCTION

With the growing energy demand, expected to be increased by 40% by 2040, the consumption of fossil fuels has already started to reach its peak [1]. The shortage of fossil fuels like coal, oil, natural gas, and other resources is inevitable in the near future. Correspondingly, the increasing rate of carbon emission due to fossil fuel consumption in power generation, estimated to be roughly 25%, is also a major concerning issue for global warming [2]. So, more and more renewable energy resources are getting into the picture of the power generation field. However, renewable energy brings with it an additional challenge of inherent stochasticity. Therefore, an accurate energy forecast can ease the road of application of renewable into grid [3]. Moreover, its significance is only going to increase because of increased penetration of inherently volatile distributed renewable energy resources in the power grid [4].

Additionally, Short-Term Load Forecasting (STLF) and Long-Term Load Forecasting (LTLF) are vital for today's deregulated market as an efficient way of planning, load switching, and energy buying strategy [3]. Any good STLF and LTLF methods should satisfy the following two criteria:

1) accuracy and 2) speed. The significant variables affecting energy demand should also be considered for forecasting [3]. Therefore, in the power grid, variables like weather, time of the day, season, and the base demands are the crucial factors to consider [5].

Energy load forecasting methodologies can be categorized into three major groups: 1) statistical techniques, 2) artificial intelligence techniques, and 3) a hybrid of the first two methods [6-10]. Here, the classical statistical models are referred to as the white-box models. The relationship between outputs and inputs is expressed with mathematical equations. These methods are simpler in their implementation. However, they lag the AI-based methods in terms of accuracy. The AI-based models are generally termed black box models and based on machine learning algorithms. These models are somewhat complex but can be applied to a wider range of scenarios. Hybrid methods couple artificial intelligence and optimization algorithm together, which results in higher accuracy, computational period, and complexity.

Despite usage complexity, Time series methods have gained popularity for both STLF and LTLF recently. Modern data-driven systems can analyze and predict result even from a big data system [11]. ARIMA model is designed only to reflect the behavior of observed data over time. Other explanatory variables for forecasting are not considered in the case [12]. ARIMA is generally used in stationary processes; however, ARIMA can also be used in non-stationary processes although, a differencing operation or other necessary transformations need to be carried out to alter the non-stationarity of the process. ARIMA model is characterized by three parameters: p, d, and q, where they represent the order of the autoregressive terms (p), differencing terms (d), and moving average terms (q), respectively.

Machine learning algorithms have already proven their efficacy in capturing complex load characteristics. The two most widely studied machine learning techniques in the arena of load forecasting are support vector machine (SVM) and artificial neural network (ANN) [13][14]. Despite the ability of computation and incorporating non-linearity, these methods carry major drawbacks: tuning of parameters in SVM and being trapped in local optimization for ANN [15][16]. Moreover, another major issue with forecasting problems in the selection of an optimal number of features; both SVM and ANN must deal with this issue. However, random forest (RF), which is a kind of ensemble method,

aims to tackle this issue [17]. RF is a fast forecasting method, where accuracy is as good as ANN and SVM. Moreover, parameter tuning is not essential in RF as even bad selection of parameters does not worsen the prediction accuracy drastically [15]. Finally, RF results in a globally optimal solution through formulating a convex optimization problem [14].

2. SYSTEM MODEL

2.1 ARIMA Model

For forecasting a stationary time series, the most widely used methodology is ARIMA models. The ARIMA model acts as a regression-type linear equation for stationary time series, where the predicted value (dependent variable) consists of lag terms of the projected value and lag terms of the residuals. So, the general format of the ARIMA forecasting equation is as follows [18]: the forecasted value of Y **= a** weighted sum of one or more autoregressive terms of Y and/or a weighted sum of forecast errors (along with associated lag terms) and/or a constant. The ARIMA model is purely autoregressive if it contains only the lagged terms of Y. Autoregression is a specific variation of regression and can be fitted with any standard software of regression. A first-order autoregressive model **(AR(1))'s** independent variable is $Y_{(t-1)}$, which is one time period lagged version of **Y**.

When the model includes the lagged terms of the errors, it deviates away from being a linear regression model. Although the predictions are still linear functions of past values, the prediction does not have a linear relationship with the coefficients. That is why the coefficients of an ARIMA model that contains lagged errors need to be optimized by non-linear techniques like hill-climbing.

2.2 Non-Seasonal ARIMA

An ARIMA (p, d, q) model is the non-seasonal variation, where p, q, and d represent the number of total autoregressive terms, lagged forecast error terms and differencing needed to ensure stationarity, respectively. If the dth (d = 0, 1, 2) difference of Y is denoted as y, then the autoregressive terms are constructed respectively as follows [19]:

$$y_t = Y_t \dots\dots (1)$$

$$y_t = Y_t - Y_{t-1} \dots\dots\dots (2)$$

$$y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) \dots\dots\dots (3)$$

A very interesting point to be noted here is that the second difference, Equation 2, is not actually the difference between two time periods, rather, it is analogous to the second derivative. Finally, the forecasting equation can be presented in the following way:

$$y_t = \mu + \varphi_1 y_{t-1} + \dots + \varphi_p y_{t-p} - \theta_1 e_{t-1} - \dots - \theta_p e_{t-p} \dots\dots (4)$$

The parameters of autorepression and moving average operations are represented by φ and θ, respectively. In order to determine the relevant ARIMA model for a forecasting purpose, first the order of differencing (d) needed for series stabilization is determined. Then the gross seasonality features are reduced and variance-stabilizing transformations like deflating or logging have been performed. Without the deflating process of the data set, this model will just be considered as the random trend or random walk model. However, the stationary series would still need MA terms (q ≥ 1) and AR terms (p ≥ 1) to represent the autocorrelated errors.

2.2.1 Model Formulation

The framework to fit non-seasonal time series data into an ARIMA model is described in the following steps and in Figure 1 below:

- Data plotting and identifying unusual patterns

- Data transformation for variance stabilization, if necessary

- Conversion of the time series into a stationary one

- Plotting and analyzing the correlation functions – Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF)

- Model selection and optimizing it using Akaike Information Criteria (AIC)

- Residual checking of the chosen model by conducting a Portmanteau test and plotting the residual ACF; the model needs to be modified if the residuals do not indicate the presence of white noise only

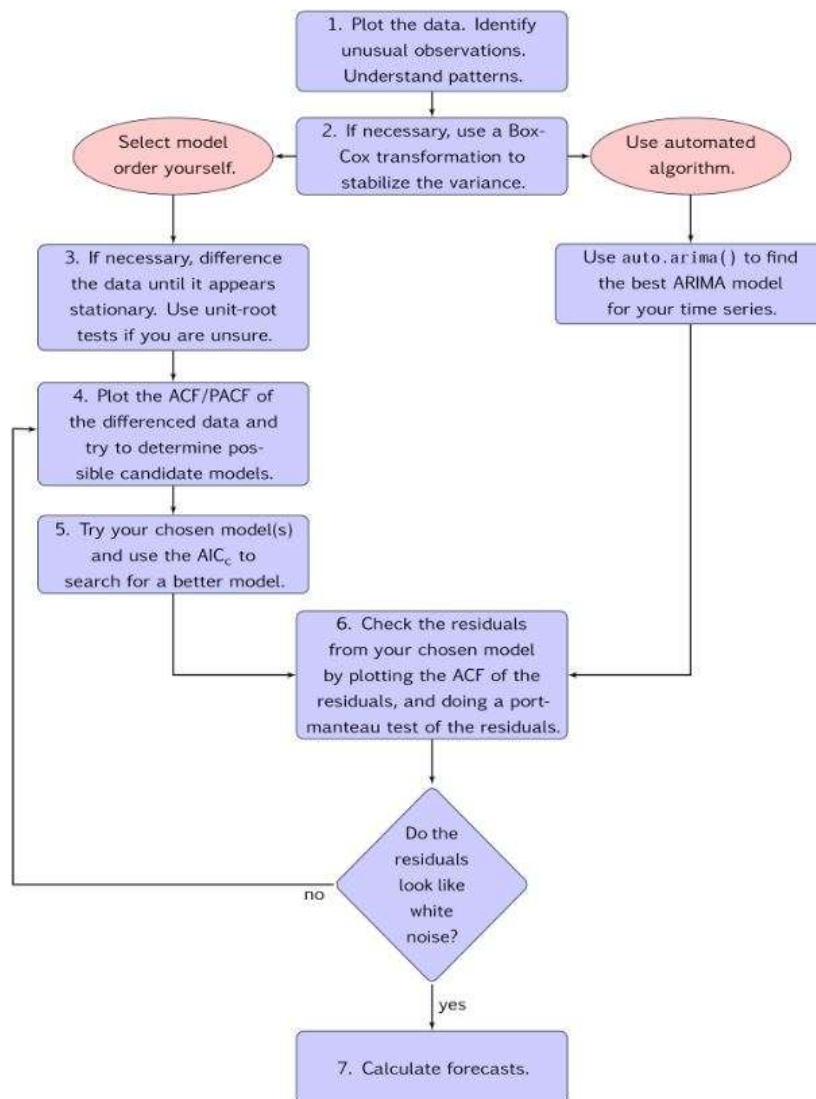- Forecast calculation, when the residuals represent white noise only

Figure 1: Forecasting Framework for ARIMA Model

2.3 Seasonal ARIMA

Seasonality is the presence of a regular pattern in the data set where the pattern is periodic. The seasonality in a time series is represented by parameter **S**, the span of the seasonality. For example, if yearly sales data of some equipment tend to have high and low values during winter and summer respectively, then **S = 12**. Just like the non-seasonal time series, seasonal data can also be modeled and forecasted as an ARIMA process.

A seasonal ARIMA is a multiplicative model that incorporates both the variations, seasonal and non-seasonal. The generalized seasonal ARIMA model is expressed in the following way [21]:

$$ARIMA(p, d, q) * (P, D, Q)_S \ldots \ldots (5)$$

where, p = order of AR terms (non-seasonal), P = order of AR terms (seasonal), q = order of MA terms (non-seasonal), Q =

order of MA terms (seasonal), d = order of differencing (non-seasonal), D = order of differencing (seasonal), and S = span of pattern in seasonality

A seasonal ARIMA model is expressed in a more mathematically detailed way by Equation 6:

$$\left(1 - \varphi_1 B - \cdots - \varphi_p B^P\right)\left(1 - \varphi_1 B^S - \cdots - \varphi_p B^{PS}\right)(1 - B)^d (1 - B^S)^D y_t$$
$$= \left(1 + \theta_1 B + \cdots + \theta_q B^q\right)\left(1 + \theta_1 B^S + \cdots + \theta_Q B^{QS}\right)\epsilon_t \ldots \ldots (6)$$

where B represents the backshift operator which is defined by the following operation:

$$B^m y_t = y_{t-m} \ldots \ldots (7)$$

2.3.1 Model Formulation

The seasonal ARIMA model can be formulated using the following steps:

- Data plotting and identifying patterns of seasonality and trend.

- Performing differencing operation if either seasonality or trend is present. For only seasonality, differencing of lag S needs to be done. When the only trend is present, a first-order differencing needs to be performed. Finally, when both seasonality and trend are present, a first-order differencing should be done after seasonal differencing if the presence of trend is still there.

- Analysis of the differenced time series data using ACF and PACF. ACF and PACF give us the order of MA terms and AR terms respectively for both seasonal and non-seasonal data.

- Estimation of the seasonal model.

- Analysis of residual to check whether the model is a good fit.

2.4 Random Forest

Random forest, a supervised learning algorithm, was developed by Hyndman and Athanasopoulos [21] in 2001. It is based on bagging and Classification and Regression Trees (CART) techniques. CART is the basic building block of RF. CART is a classification algorithm with a tree-like structure. CART maps observation about a sample into a decision about the sample's class. A simplified CART algorithm is illustrated in Figure 2.
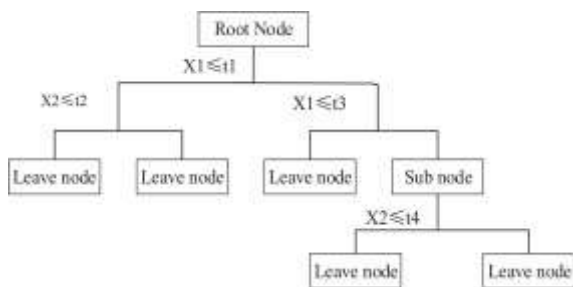
Figure 2: CART Algorithm

Every node is a decision point in CART and the decision process propagates until a leaf node is reached. Based on the GINI index [22], every node is split into two sub-nodes. CART has a good fitting ability; however, the generalization error is relatively high in CART. Bagging method is another basic building block of RF, which solves the overfitting problem [13]. When used alongside CART, it significantly increases the latter method's generalization ability. Bootstrap sampling is the basis of the bagging method.

The training data are used for the performance analysis of this generalization ability and it is possible because of the existence of out-of-bag (OOB) samples. RF, which contains a lot of CARTs, decides on the final prediction by averaging the outputs from all the CARTs. Moreover, RF further increases its variance by utilizing random node optimization. The bagging method, along with other modifications, enhances the performance of CART and makes RF more robust.

It is highly probable that the trees in RF are correlated as they use the bagging principle and use the same data. To tackle this issue and make the trees uncorrelated, Breiman [21] proposed to grow each split of the tree randomly, both in terms of features and number of samples. This decorrelation increases the accuracy of RF prediction [23]. A complete specification of RF needs a setting of three parameters: **B**, **m** and **n_{min}**. They represent forest size or several trees, the number of randomly chosen predictors for each split, and minimum leaf size or number of nodes, respectively.

The RF algorithm is built using the following three steps:

- Extract **B** sample datasets, which can be overlapped and replaced, from the training data.

- For each of the **B** datasets, grow a tree T_b by following the steps in each node, until n_{min} is reached:

  - Select **m** randomly from the total number of variables, **p**

  - Select the best predictor out of the **m** predictors

  - Split the node into two sub-nodes according to an established criterion

- Summarize the outputs from all the trees by finding the ensemble, $\{T_b\}_1^B$.

Finally, at any given point **x**, the prediction is given by Equation 8 [24]:

$$f_{RF} = \frac{1}{B} \sum_{b=1}^{B} T_b(x) \ldots \ldots (8)$$

The general framework of RF is illustrated in Figure 3 [24].
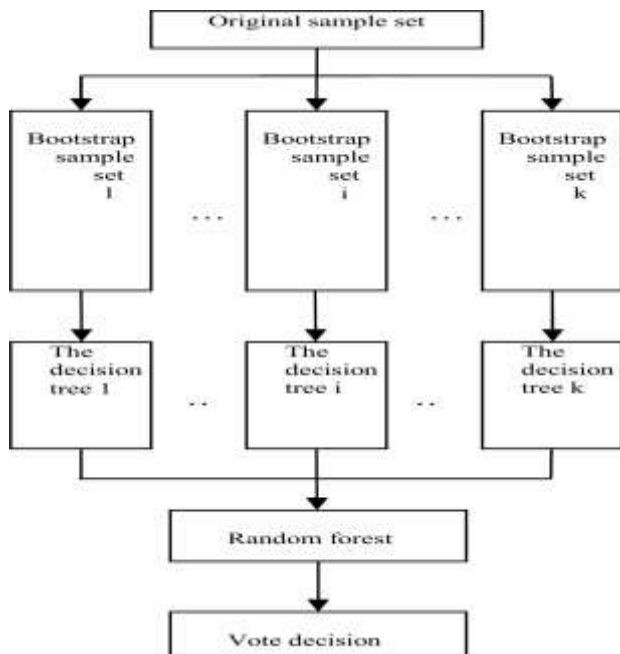
Figure 3: Generalized RF Framework

3. ANALYSIS

The ACF and PACF plots of a time series can demonstrate the stationarity of a time series. If the ACF of a time series decreases quickly or the PACF of a time series has a sharp cutoff after the first lag [23], then the time series is deemed to be stationarity. Otherwise, the time series is non-stationary and differencing operation needs to be performed to ensure stationarity. After the necessary ACF and PACF plotting, Augmented Dickey-Fuller (ADF) test is performed for hypothesis testing to confirm stationarity.

ADF [24] is a widely used method for checking the stationarity of a time series [26-28]. ADF is also called the unit root test. Presence and absence of a unit root in the characteristic equation indicate non-stationarity and stationarity, respectively. The model for the ADF test is as follows:

$$\partial Y_r = \mu + \beta t + \rho Y_{t-1} + \partial_1 Y_{t-1} + \cdots + \partial_p Y_{t-p} + e_t \dots..(10)$$

Here, μ, ρ and β represent a constant value, autoregressive order and trend, respectively. Moreover, e_t represents a sequence of zero mean and unit variance independent normal random variables. So, the hypotheses for ADF are presented in the following way [23]:

$$Null\ Hypothesis:\ H_0:|\rho| = 0\ (Non\ Stationary)$$

$$Alternative\ Hypothesis:\ H_1:|\rho| \neq 0\ (Stationary)$$

The p-value that we obtain after running the ADF test decides whether to reject or accept the null hypothesis. For a 95% confidence level, if $p \geq 0.05$, null hypothesis is true. For $p<0.05$, the value is significant enough to reject the null hypothesis and the time series is stationary.

3.1 Short Term Load Forecasting

The load profile used for short-term load forecasting is plotted in Figure 4. This is the industrial load profile for the month of January 2017. The total daily load of this timeline, along with the rolling mean and standard deviation is displayed in Figure 5. Finally, this short-term daily load is decomposed into the trend, seasonal and residual components, as demonstrated in Figure 6.
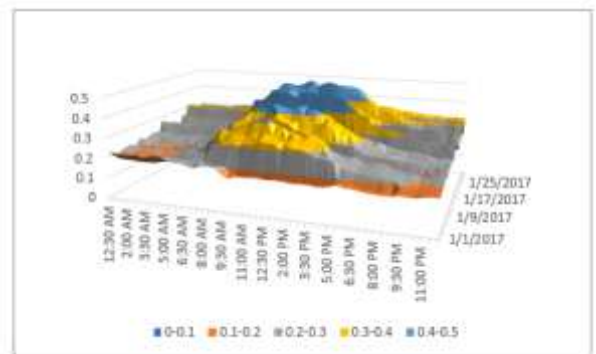

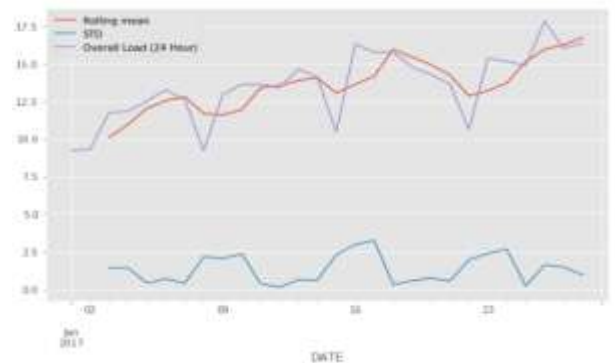Figure 4: Short-Term Load Profile

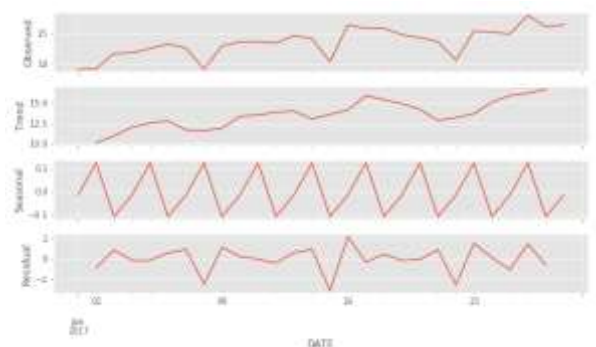Figure 5: Short-Term Load Profile with Rolling Mean and Standard Deviation

Figure 6: Decomposition of Short-Term Load Profile

As evident from Figure 6, the short-term load profile contains an increasing trend on average, as well as seasonality. So, the time series data of short-term load is not stationary and would need to be modeled using seasonal ARIMA. A first-order differencing operation is performed on the time series data. The ADF test is conducted on the differenced time series data and the obtained p-value is $1.98*10^{-14}$. As the p-value is

well below 0.05, it can be concluded that the differenced time series is stationary and can be modeled using ARIMA. The ACF and PACF plots of the stationary time series are demonstrated in Figures 7 and 8, respectively. The ACF and PACF confirm the stationarity of the differenced time series. Moreover, the significant terms of the ACF and PACF plots would represent the order of MA and AR terms, respectively.
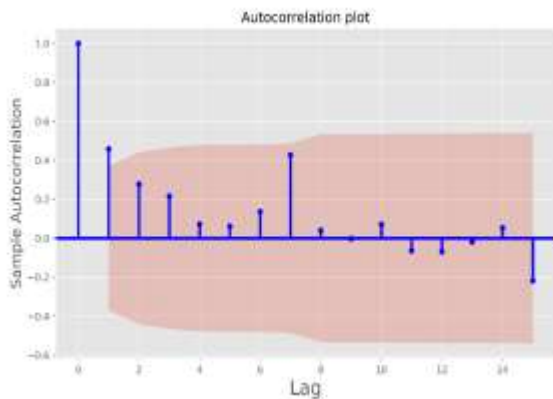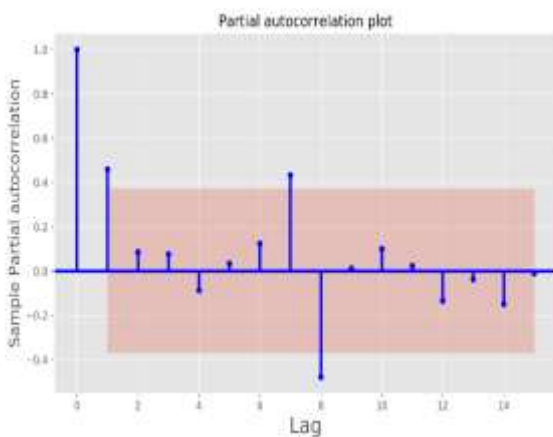

Figure 7: ACF of Short-Term Load

Figure 8: PACF of Short-Term Load

ARIMA $(0,1,0)$ $(1,1,1)_7$ model has been used to forecast the short-term loads. So, the system model equation becomes:

$$(1 - \varphi_1 B^7)(1 - B)(1 - B^7)y_t = (1 + \theta_1 B^7)e_t \dots\dots (11)$$

The residual, along with their histogram, q-q plot and correlogram have been plotted in Figure 9. The residual mostly follows a normal distribution, which proves the validity of our SARIMA model.
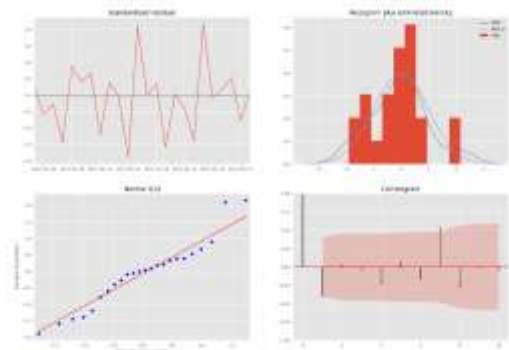
Figure 9: Residual analysis of SARIMA modeling of short-term load

Finding the variables with the most predictive power is one of the major topographies in the prediction process using RF methodology. Variables with high importance are the main drivers of the prediction result. Additionally, low important variables can be removed from the process which makes it simple and fast for fitting and predicting the outcome. Figure 10 shows the importance of the given variable when predicting the outcome. It shows that the hours of the day alongside the weather feature like temperature have a high importance rate in the prediction process.
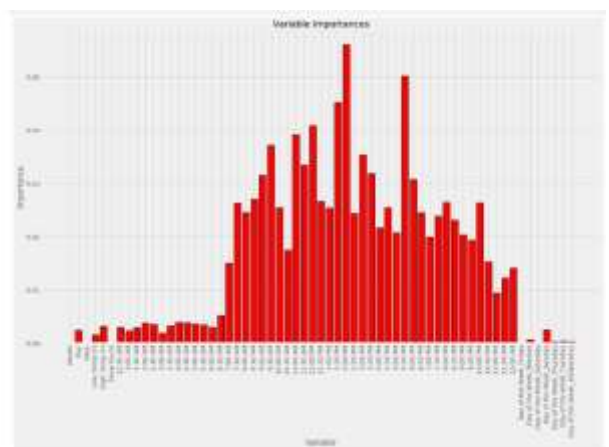

Figure 10: RF variables of short-term load

3.2 Long Term Load Forecasting

The load profile used for long term load forecasting is plotted in Figure 11. This is the industrial load profile for the entire calendar year of 2017. The total daily load of this timeline, along with the rolling mean and standard deviation, has been displayed in Figure 12. Finally, this long-term daily load is decomposed into the trend, seasonal and residual components, as demonstrated in Figure 13.
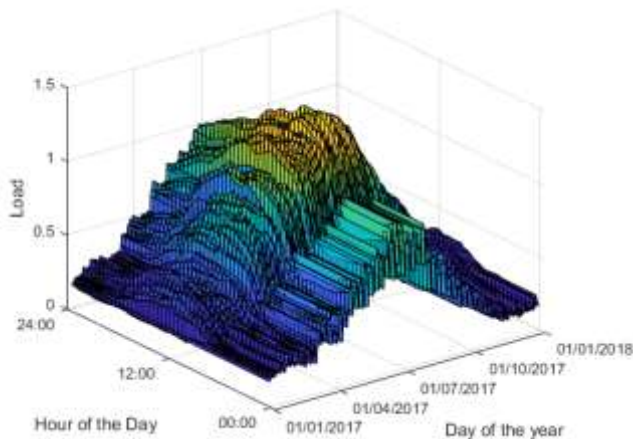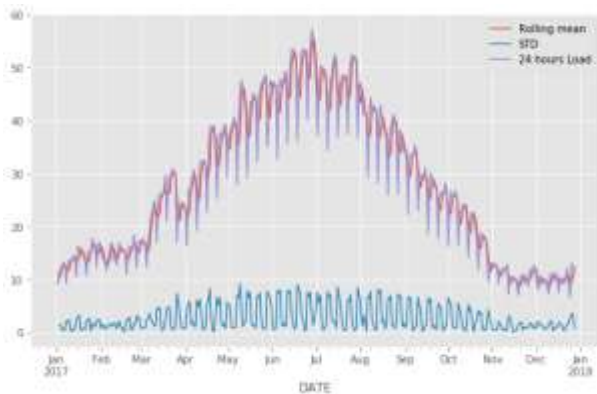
Figure 11: Long-term load profile

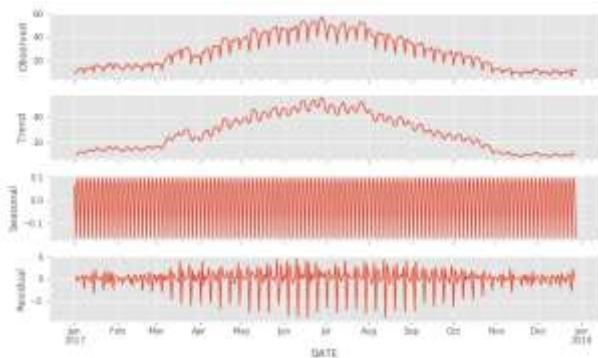Figure 12: Long-term load profile with rolling mean and standard deviation

Figure 13: Decomposition of long-term load profile

As evident in Figure 13, the long-term load profile contains an initial increasing trend and a decreasing trend later, as well as seasonality. So, the time series data of long-term load is not stationary and would need to be modeled using seasonal ARIMA. A first-order differencing operation is performed on the time series data. The ADF test is conducted on the differenced time series data and the obtained p-value is 0.005. So, one can reject the null hypothesis and consider the differenced time series as stationary. The ACF and PACF plots of the stationary time series are demonstrated in Figures 14 and 15, respectively. The ACF and PACF confirm the

stationarity of the differenced time series. Moreover, the significant terms of the ACF and PACF plots would represent the order of MA and AR terms, respectively.
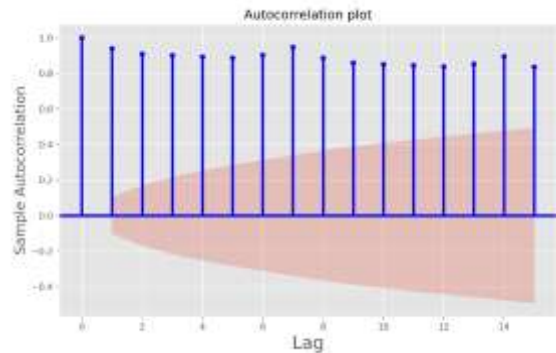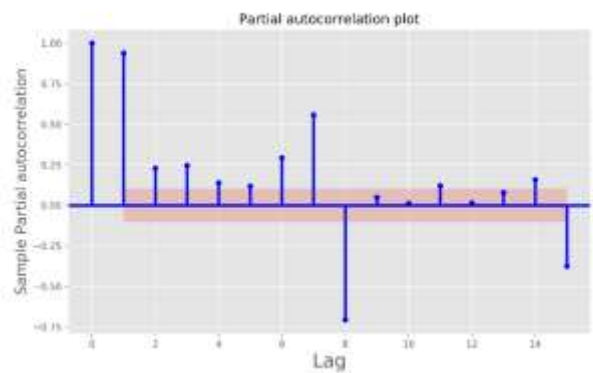

Figure 14: ACF of long-term load
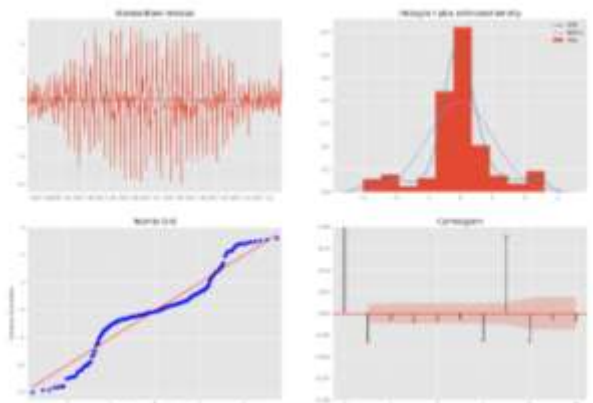

Figure 15: PACF of long-term load

Figure 16: Residual analysis for SARIMA modeling of long-term load

ARIMA $(0,1,0)$ $(1,1,1)_{12}$ model has been used to forecast the long term loads. So, the system model equation becomes:

$$(1 - \varphi_1 B^{12})(1 - B)(1 - B^{12})y_t = (1 + \theta_1 B^{12})e_t \ldots \ldots. (12)$$

The residual, along with its histogram, q-q plot and correlogram have been plotted in Figure 17. The residual mostly follows a normal distribution, which proves the validity of our SARIMA model.

Figure 17 also shows the importance of variables for predicting the outcome. The feature importance figure shows that the hours of the day together with the weather feature like temperature have a high importance ratio.
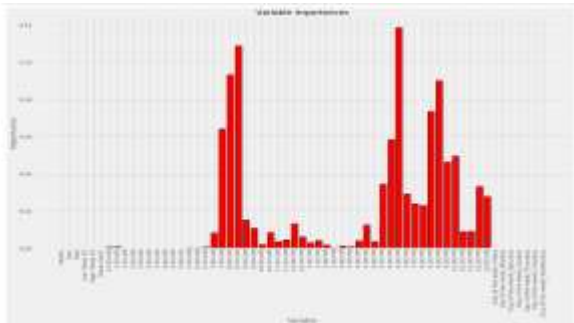

Figure 17: RF variables for long-term load profile

4. RESULTS

4.1 Short Term Forecasting

For the short-term load profile, SARIMA has been used to forecast the total daily load for the second half of January and the predicted values are plotted together with the actual load values in Figure 18.
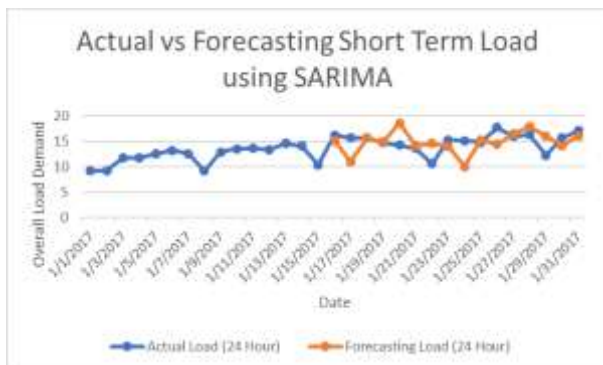

Figure 18: Actual versus forecasted short-term load using SARIMA

RF is used to predict the total load from January 22 to January 31, and the predicted values are demonstrated along with the actual load values in Figure 19.
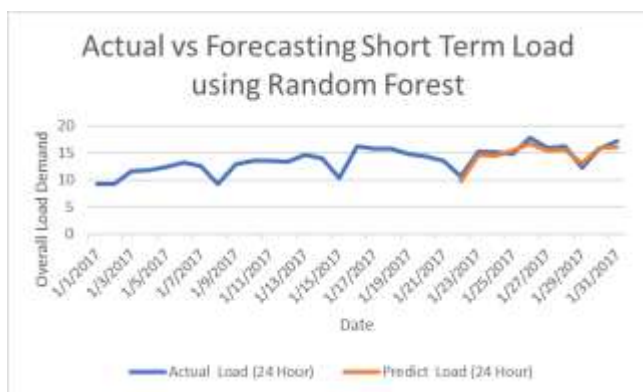

Figure 19: Actual versus forecasted short-term load using RF

Finally, the comparison of the forecasting accuracy between SARIMA and RF is illustrated in Figure 6.20. The accuracy of forecasting using SARIMA and RF is 85.74% and 97.02%, respectively. So, it can be noted that RF based forecasting is a significant improvement over SARIMA based forecasting for short-term loads.
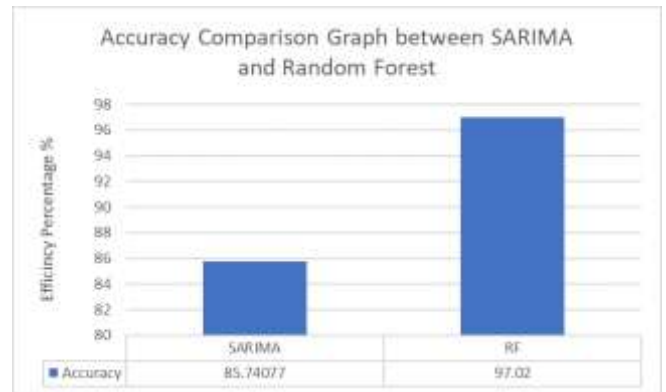

Figure 20: Accuracy comparison for short-term load forecasting

4.2 Long Term Forecasting

For the long-term load profile, SARIMA has been used to forecast the total daily load for the last two months of the year and the predicted values are plotted together with the actual load values in Figure 21.
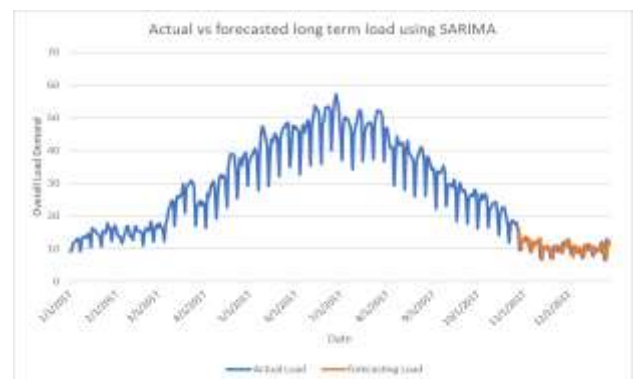

Figure 21: Actual versus forecasted long-term load using SARIMA

RF is used to predict the total load for the last three months of the year and the predicted values are demonstrated along with the actual load values in Figure 22.
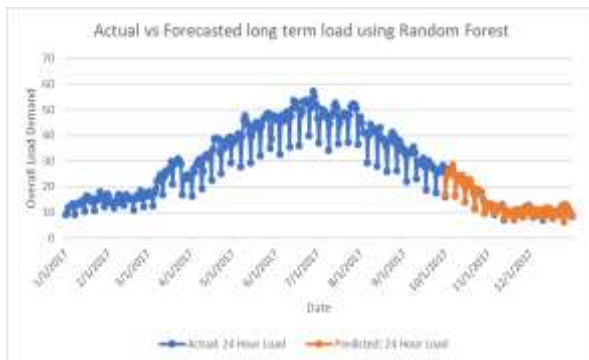
Figure 22: Actual versus forecasted long-term load using RF

Finally, the comparison of the forecasting accuracy between SARIMA and RF for long-term loads is illustrated in Figure 23. The accuracy of forecasting using SARIMA and RF is 83.65% and 97.25%, respectively, which is a clear indicator of the superiority of RF over SARIMA for long-term load forecasting.
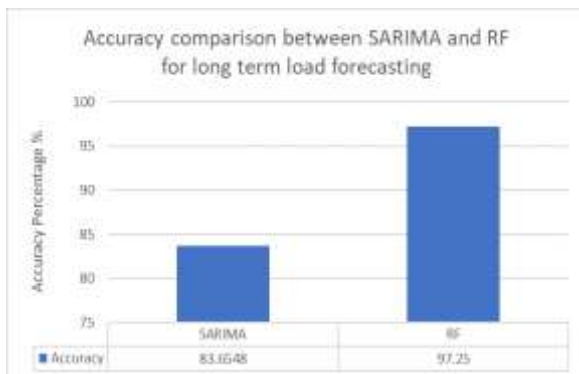

Figure 23: Accuracy comparison for long-term load forecasting

5. CONCLUSION

In this work, a comparative performance analysis has been conducted between the widely used classical time series modeling tool ARIMA and recently introduced but highly effective machine learning algorithm RF. These two methods have been applied for forecasting of short-term and long-term industrial loads. As the loads have seasonality in their profile, the seasonal variation of ARIMA (SARIMA) has been used for forecasting purpose. Both the ARIMA and RF have been introduced and their modeling techniques are discussed briefly in this work. Classical statistical analysis tools like ACF, PACF, and ADF test are used to aid in the SARIMA modeling process. For both the short-term and long-term load profiles, RF demonstrates superior performance over SARIMA in terms of accuracy. However, the tradeoff among accuracy, complexity, and speed of execution is an issue that should be further studied. Forecasting using machine learning methods is a promising arena of research and more ML algorithms need to be tested for forecasting performance. Moreover, deep learning would be explored in future research to check their feasibility to enhance forecasting accuracy.

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