DAILY LOAD FORECASTING WITH HOURLY TEMPERATURES

by

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ABSTRACT

SHREYASHI SHUKLA. Daily load forecasting with hourly temperatures. (Under the direction of DR. TAO HONG)

Load forecasting at the daily resolution is generally performed by aggregating the predicted hourly load. Long-term daily load forecasting is essential for resource planning in the power system and price evaluation of energy contracts. Short-term daily load forecasting is required for balancing operation of the grid and trading strategies of the day-ahead energy market. Another relevance of daily load forecasting is the disaggregation of the monthly consumption data into daily load curves to determine the supplier obligation. Most of the published study on daily load forecasting is focused on daily peak load forecasting. While the other two modules of daily load, that are, the daily energy and daily minimum load have not been covered extensively. In this research, we have modeled hourly temperatures of a day to forecast daily load directly. The study delves into the hourly temperature data to find the best subsets that influence the daily load using the daily load series. This kind of study on multi-frequency series is unique. The study also finds that the daily load is strongly influenced by human activity pattern and hence, temperatures of specific hours of a day are more significant than the highest or the lowest temperature of the day. The proposed model uses Multiple Linear Regression (MLR) technique to model the methodology on two real case studies. The study also employs two MLR based benchmark models; one is the hourly load forecasting model that frames the recency effect of temperatures using the big data approach. The aggregation of predicted hourly loads gives the daily load forecasts. The other benchmark is a direct daily load forecasting model that is based on Tao's vanilla model using maximum and minimum temperatures of a day. Since daily load forecasting finds its application in long-term as well as short-term, the proposed model is evaluated for a year ahead, as well as, one day ahead forecasting. The research empirically demonstrates that the proposed model, using the groups of hourly temperatures and daily load series, performs reasonably well in comparison to benchmarks models in ex-post forecasting while in ex-ante forecasting the proposed methodology emerges out to be the most robust model.

DEDICATION

To my daughter, Aanya

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As said, nothing arises in a vacuum, and hence nothing that is achieved, is without the influence of various cohesive forces in this world. My advisor, Dr. Tao Hong is one such energy that drives my self-motivation. When I first approached Dr. Hong, I was unaware of the forecasting domain, and since then I have been introduced to various dimensions of the forecasting field. He inducted me into the BigDEAL, which is a great honor for me. I would like to thank him for guiding me all along and for believing in me. I would also like to thank Dr. Simon Hsiang, who introduced me to the practical approach of statistical techniques, during a course taught by him. His course helped me visualize the concepts of statistics beyond the theories and numbers. I would also like to convey my heartfelt thanks to Dr. Churlzu Lim for extending his support and guidance. I am also grateful to all my BigDEAL lab mates for their cooperation and valuable feedbacks.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
Day	Weekday of the week
GEFCom2012	Global Energy Forecasting Competition 2012
Hour	Hour of the day
ISONE	Independent System Operator, New England
kW	Kilowatts
LTLF	Long term Load Forecasting
Month	Month of the year
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
MLR	Multiple Linear Regression
MTLF	Medium term Load Forecasting
MW	Megawatts
RMSE	Root Mean Square Error
PCA	Principal Component Analysis
STLF	Short term Load Forecasting
SVR	Support Vector regression
T	Current hour temperature
TA	Temporal aggregated
T_{avg}	Average temperature of the day
T_{day}	Average of temperatures of daytime hours
T_{gmax}	Average temperature of hours with maximum temperatures of the day
T_{gmax}	Average temperature of hours with minimum temperatures of the day
T_{gAM}	Average of temperatures of morning
T_{gPM}	Average of temperature of evening

T_{lg}	Average temperature of previous day
T_{lgday}	Average temperature of daytime of previous day
T_{MdNt}	Average temperature of midnight
VSTLF	Very Short- term Load Forecasting

1. INTRODUCTION

This research proposes a robust daily load forecasting model based on Multiple Linear Regression (MLR) using hourly temperature series and daily load series. The performance of the proposed model is empirically investigated using real and simulated data. This chapter introduces the basic concepts of the forecasting approach employed here, the underlying idea that drives the proposition and the structure of the composition.

It is important to understand what is meant by the term load. Electricity is measured in terms of watts, typically in kilowatts (kW) or megawatts (MW). From the viewpoint of energy consumption, load can be termed as the amount of energy used up over time. If the load is measured as the demand per hour, it would be called Power (kW or MW), while for lower resolutions such as daily, monthly, etc., demand per hour would be added to give the load, which is then called energy, measured in kilowatt-hour(kWh) or megawatt-hour (MWh). In other words, for hourly data, power and energy would be same. Another important term is the forecasting horizon. The forecasting horizon can be explained as the time in the future for which the load is to be forecasted. This can be a day or a week or several months or several years. Based on the forecasting horizon, the load forecasting can be grouped into very short term (VSTLF), short-term (STLF), medium term (MTLF) or the long-term load forecasting (LTLF). The cut-off horizons for these four categories are one day, two weeks, and three years respectively [1]. In this research, we have deployed two routes. One is the day ahead rolling forecasting, where we predict one step ahead load, that is, the next day load and this process is iterated for a year. So, the first day of the year is forecasted using the previous year's data only, while the day two is forecasted with previous year's data and the day one's actual load and so on. This route would fall in the category of STLF. The second route is a year ahead forecasting where we predict one year of unknown electric load in a single iteration. By predicting one year ahead of electric load, this course categorizes the forecasting horizon as MTLF. The other notion to be understood here is the frequency of the forecast which can be hourly, daily, weekly, etc. This basically represents the period between each forecast. In this research, the frequency of forecast is daily, that is the forecasted load is a predicted load for each day. In nutshell, this research is trying to predict load for a period of one year at daily frequency with two routes, one is a day ahead and another year ahead. The load forecasting at different levels of temporal scale, such as hourly, daily, monthly, is called hierarchical load forecasting. The conventional approaches to hierarchical load forecasting usually involve either a top-down method or a bottom-up method or a combination of both methods often referred to as the middle-out approach [44]. The top-down method involves forecasting the aggregated series such as monthly or daily load series, then disaggregating the forecasts based on the historical or forecast proportions. The bottom-up method involves forecasting each of the disaggregated series at the lowest level of the hierarchy and then using aggregation to obtain forecasts at higher levels of the hierarchy. This is how daily load forecasting is generally done in practice, by temporal aggregation of the forecasted hourly load. The middle-out method starts at an intermediate level of the hierarchy and then aggregation is used to obtain forecasts at higher levels and disaggregation is used to obtain forecasts at lower levels.

The supply and demand of electricity load is quite distinctive. It is well known that the electricity cannot easily be stored in large quantities and must be produced the instant it is needed. The ongoing integration of the intermittent energy resources such as solar and wind to the grid brings its own challenges to the supply side. On the other hand, the demand is quite sensitive to various exogenous factors such as human lifestyles, weather variables, calendar variables, growth or recession of the economy, etc. This makes the role of an accurate load forecast very crucial for an effective operation of the power system.. The daily load forecasting with its three featuring modules of daily energy, daily peak, and daily minimum, is essential for scheduling and maintenance operations. Accurate daily load forecasting holds up an important purpose in appropriate scheduling of generators by employing the medium-term load forecasts. Specifically, daily peak load forecasting is one of the basic operations of day-ahead generation scheduling. It ensures sufficient power resources to meet the demand, also preventing overloading and grid failure. Most of the vertically integrated utilities prepare Integrated Resource Plan for next 10-15 years for meeting forecasted peak demand and energy demand. The daily minimum load forecasting gives the base load on a grid that is the minimum level of demand on an electrical grid. In day- ahead or spot market, energy pricing are very volatile. Many times generators and retailers get into long term base load contract and peak load contract. Time period of these contracts vary from a week to a quarter. The daily peak load and minimum load plays an important role here for price evaluation of these contracts. The three modules together are very useful in constructing the daily load curve. With the new emerging changes in the grid, such as distributed energy resources (DER), demand response programs, etc., it is expected that a daily curve would experience many short steep ramps which make the task of ensuring grid reliability more daunting. Hence, it becomes very important to estimate the daily load curve in short-term as well as long-term. Many a time, utilities are facing with the challenge of handling missing or inaccurate data of hourly load history. In such cases, where we do not have the precise 24-hour load history, the accuracy of hourly prediction is compromised, leading to the wrong forecast of daily energy, daily peak load as well as daily minimum load. The daily load forecasting is also important for disaggregation of daily load series into hourly load series or sometimes, monthly load series into hourly load series. The daily load forecasts are useful in generating coherent forecasts by aggregating or disaggregating the load series. In this research, we propose a direct daily load forecasting methodology that could address the business problems mentioned above, by forecasting the three modules of daily load using hourly temperatures and daily load series.

The hourly temperatures, with 24 data point a day, are quite an information for modeling the daily load as many of these data points may be redundant. As understood, with more variables comes more trouble. Hence, to solve this issue, we would be investigating a simple dimension reduction technique by creating subsets of hourly temperatures. The study of the daily energy module finds the most likely hours of the day with maximum and minimum temperatures and ranks them. It then groups the top-ranked hourly temperatures to be used in the forecasting model. Hence, in this way, temperature of hours with the maximum likelihood of highest and lowest temperatures are captured in two separate groups and modeled for daily energy forecasting. The daily peak and daily minimum load study find a reduced area that is relevant for the forecasting and uses the hourly temperatures of this area as the predictor variables. The performances of the three modules of the proposed model are then evaluated against the two benchmark models. The first benchmark model fabricates the recency effect of hourly temperatures for forecasting the hourly load through a big data approach [13]. This benchmark model is rated quite high in accuracy as well as computation. The forecasted hourly loads are then temporally aggregated. The daily peak load and daily minimum load are pulled out from the maximum and minimum load points of the 24 hours predicted loads. The other benchmark is based on using the maximum and minimum temperature of the day as the predictor variables in the framework of Tao's Vanilla model. The three models are first subjected to ex-post forecasting, using the real temperature data of forecasting period. Finally, the models are also experimented in the aspect of ex-ante forecasting, assuming we don't know the predictor variables (temperature) with certainty. This is done by simulating noises in the temperature series of the forecasting year to assess the robustness of the three models.

In this research, we have used two case studies based on data from, (i) the load forecasting track of the Global Energy Forecasting Competition 2012, and (ii) the eight load zones and aggregated ninth zone of ISO New England. Both are public data, which makes this work transparent and reproducible.

The rest of this paper is organized as follows. Chapter 2 reviews the literature work on the subject. Chapter 3 gives the background of the techniques and the datasets being used.

Chapter 4 then dives into the modeling of the proposed methodology. Chapter 5 describes the setup of the experiment on the two case studies and tabulating the results. Finally, chapter 6 discusses the forecasting results and concludes the paper.

2. LITERATURE REVIEW

Several researchers have compiled extensive studies on electric load forecasting. These researches have wide range in terms of load forecasting techniques, methodologies, forecasting horizon and even forecasting frequency. In practice, daily load forecasting can be done in two ways, one is by aggregation of hourly forecasts, which is a very common way, and the other is forecasting the daily load directly. Hence, we would be dividing the review in two parts, a) hourly load forecasting, b) daily load forecasting.

2.1 Hourly Load Forecasting

The literature on hourly load forecasting is quite profuse with significant contributions from researchers. The following section reviews some notable papers in this rich pool of literature that are published in the field of load forecasting.

In 1997, Khotanzad et al. [2] described an artificial neural-network (ANN) hourly short-term electric load forecasting system that received wide acceptance by industry. The building block of the forecasting engines was multilayer feedforward ANN also known as a multilayer perceptron (MLP) network trained with the back-propagation algorithm. An adaptive scheme was developed that adjusted the trained weights of the MLP during on-line forecasting based on its most recent performance.

Another very prominent work is by Ramu Ramanathan, Robert Engle, Clive W.J. Granger, Farshid Vahid-Araghi, Casey Brace [3] in 1997. The paper outlines the design and implementation of a short-run forecasting model of hourly system loads and an evaluation of the forecast performance. The model was applied to historical data for the Puget Sound Power and Light Company for winter only. The approach used was a multiple regression model, one for each hour of the day (with weekends modelled separately), with a dynamic error structure as well as adaptive adjustments using exponential smoothing of forecast errors of each hour to correct for forecast errors of previous hours.

In 2008, Hyndman [4] proposed a semi parametric model to forecast the half hourly electricity demand for up to seven days ahead for power systems. The additive models of calendar effect, temperature effect and lagged demand effect are used in regression framework to capture nonlinear and non-parametric relationship. The paper also proposes a modified bootstrap methodology for obtaining Forecasting distributions. The block bootstrapping of forecast residuals is to use to create simulated forecast errors. Block bootstrapping is used since there are correlations between the forecasting residuals from different half-hourly models, and growing variances also result from multi-step ahead forecasts iteratively derived.

In 2009, Fan et al. [5] investigated the load diversity with respect to weather characteristic of a large geographical area in the Midwest U.S. to improve the hourly load forecast. The optimal partition/ combination of region which gives the minimum forecasting error at the aggregated level is found. A support vector regression (SVR) based forecasting model was employed for hourly load forecasting in each area.

In 2010, Hong [6] reviewed different techniques used in load forecasting, various methodologies used for variable selection and modelling of short-term load forecasting. The author acknowledged that multiple linear regression (MLR) is a powerful statistical technique which had been underutilized. The author proposed a benchmark model based on MLR that was compared with different techniques and empirically proved to be relatively accurate and easy to produce. The proposed methodology is being used as a benchmark model in the field of research as well as industry.

With the aim of improving the forecasting practices of the utility industry and bringing together state-of-the-art techniques for energy forecasting, a team led by Hong organized a world level competition on load forecasting Global Energy Forecasting Competition in 2012. The competition asked the contestants to forecast and backcast the electricity hourly demand for 21 zones, attracting the best pool of techniques and methodologies for hourly load forecasting. Hong, Pierre, and Fan [7] summarized the methodologies and the results of winning teams The benchmark was created based on a MLR model as discussed by Hong (2010)[6]. Among the top 5, four winning teams also published their solutions in the International Journal of Forecasting (Ben Taieb & Hyndman, 2014[8]; Charlton & Singleton, 2014[9]; Lloyd, 2014[10]; Nedellec, Cugliari, & Goude, 2014)[11]. Ben Taieb & Hyndman used 24 different models for one day with each hour modeled by gradient boosting with univariate penalized regression splines. James Lloyd used three techniques a) gradient boosting machines b) Gaussian process regression and the c) benchmark solution (MLR). The final prediction was formed as the ensemble (weighted average) of predictions from these models. Charlton N., & Singleton, C. (2014) used MLR technique modelling various other features such as holiday effect, day of season and temperature smoothening. The authors also used local averaging on predicted load for better results. Nedellec et al. used three temporal multi scale models of three components. The long-term component models trend estimated by means of non-parametric smoothing. The medium-term component describing the sensitivity of the electricity demand to the temperature is modelled by using a generalized additive model. Finally, a short-term component models local behavior using a random forest model.

Hong, Wang, White (2015) [12] probed into very basic practice of assigning a fixed number to the selection of weather station to a zone. In general, given a number of weather stations associated with a zone, the practice followed is to select best one or best three or all. This was also observed in the GEFCom2012, where the participants had used this approach of using a fixed number for selecting the best stations. The paper proposed a novel algorithm of seven steps with an idea of unconstrained approach for selection of weather stations. The paper empirically demonstrated on GEFCom2012data track that using this approach improves the forecasting accuracy significantly.

Wang, Liu, Hong, [13] coined the term ‘recency’ in the world of load forecasting. The recency effect is the effect of temperatures of preceding hours on the load. The paper uses GEFCom2012data to analyze the effect of recency on forecasting accuracy. The recency model considers the temperature at the h^{th} hour lag and moving average of temperature for d^{th} day. The value of d and h is evaluated by hit and evaluated by lowest forecast error. The analysis concluded that the forecast was 18% more accurate than the Tao’s Vanilla benchmark mode at all 20 zones (lower hierarchy) as well as the 21st zone (higher hierarchy).

Keeping up the momentum created by GEFCom2012, the organizers recreated the competition platform in 2014 with a theme of Probabilistic Forecasting. In GEFCom2014, four different tracks were introduced - on forecasting the electric load, on electricity price, on wind and on solar power. Under the track of electricity load forecasting the participants were provided with data from 25 weather stations but no identification of their geographical locations. Throwing up the challenge of weather station selection this was similar to the setup of the hierarchical load forecasting track in GEFCom2012. Hong et al. (2016) [14] summarized what went into the organization of GEFCom2014 and gave overview of the problem, the dataset, and the methods followed by the winning teams.

In 2016, Nowotarski et al. [15] demonstrated that combining sister forecasts outperforms the benchmark methods significantly through analysis of two case studies developed from public data Global Energy Forecasting Competition 2014 and ISO New England. This is the most extensive study on combining point load forecasts of sister forecasts that are obtained from the models constructed by different (but overlapping) subsets of variables sister models.

In 2014, Hong and Wang [16] proposed a fuzzy interaction regression approach to STLF. The paper compares three models (two fuzzy regression models and one multiple linear regression model) without interaction effects, the proposed approach shows superior performance over its counterparts. This paper also offers critical comments to a notable but questionable paper in this field. Oleg Valgaev et al. [17] used K-Nearest Neighbors model to forecast the load of low-voltage consumers using smart meter data provided by Irish Commission for Energy Regulation (ICER) for two different types of customers, residential and 418 Small and middle enterprises (SME)) LV end-customers instead of using standardized load profiles (SLPs) predefined for their general consumer group.

Jain et al. [18] investigated sensor-based energy forecasting for multi-family residential buildings using support vector regression SVR. Sensor based energy forecasting feeds the smart meter readings to machine algorithm to infer the complex relationships between energy consumption and variables of influence such as temperature, time of day and occupancy. The authors tried to understand the behavior of on their forecasting accuracy of their model by varying the aggregation granularity of monitoring data across several temporal (i.e., daily, hourly, every 10 min) and spatial (i.e., whole building, by floor, by unit).

Sevlian Rajagopal, 2018[18] identify the effect of aggregation on load forecasting. Aggregation reduces the inherent variability in electricity consumption thus the higher aggregation levels are easier to predict. The authors explain this as ‘law of large numbers’ which smoothens the signal. They propose a scale law with respect to aggregation size that fits experimental data of low load regime.

Lua et al. [19] investigate into the robustness of hourly load forecasting modes based on four different techniques – MLR, SVR, FIR, ANN in scenario of attach on data integrity. To simulate the data integrity attack the training data is distorted by adding the normally distributed or uniformly distributed noise(p%) to randomly selected data, where p is generated by a normal distribution N (or uniform distribution U) with mean μ and standard deviation σ .The paper concluded that the support vector regression model is most robust, followed closely by the multiple linear regression model, while the fuzzy interaction regression model is the least robust of the four.

To forecast the electric load, it is common practice to divide the data into classes and to use a different predictive model for each cluster for predicting hourly temperature. The authors [20] examines different clustering algorithms classify daily profiles and finally uses Principal Component Analysis (PCA) to classify daily profiles examining various features for improving the clustering. The study concluded that the Morning Slope (the difference in load at 10 AM and 6 AM) is the best performing feature.

Xie presented her submission to the probabilistic load forecasting track of the Global Energy Forecasting Competition 2014 (GEFCom2014) in [21]. The paper explains how the point forecast of hourly load is obtained using MLR technique and then residual forecasting is obtained to get using different technique namely unobserved component models (UCM), exponential smoothing models (ESM), three-layer feedforward artificial neural networks (ANN), and autoregressive integrated moving average models (ARIMA). This point forecast is then used to create forecast based on ten temperature-based scenarios for probabilistic load forecasting and then further refined by modeling and simulating the residuals from the forecast combination.

Lui et al. [22] in 2017 proposed to use a set of sister forecasts in quantile regression framework to generate prediction intervals (PI) for probabilistic load forecasting. In the case study, using the data from the GEFCom2014 probabilistic load forecasting track, they showed that the proposed methodology can generate better PIs than the benchmark methods do, according to the pinball loss function and Winkler scores.

2.2 Daily Load Forecasting

The research on forecasting the daily load directly is not widely published. Since a problem encourages creative efforts to solve the problem, most of the work has been focused on peak load forecasting, which has a larger application in power demand and supply system. The area of forecasting daily energy and minimum load has not been explored so far. Nevertheless, the related notable works have been reviewed here.

A very early work on Peak load forecasting is by Gillies and Bernholtz [23] in 1955 that uses the illumination and load relationship as the primary way of forecasting load for Southern Ontario System. The model predicts the load increment and trend separately. A yearly standard demand curve is made from historic demand on a day with standard illumination value and the load increment is obtained from appropriate peak load increment-illumination curve. The trend is obtained as the difference in the standard load on consecutive years. The two elements are summed to get the final forecast.

One very significant work is by Alex D. Papalexopoulos & Timothy C. Hesterberg [24] who have presented very a profound study of using Multiple linear regression for Peak load forecasting, discussing the issues such as heteroskedasticity and addressing it by using weighted least square, proposing robust parameter estimation, the use of "reverse errors-in-variables" techniques to mitigate the effects of potential errors in the explanatory variables: and distinction between time-independent daily peak load forecasts and the maximum of the hourly load forecasts in order to prevent peak forecasts from being negatively biased. As well mentioned in PLF review by Hong [1], this paper provides a solid background of MLR on load forecasting.

In 1994, Takeshi Haida & Shoichi Muto [25] described a transformation technique in conjunction with the effect of season transition using a transformation technique that converts the temperature data into a function to model a regression based peak load forecasting. The model reflects both the latest load characteristic and the annual weather-load shape. Moreover, the coefficients represent two kinds of annual load growth, namely, base load growth and weather sensitive load growth.

Haida et al. (1998) [26] expanded this model by using historic data introducing two trend-processing techniques designed to reduce errors. They studied methods which use data for past years for forecasting peak power loads for the same day and following day. One of these methods employs the load on the morning of the forecast day as a reference load, creating target variables with minimal trend behavior and using historical data. The other method applies the notion of transformation of explanatory variables in a regression model to explicitly calculate trend characteristics.

Amjady in 2001 [27], proposed a ARIMA model with input feature based on multivariate regression approach for STLF, which incorporated the time series modeling (Box–Jenkins) with the knowledge of experienced human operators. The hourly load and daily peak of the Iran's power network is predicted by using initial estimate of future peak load by an experienced operator as one of the input. The modified ARIMA method combines the operator's estimation with the temperature and load data. From the mathematical point of view, this method employs the operator's estimation as initial forecasting. Then it combines, this initial forecasting with temperature and load data in a multi-variable regression process to obtain a better forecasting.

Moazzami et al. [28] proposed a hybrid framework for day-ahead peak load forecasting using seasonal historical data of similar day peak load and weather condition for forecasting the day ahead peak load value. The similar day databases of every season were decomposed to low and high frequency components by using wavelet decomposition. Two different ANNs with genetic optimization training algorithm were used for each low and high frequency data base.

In 2017, Negishi et al. [29] proposed a new methodology for forecasting daily peak to address the issue of collinearity among the explanatory variables by using the nonlinear correction T method which is one of the multivariate analysis techniques under Mahalanobis–Taguchi (MT) system. Signal to noise ratio (S/N ratio) is evaluated for each explanatory variable. Day-Ahead

Peak Demand Forecast was made using the data from Kansai Electric Power Co. demonstrating significant improvement in forecasting error.

Chen et al. [30] proposed their modeling scheme based on SVR for the competition EUNITE 2001 which was the winning entry. The problem presented was predicting the daily peak load for next 31 days. The authors advocated that temperature not be considered approached the problem with SVR technique which can be used for time series prediction. The parameters for the SVR are determined through cross validation.

In 2008, Cancelo et al. [31] outlined the load forecasting technique used by a Spanish Operater for forecasting daily load of next ten days and hourly load of next day. Multivariate Arima model is designed with trend seasonality special day, weekday as the subcomponents. The daily model focuses on the relationship between consumption and maximum temperature which is modelled using Cooling Degree Days and Heating Degree Days with reference to a comfort zone. A fourth-order polynomial was fitted to give a tentative indication of its shape.

In 2014, Chang [32] employed Electric daily peak load movement as a time series and introduced the elliptic-orbit model for analyzing daily peak load movement. One-week load series is represented in an elliptical-orbit model. Least square optimization is done to get the optimum orbital parameters. The model is compared with ARIMA time series model and found that the elliptic-orbit model yields satisfying results in the evaluation and forecasting tasks for the electric daily peak load movements of the Great Britain National Grid.

Carcedo and García [33], 2017 proposed to model trend component capturing the effect of exogenous factors such as demographic change, variations in economic activity, substitution effects between energy sources, adoption of more efficient technologies, etc. on long term daily peak load forecasting. The proposed methodology is based on multiple linear regression models with prediction in two parts. The first part of the model estimates the trend component giving the demand at annual frequencies which is then broken down into daily frequencies consistent with annual demand by using the Boot-Feibes and Lisman (BFL) disaggregation method. The second part of the model includes calendar effect, temperature effect and the daylight effect. In [34], authors proposed to modify the temperature variable used in the forecasting model as a function of present and historical temperatures. To enhance the predicting power of the modified temperature, genetic-algorithm (GA) is adopted to get the optimal parameters of the modification function for summer daily peak load forecasting.

In nutshell, it can be inferred that most of the work on daily peak load is modelled as time series or based on the relationship of temperature with the peak load. It may be noted that most of the research works that have modelled temperature-peak load relationship have used maximum or minimum temperatures of the day as the main predictor variable.

With this review, we found that while the research work is rich in the field of load forecasting at hourly resolution and daily peak load, the daily energy and minimum load forecasting have not been covered in a comprehensive way. It is imperative to mention here that the review of the work presented here are some noteworthy research work published in the domain of hourly and daily load forecasting.

3. BACKGROUND

The research uses Multiple Linear Regression (MLR) as the modelling technique. The proposed approach uses hourly temperature and calendar variables for prediction of daily energy, daily peak load and daily minimum load based on linear regression analysis. In this chapter, the background of the following subjects are presented; (1) Multiple Linear Regression (2) Evaluation measures (3) Random Number generation using Normal or Uniform distribution (4) Dataset for case studies.

3.1 Multiple Linear Regression

Regression is a statistical technique that models the relationship between predictor variables and the response variable. The response variable is also called dependent variable and the predictor variables are called independent variables. A model with a single regressor x1 that has a relationship with a response y, that is a straight line, is called simple linear regression. This simple linear regression model is

$$y = \beta_0 + \beta_1 \ x_1 + \varepsilon \qquad (1),$$

where the intercept β0 and the slope β1 are unknown constants and ε is a random error component. The errors are assumed to have mean zero and unknown variance σ^2. A regression model that involves more than one regressor variable is called a multiple regression model. The multiple linear regression model with multiple regressors x_1, x_2, x_3,.. x_k is

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j \ x_j + \varepsilon \qquad (2)$$

The linear regression (Eq.1) is a general model for fitting any relationship that is linear in the unknown parameters β. This includes the important class of polynomial regression models. In the polynomial regression models, the predictor variables can be transformed to reach the standard form of the General Linear Model.

3.2 Evaluation Measures

The evaluation measure is crucial to determine the performance of a forecasting model. Often parameter estimation and the selection of model are based on the empirical evaluation measure. A simple way to measure the performance would be calculating the difference between the actual (y_t) and forecasted values ($\hat{y}_t$). Using the difference in absolute form or squared form, we can have two scale dependent measures Mean Absolute Error, MAE and Root mean Squared Error (RMSE).

$$\text{MAE} = 1/\text{n}\backslash \sum_{t=1}^{n} |y_t - \hat{y}_t| \quad (3)$$

$$\text{RMSE} = \sqrt{1/n \sum_{t=1}^{n} |(y_t - \hat{y}_t)|^2} \quad (4)$$

These scales dependent measures are good to compare two series with equal units. The MAE (also known as median regression) is quite interpretable and easy while RMSE is difficult to understand. Another popular accuracy measure is the Mean Absolute Percentage Error (MAPE) which can be calculated as

$$\text{MAPE} = \sum_{t=1}^{n} |y_t - \hat{y}_t|/y_t \times 100 \quad (5)$$

The MAPE is often used in practice because of its very intuitive interpretation in terms of relative error. In real world applications, the MAPE is frequently used when the quantity to predict is known to remain way above zero. Hence, MAPE is commonly used in the domain of load forecasting. We would also be using MAPE as the main criterion for assessing forecast accuracy.

3.3 Random Number generation for noise simulation

Random number generation is the generation of a sequence of numbers based on probability density function. The normal distribution is a very common continuous probability distribution. It is a symmetric distribution where most of the observations cluster around the central peak and the probabilities for values further away from the mean taper off equally in both directions. The general formula for the probability density function of the normal distribution, denoted ***N* (μ, *σ*^{2})**, is

$$f(x) = \frac{e^{-\frac{(x-\mu)^2}{2\sigma^2}}}{\sigma(2\pi)^{1/2}} \qquad (6),$$

where μ is the location parameter of the distribution or the central tendency of the distribution. It basically defines the location of the peak for normal distributions. And σ is the standard deviation, the measure of variability. It defines the width of the normal distribution.

Another common and simple distribution is the Uniform distribution. A uniform distribution, denoted ***U* (*a*, *b*)**, is a distribution that has constant probability of 1/(b-a), where b=the maximum and a= the minimum value. Hence its probability density function is:

$$f(x)=1/(b-a) \qquad (7),$$

where [a, b] is the interval of the continuous uniform distribution.

3.4 Datasets for study and experiment

A. GEFCom2012 data track

The GEFCom2012 data track consists of the hourly temperature and load data of 4.5 years from 20 different zones and the 21st zone summed these 20 zones from a US utility. These zones had different land use and hence had different load profiles. Z4 experienced a major outage, and Z9 is an industrial customer causing aberrant load curves. Hence, these two zones have been excluded from the study. We would be using data of the period 2004 to 2005 as training data, the data of period the period 2006 as validation, that would be used for variable selection and modelling. The data of year 2007 would be used as the test data, on which we compare all are experiment results. The weather station selection from 11 stations given for each zone is done following the unconstrained approach presented by Hong, Wang and White in [12].

B. ISONE dataset

This case study is the historic load and weather data of eight load zones served by ISO New England (ISONE). ISONE is the independent, not-for-profit company authorized by the Federal Energy Regulatory Commission (FERC) to perform grid operation. The ninth zone is the aggregation of the eight zones. The data used are from the period 2012 to 2014 as training data, 2015 as validation data and 2016 as testing data.

4. PROPOSED MODELS OF DAILY LOAD FORECASTING

In this chapter we use descriptive analysis to delve into the data of the two case studies and come up with a robust model for daily load forecasting. The two datasets are analyzed separately to identify the relationship between the hourly temperatures and the daily load. Further, the study aims to find the best groups of hourly temperatures that predicts the daily load. We could also have used the highest temperature of the day and lowest temperature of the day, i.e., the two extreme points to determine characteristics of a daily curve. But we have tried to study how grouped hourly temperature influence daily load curve as compared to the two extreme points. Another approach could have been to use all 24 hours temperatures as the parameters to forecast the daily load. This would be a vast dimension of data to handle with high computation time and, not all components of this dimension would be relevant. Hence, it is required to get a subset of data points that conveys the relevant information concisely with an aim to find an optimum dimension of the data that would have an advantage in two ways (1) reduce the number of parameters, thus reducing the time and computation and (2) eliminate any extreme short-lived effect that sways away the daily temperature curve. With this scheme in mind, the following sections now studies the two datasets to model the three modules of the daily load forecasting separately.

4.1 Daily Energy Model

The daily energy model requires to explore the relationship of the hourly temperatures on the daily load. We would try to find the group of temperature hours that concisely conveys the relevant information. As it is observed, there are two seasonal blocks of temperature series: yearly, daily. The daily average temperature has a yearly seasonal pattern, while hourly temperature has daily pattern, as depicted in the figure 1. To understand the daily temperature curve across the year we need to de-season the daily temperature series. This is done by normalizing the hourly temperatures of day by scaling between 0 and 1, with 0 being the minimum temperature of the day and 1 being the maximum temperature of the day. The normalized temperatures are then averaged across the months of the years.

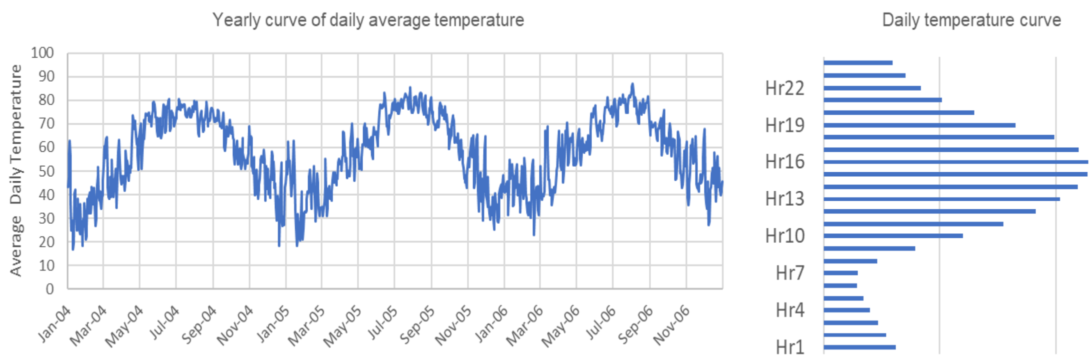

Figure 1: Yearly Temperature Curve & Daily Temperature Curve: GEFCom2012

Since it is not known a priori which of these 24-hour temperature are relevant, we would start with selecting the top *three* for grouping hourly temperatures. Hence, the proposed model would use the groups of top three hours with maximum temperatures as parameter $Tmax_{3\ (grp)}$, and the top three hours with minimum temperatures as the parameter $Tmin_{3\ (grp)}$. To find out the candidate for these groups, the normalized hourly temperature has been represented in figure 2 and 3.

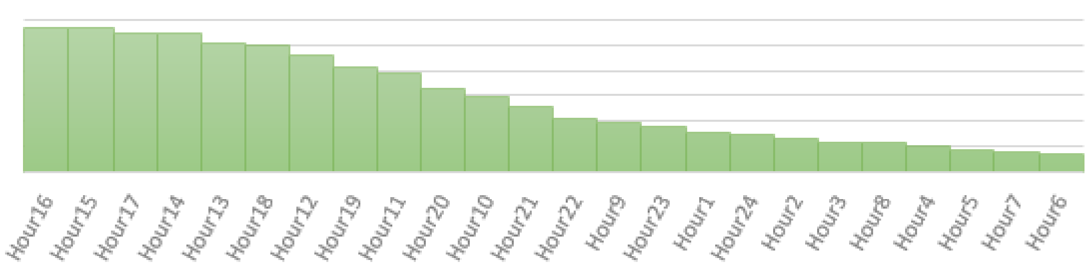

Figure 2: Yearly Temperature Curve & Daily Temperature Curve: ISONE

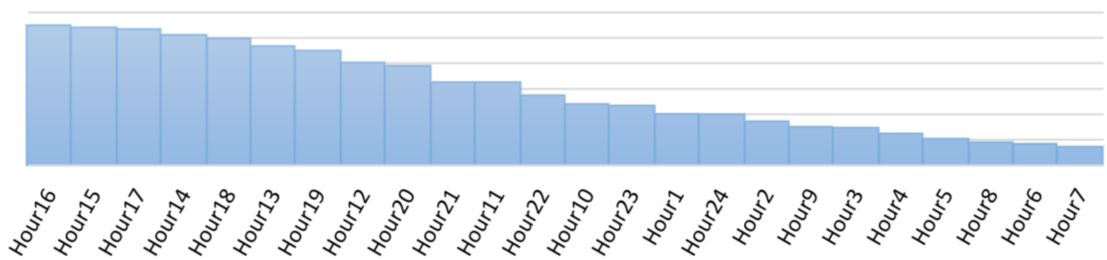

Figure 3: Normalized Hourly Temperature across a day for ISONE dataset

Having found the groups of hourly temperature, we would use the average of the three hourly temperatures of the groups in the linear regression framework to model the daily energy forecast.

Table 1: Groups of Hourly temperature based on top three in each group

	Case Study: GEFCom2012	**Case Study: ISONE**
T_{gmax}	*Average (Hour 15, Hour16, Hour17)*	*Average (Hour 15, Hour16, Hour17)*
T_{gmin}	*Average (Hour5, Hour6, Hour7)*	*Average (Hour6, Hour7, Hour8)*

The benchmark model proposed by Hong [3], widely known as Tao's Vanilla benchmark model is employed here. This model uses the 'Trend' that captures locally increasing (or decreasing) trend, 3rd ordered polynomials of the temperature (T) along with its interaction with the calendar variables (Hour, *Day, Month)* to predict the hourly load. The Vanilla benchmark model, B1 can be written as:

$$Load = \beta_0 + \beta_1\,Trend + \beta_2\,Day + \beta_3\,Hour + \beta_4\,Month + \beta_5\,Hour.Day + \beta_6\,T \cdot Month + \beta_7\,T^2 \cdot Month + \beta_8\,T^3 \cdot Month + \beta_9\,T \cdot Hour + \beta_{10}\,T^2 \cdot Hour + \beta_{11}\,T^3 \cdot Hour \quad (8),$$

where

- *Trend* is a quantitative parameter, any increasing or decreasing linear trend,
- *Day* is a class variable, representing 7 days of a week,
- *Hour* is a class variable, representing 24 hours of a day,
- *Month* is a class variable, representing 12 months of a year,
- *T* is Current hour temperature.

We modify this model for daily load by getting rid of the qualitative parameter hour and using the average temperature of a day (*Tavg)* in place of hourly temperature, T. The model is then added with the 3rd ordered polynomials of Tgmax and Tgmin along with their interaction with month variable. This modified proposed model P1 can be written as:

$$Load = \beta_0 + \beta_1\, Trend + \beta_2\, Day + \beta_3\, Month + \beta_4\, Tavg \cdot Month + \beta_5\, Tavg^2 \cdot Month + \beta_6\, Tavg^3 \cdot Month + \beta_7\, Tgmax \cdot Month + \beta_8\ Tgmax^2 \cdot Month + \beta_9\, Tgmax^3\ \cdot Month + \beta_{10}\, Tgmin\ \cdot Month + \beta_{11}\ Tgmin^2 \cdot Month + \beta_{12}\, Tgmin^3\ \cdot Month, \qquad (9)$$

Further adding the best fit lagged variable of the three temperatures is evaluated by comparing the MAPE of the validation period for both the datasets. The evaluation of the validation period of GEFCom 2012 data track and ISONE dataset reveals that the addition of first lag of temperature (*Tlag*) to P1 yields the best results and same is the result for the ISONE datasets.

Table 2: Performance of Model with different temperature lags in Average MAPE (%) of the respective zones

Models	GEFCom2012	ISONE
P1	4.60	3.36
P1 + lag1(Tavg)	**4.37**	**3.01**
P1 + lag1(Tavg)+lag2(Tavg)	4.49	3.06
P1 + lag1(Tavg)+lag2(Tavg)+lag3(Tavg)	4.61	3.11

So, the final model P2 found for both the datasets is:

$$Load \quad = \beta_0 + \beta_1\, Trend + \beta_2\, Day + \beta_3\, Month + \beta_4\ Tavg \cdot Month + \beta_5\, Tavg^2 \cdot Month + \beta_6\, Tavg^3 \cdot Month + \beta_7\ Tgmax \cdot Month\ + \beta_8\ Tgmax^2 \cdot Month + \beta_9\ Tgmax^3\ \cdot Month + \beta_{10}\ Tgmin\ \cdot Month + \beta_{11}\ Tgmin^2 \cdot Month + \beta_{12}\, Tgmin3\ \cdot Month + \beta_{13}\ Tlag \cdot Month + \beta_{14}\, Tlag^2 \cdot Month + \beta_{15}\, Tlag^3 \cdot Month \qquad (10)$$

Going beyond the the selection of top three, we also tried various grouping combintions (m,n) upto the groups of top five maximum(m=1,2,3,4,5) and top five minimum(n=1,2,3,4,5) hourly temperatures. As shown in the table 3, the forecast accuracy merely changes with different combination of groupings. In both cases in can be noticed that the combination (m=1, n=1) gives comparable results with the combination (m=3, n=3), but this model would be quite vulnerable to any variations to these single data points. Hence, it is prudent to go ahead with the combination (m=3, n=3), as the idea here is find a robust model for daily energy forecasting.

Table 3: Heat map showing the performance of Model P2 with different groups of (m,n) in Average MAPE (%)of the respective zones

GEFCom2012

Maximum Temperature groups (m)	Minimum temperature groups(n) **1**	**2**	**3**	**4**	**5**
1	4.36	4.36	4.36	4.36	4.36
2	4.37	4.37	4.37	4.37	4.37
3	4.39	4.37	**4.37**	4.38	4.37
4	4.38	4.38	4.39	4.39	4.39
5	4.40	4.41	4.41	4.41	4.41

ISONE

Maximum Temperature groups (m)	Minimum temperature groups(n) **1**	**2**	**3**	**4**	**5**
1	3.00	3.02	3.02	3.01	3.00
2	3.02	3.03	3.03	3.03	3.01
3	3.00	3.02	**3.01**	3.02	3.02
4	3.00	3.01	3.01	3.01	3.01
5	3.00	3.01	3.00	3.01	3.01

4.2 Peak Load Model

The modelling of this module would require the analysis of the daily load pattern along with hourly temperature series. This would allow us to comprehend the hours with peak demand of the day. The daily load profiles are analyzed by normalizing the hourly loads, scaling them between 0 and 1. The normalized loads are then averaged across the months of the years.

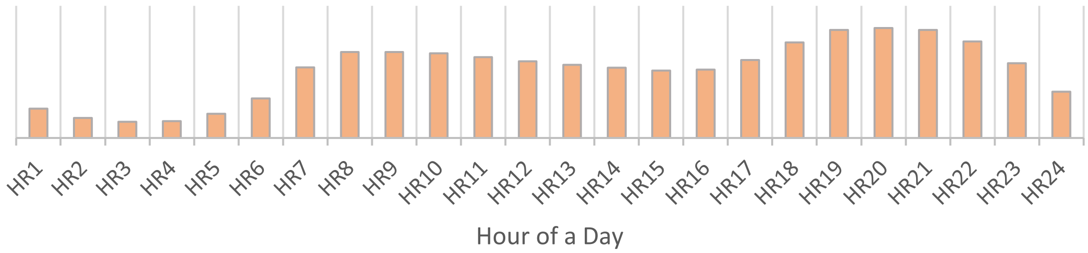

Figure 4: Daily Load Pattern generalized over years 2004-06 for GEFCOM dataset

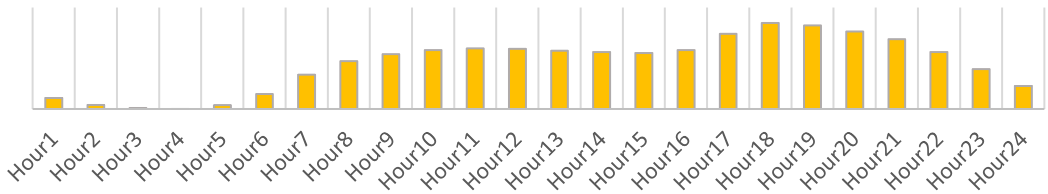

Figure 5: Daily Load Pattern generalized over years 2004-06 for ISONE dataset

For the GEFCom2012 data track, the daily load curve of a day in summer looks like a half cross sectioned cylinder as in figure 5. The extended hours of peak load are well noticed between 1800 hour and 2100 hour. During winters, the load pattern has notably two peaks, one is during the hours of 0800 to 0900 hour, and another during the late evenings between 1900 hour and 2100 hour. The summer peak hours extend for longer periods creating numerous hours of consistently high demand from midday to late evening. While in winter, a two-to-three-hour peak can be observed that typically occurs during evening or morning hours. Largely, it can be concluded from the figure 5 that, except for the month of February and March, the peak load is observed during late evenings. It should also be noted that the daily maximum temperatures lie between 1500 to 1700 hours. Perhaps, it is mainly human energy consumption pattern in combination to the daily maximum temperatures of preceding hours that leads to the peak load in the late evening in most part of the year.

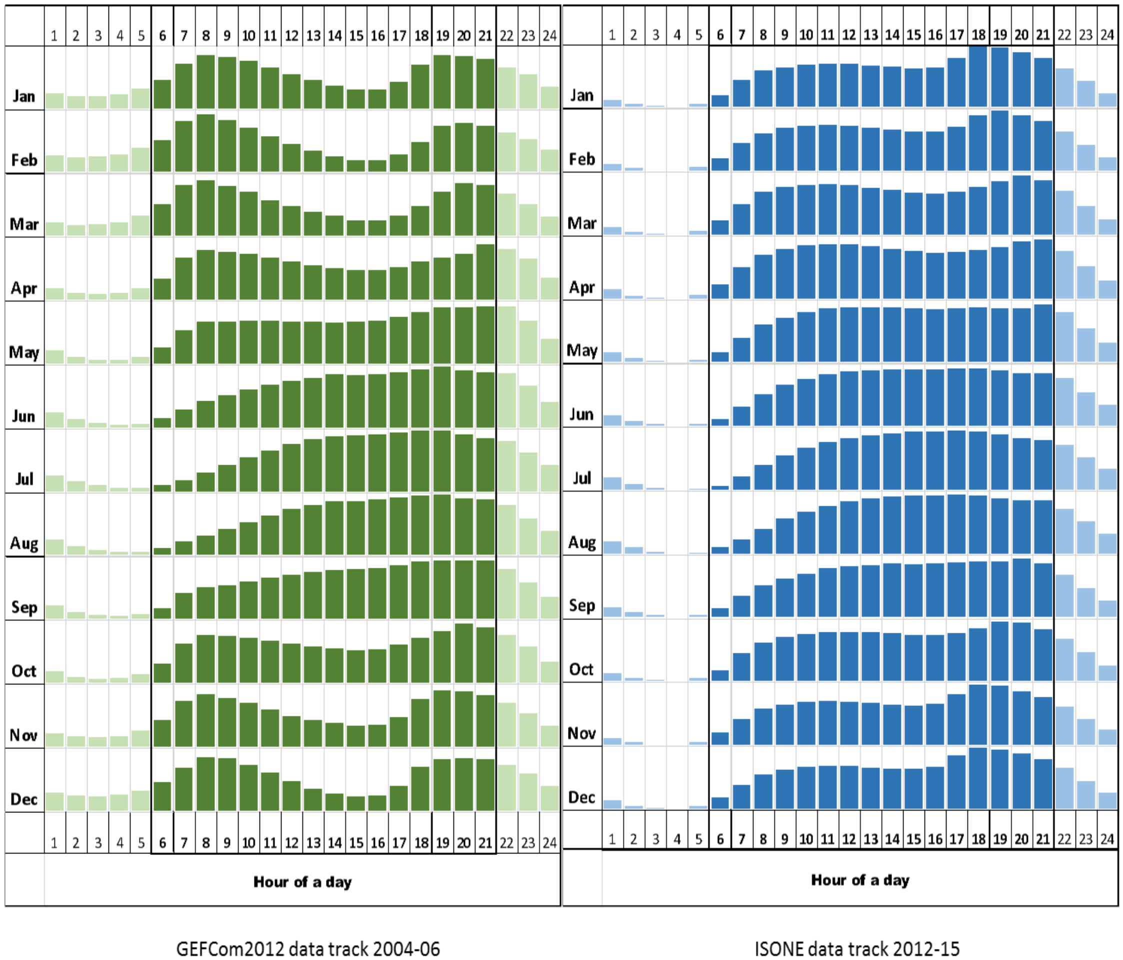

Figure 6: Month wise Normalized daily load pattern GEFCom2012 & ISONE datasets. This figure shows the long extended peak load hours during summers and two humps during the winter season. It also highlights the reduced space of 0600-2100 hours that has m maximum likelihood of observing peak load.

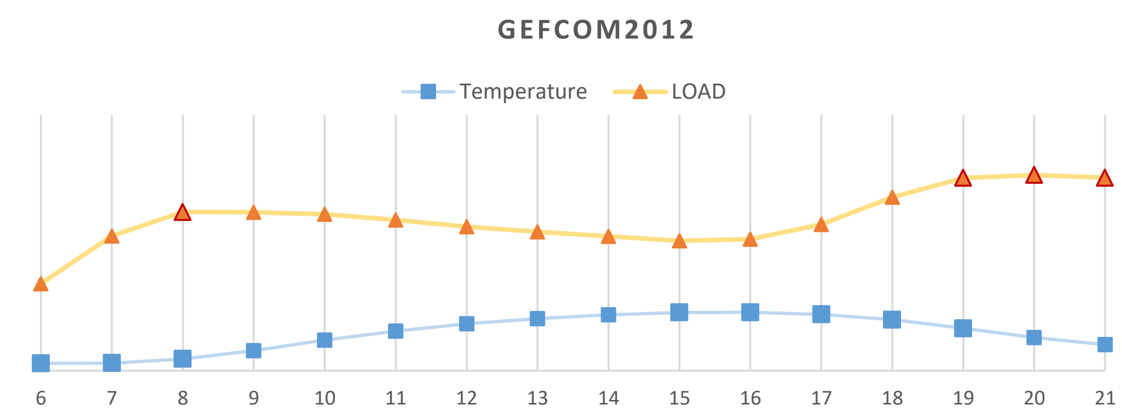

Figure 7: Normalized daily load pattern along with Normalized daily temperature curve marking the peak load hours and maximum and minimum temperature hours for GEFCom2012 dataset.

However, during winters (particularly in month of February and March), the daily peak load is observed during the hours 0800 to 0900 and the daily minimum temperature are observed during 0600 to 0800 hours as in figure 5. Apparently, the typical low temperatures of early mornings contribute to the peak load in the winters. For the ISONE dataset, the daily peak load is largely observed during evening hours and the load curve has a long-extended hour of peak load in summers. In winters, the peak load is usually observed during an early winter evening with few distinct hours of peak. Comparing the two datasets, it is observed that the temperature variation during the day in ISONE zones is quite high as compared to GEFCom2012 dataset. This dramatic behavior of temperature curve may also be the reason for peak load in the evenings. Other factors that differentiates the ISONE load curves could be the higher latitude, overall lower temperature, and urban population percentage of the area covered in the zones.

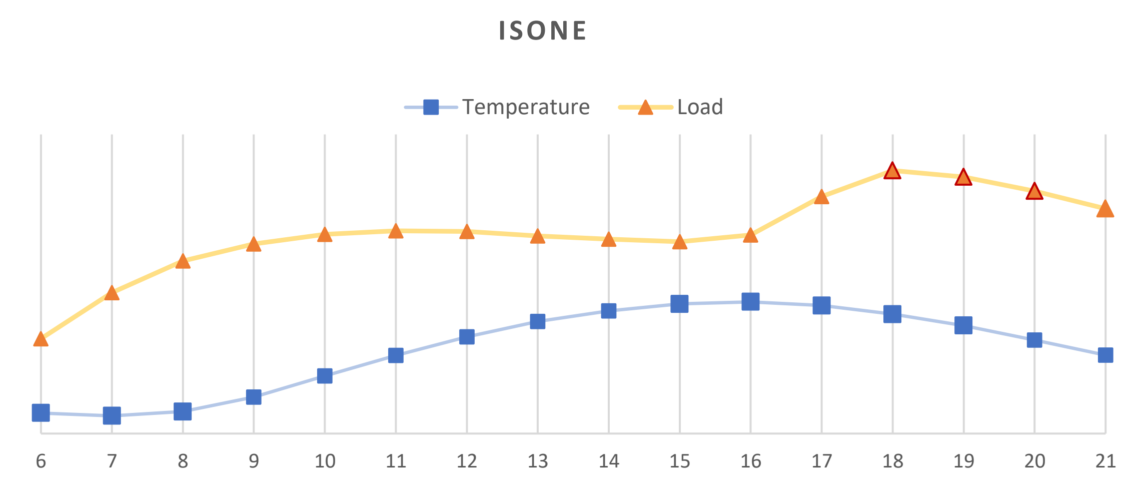

Figure 8: Normalized daily load pattern along with Normalized daily temperature curve marking the peak load hours and maximum and minimum temperature hours for ISONE dataset.

The study of both datasets reveals that the peak load is observed during the daytime hinting us to shrink the area of interest to the period between 0600 hour and 2100 hour. Hence, we would apply the dimension reduction technique to the average temperature of the day, using T_{day}, as the average of hourly temperatures between 0600 and 2100 hours in place of 24-hour average temperature. In addition, we would also capture the characteristic of the temperature curve of this reduced space by grouping the maximum hourly temperatures and minimum hourly temperatures within this reduced space. For this, we group the extended hours of late afternoon to evening to get T_{gPM}, and the early morning hours are grouped to get T_{gAM} as in table 5.

Table 4: Groups of hourly temperatures based peak load analysis

	Case Study: GEFCom2012	**Case Study: ISONE**
T_{day}	Average (Hour6-Hour21)	Average (Hour6-Hour21)
T_{gPM}	Average (Hour 15-Hour19)	Average (Hour 15-Hour19)
T_{gAM}	Average (Hour6-Hour8)	Average (Hour6-Hour8)

From the descriptive analysis above, we can conclude that the peak load is influenced by a combination of human's energy consumption behavior and weather factors of the hour. It is also understood that peak load is generally observed during the daytime.

So, the daily peak model P3 found for both the datasets is:

$$Load = \beta_0 + \beta_1\, Trend + \beta_2\, Day + \beta_3\, Month + \beta_4\, Tday \cdot Month + \beta_5\, Tday^2 \cdot Month + \beta_6\, Tday^3 \cdot Month + \beta_7\, TgPM \cdot Month + \beta_8\, TgPM^2 \cdot Month + \beta_9\, TgPM^3 \cdot Month + \beta_{10}\, TgAM \cdot Month + \beta_{11}\, TgAM^2 \cdot Month + \beta_{12}\, TgAM^3 \cdot Month \tag{11}$$

4.3 Minimum Load Model

This module of daily load aims to find the minimum load of a day. The daily load curve analysis of the daily load curve as done in the previous section (figure 5) reveals that that minimum load of the day is mostly observed between 0200-0400 hour for both the datasets, indifferent of the season or the average temperature of the day. Hence if its summer or winter, the minimum load is observed post-midnight hours before the dawn.

For both datasets, the minimum temperature of the day is observed roughly during 0500 to 0800 hours and the highest temperature is roughly observed during 1500 to 1700 hour. This implies that the daily minimum load has very low dependency on the temperature of the hour, but more on the human activities. During the hour 0200 to 0400 least human activities would be observed as people are most likely to sleep during these hours, resulting in the minimum load.

Hence modelling the daily minimum load is slightly different from modelling the daily energy and daily peak loads. It is vital to capture the temperature of minimum load hours which is why the grouped temperatures of the hours 0200-0400 (T_{MdNt}) would be used in this model. We also would also the use the previous day's average temperature in the model as lag of T_{day}. It is interesting to note here that the average temperature of reduced space (0600 to 2100 hours) gives a better result than using the 24-hours average. This is probably because it captures the human activity better. Besides, the grouped maximum temperatures hour of the day was the other parameter used in the model.

Table 5: Groups of hourly temperatures based minimum load analysis

	Case Study: GEFCom2012	**Case Study: ISONE**
T_{lgday}	Average (Hour6-Hour21)	Average (Hour6-Hour21)
T_{MdNt}	Average (Hour2- Hour4)	Average (Hour2- Hour4)
T_{gPM}	Average (Hour 15-Hour19)	Average (Hour 15-Hour19)

So, the daily minimum model P4 found for both the datasets is:

$$Load = \beta_0 + \beta_1\, Trend + \beta_2\, Day + \beta_3\, Month + \beta_4\, Tlgday \cdot Month + \beta_5\, Tlgday^2 \cdot Month + \beta_6\, Tlgday^3 \cdot Month + \beta_7\, TgPM \cdot Month + \beta_8\, TgPM^2 \cdot Month + \beta_9\, TgPM^3 \cdot Month + \beta_{10}\, TgMdNt \cdot Month + \beta_{11}\, TgMdNt^2 \cdot Month + \beta_{12}\, TgMdNt^3 \cdot Month, \tag{12}$$

5. EXPERIMENT

In this section, we explain the two benchmark models adopted for the prediction of daily energy, one is a direct forecasting of daily load series built by extending the Tao's Vanilla Model and the other is based on forecasting with temporal hierarchies. The second section of this chapter evaluates the proposed models with the benchmark models for ex post daily load forecasting. The third section assesses the ex-ante forecasting performances of the models using simulations. We would design a simulation study by introducing noise in the temperature data of forecasting period. We would then compare the results of the three models.

5.1 Benchmark Models

This section describes the two models that are established as the benchmark models for the daily load forecasting in this research. Both are based on linear regression framework.

5.1.1 Direct Green Model

One of the very instinctive inputs of modelling daily load directly is the average temperature of the day (Tavg), the maximum (Tmax) and minimum temperature of the day (Tmin). Extending the Tao's Vanilla Model to forecast Daily energy forecasting model B2:

$$Load = \beta_0 + \beta_1\, Trend + \beta_2\, Day + \beta_3\, Month + \beta_4\, Tavg \cdot Month + \beta_5\, Tavg^2 \cdot Month + \beta_6\, Tavg^3 \cdot Month + \beta_7\, Tmax \cdot Month + \beta_8\, Tmax^2 \cdot Month + \beta_9\, Tmax^3 \cdot Month + \beta_{10}\, Tmin \cdot Month + \beta_{11}\, Tmin^2 \cdot Month + \beta_{12}\, Tmin^3 \cdot Month, \quad (13)$$

As discussed in the earlier chapter, the Tao's Vanilla benchmark model shapes the load-temperature relationship with the 3rd order polynomial of temperature along with their interaction with calendar variables.

5.1.2 Recency Effect Model Temporal Aggregated (TA)

This model is built on temporal aggregation and hierarchical forecasting. The hourly time series of the temperature and load is modeled with recency approach [13]. The term recency effect" represent the fact that the electricity demand is affected by the temperatures of the preceding hours. The approach uses lagged hourly temperatures (T_{t-h}, h = 1, 2, . . ., 72) and daily moving average temperatures of d days, where the daily moving average temperature of each d^{th} day is

$$\mathrm{T}_{t,d} = \frac{1}{24}\sum_{h=24d-23}^{24d} \mathrm{T}_{t-h} \quad \text{, where d= 1, 2, . . .,7.} \qquad (14)$$

Hence the modelling of this approach requires to find the best d-h pair on validation data. Then, Tao's vanilla benchmark model can be extended to:

$$Load = \beta_0 + \beta_1\ Trend + \beta_2\ Month + \beta_3\ Day + \beta_4\ Hour + \beta_5\ Day \cdot hour + f(Tt_t) + \sum_d f(T_{(t,d)}) + \sum_h f(\mathrm{T}_{t-h}) \qquad (15)$$

For the GEFCom2012 case study, the d-h pair for 21 zones has been adopted from the [13], while for the ISONE case study, the d-h pair has been found on the validation year 2015. For finding this, we used trial-and-error method, varying the number of days from 0 to 5, and the number of lags from 0 to 36. In total, there were 222 (6×37) possible ‘‘average-lag’’ (or d–h) pairs. The d-h pairs with best MAPE on validation year for 9 zones of ISONE dataset are in table 7. The hourly load forecast is then temporally aggregated to get the daily energy, the maximum and the minimum of the forecasted 24 hours load is the daily peak and the minimum load respectively. This approach also uses the hourly loads in the model which is contradictory to the approach of proposed model and direct Green model and, therefore, is expected to give a highly accurate prediction. The purpose of including this model in the study is to assess the accuracy of the proposed model in comparison to a competitively accurate and expensive model. This benchmark model has been referred to as Recency TA model in this research.

Table 6: Recency effects (in d–h pairs) for the ISONE zones

	ZONE	d	h
1	NH	2	11
2	VT	2	8
3	WCMASSS	3	8
4	ME	3	16
5	NEMASS	1	19
6	CT	2	11
7	RI	1	13
8	SEMASS	1	12
9	ISONE	2	14

5.2 Forecasting and Performance evaluation

This section employs the proposed models to forecast the respective test years of the two datasets and compare them with the benchmark models. The first sub-section presents the year ahead daily load forecasting and the second sub-section presents the results of one day ahead daily load models forecasted on rolling basis for a year.

5.2.1 Ex post One year ahead forecasting

The subsection presents the results of year ahead forecasting of the three modules of daily load for all the three models. The results of the test year of the respective datasets are produced.

5.2.1.1 Daily Energy

For the GEFCom2012 dataset, the assessment for the three models is done on the test year 2007.The proposed benchmark performs better than the direct Green model in most of the zones with an average MAPE of 4.96% for regular zones but is unable to outperform the Recency TA model which stands at an average of 4.71%. Some similar results can be observed for the ISONE dataset where the evaluation for three models is done on the test year 2016. The proposed model stands at an average MAPE of 3.08% outdoing the direct Green model while still trailing behind the recency TA model by 8.07%.

Table 7: One year ahead Ex Post Daily Energy Forecasting Results for the prediction year

	Zones	Direct Green	Recency TA	Proposed Model
REGULAR ZONES - GEFCom2012	1	5.18	4.33	4.86
	2	4.71	4.27	4.74
	3	4.71	4.27	4.74
	5	8.60	9.06	8.89
	6	4.63	4.23	4.74
	7	4.71	4.27	4.74
	8	6.00	5.62	5.69
	10	5.50	4.65	4.76
	11	7.20	5.88	6.08
	12	5.01	4.21	4.57
	13	5.23	4.9	5.07
	14	6.31	5.56	6.07
	15	4.89	4.64	5.09
	16	5.44	4.97	5.21
	17	3.47	3.06	3.31
	18	4.24	3.79	3.79
	19	4.80	4.48	4.51
	20	4.26	3.9	3.98
	21	3.81	3.42	3.48
Average		**5.19**	**4.71**	**4.96**

Zones	Direct Green	Recency TA	Proposed Model
NH	2.80	2.21	2.64
VT	3.21	2.99	3.07
WCMASSS	3.73	2.78	2.93
ME	5.35	5.54	5.49
NEMASS	3.53	2.98	3.33
CT	3.1	2.52	2.76
RI	3.18	2.37	2.76
SEMASS	3.25	2.42	2.71
ISONE	2.57	1.87	2.06
Average	**3.41**	**2.85**	**3.08**

So, the recency TA model, which frames the lagging hour temperatures using hourly demand performs the best, yielding the most accurate daily energy forecast. But the proposed model outperforms the direct Green model signifying that grouping hours for capturing the maximum temperature and minimum temperatures of the day performs much better than considering the singular maximum and minimum temperature.

5.2.1.2 Daily Peak Load

The performance of the Daily peak module is presented in Table no. 9 for GEFCom2012 and ISONE datasets respectively. The results are quite analogous to the daily energy model. The proposed model stands at an average MAPE of 5.73% for GEFCom2012 data track, outdoing the direct Green model while still trailing behind the Recency TA model by 3.06%. For the ISONE dataset, the proposed model stands at an average MAPE of 3.32% outdoing the Direct Green model but trailing behind the recency TA model by 5.73%.

Table 8: One year ahead Ex Post Daily Peak Forecasting Results for the prediction year

	Zones	Direct Green	Recency TA	Proposed Model
REGULAR ZONES - GEFCom2012	1	6.31	5.48	5.89
	2	5.50	4.99	5.17
	3	5.50	4.99	5.17
	5	9.37	7.84	9.32
	6	5.37	4.82	5.08
	7	5.50	4.99	5.17
	8	6.29	6.48	5.92
	10	7.81	6.06	7.23
	11	7.59	7.25	7.15
	12	5.74	5.07	5.58
	13	6.11	5.25	5.99
	14	6.02	6.55	6.13
	15	5.37	5.68	5.41
	16	6.00	5.96	6.26
	17	3.92	4.01	4.14
	18	5.27	5.44	5.03
	19	5.46	5.76	5.51
	20	4.84	4.88	4.44
	21	4.41	4.09	4.31
Average		**5.91**	**5.56**	**5.73**

Zones	Direct Green	Recency TA	Propose d Model
NH	3.4	2.9	3.03
VT	2.62	3.13	2.63
WCMAS	3.61	2.95	3.59
ME	4.65	4.62	4.49
NEMASS	4.25	3.81	3.99
CT	3.25	2.79	3.22
RI	3.63	2.76	3.29
SEMASS	3.35	2.88	2.93
ISONE	2.85	2.42	2.69
Average	**3.51**	**3.14**	**3.32**

5.2.1.1 Daily Minimum

The performance of the Daily minimum module is presented in Table no. 10 for GEFCom2012 and ISONE datasets respectively. The results are incongruent to the other two modules of daily load forecasting models. The proposed model stands at an average MAPE of 6.00% for GEFCom2012 data track, outdoing the direct Green as well as recency TA model by 14.8% & 3.4% respectively. Similarly, for ISONE dataset the proposed model outdoes both benchmark models by 24.88% and 13.98% on average respectively.

Table 9: One year ahead Ex Post Daily Minimum Forecasting Results for the prediction year

	Zones	Direct Green	Recency TA	Proposed Model
REGULAR ZONES - GEFCom2012	1	6.89	5.96	6.25
	2	5.78	4.95	5.00
	3	5.78	4.95	5.00
	5	10.13	11.81	9.44
	6	5.81	4.97	5.11
	7	5.78	4.95	5.00
	8	7.83	6.44	6.82
	10	7.01	5.84	5.42
	11	8.07	6.56	5.61
	12	8.09	6.16	5.23
	13	7.19	6.57	6.29
	14	10.89	9.26	8.64
	15	7.91	6.41	6.95
	16	8.2	6.92	6.41
	17	6.35	4.52	4.87
	18	6.96	5.45	5.42
	19	8.34	6.93	6.53
	20	6.14	4.68	5.41
	21	5.35	4.61	4.55
Average		**7.29**	**6.21**	**6.00**

Zones	Direct Green	Recency TA	Proposed Model
NH	3.63	3.29	2.50
VT	3.32	4.38	2.63
WCMASS	4.67	4.74	3.30
ME	7.48	6.91	7.54
NEMASS	4.15	2.45	2.90
CT	4.99	2.88	3.26
RI	3.70	3.41	2.83
SEMASS	3.56	3.82	2.37
ISONE	3.59	2.25	1.99
Average	**4.34**	**3.79**	**3.26**

5.2.2 Ex post one day ahead forecasting

This section explores the performance of the three models for short term load forecasting. The idea here is to forecast the next day energy, peak load and minimum load on rolling basis for a year. This would mean that the previous years' history would be used for forecasting the day one of the test year. For the day two, actual load data of the first day would be used along with the history of previous years and so on. Hence, the final one-year forecast would be compiled adding the day one by one. This methodology is employed on all the three models for all three modules and the performances are appraised.

5.2.2.1 Daily Energy

The proposed model and Direct Green model is implemented for forecasting the total energy of the next day on rolling basis for a year. The recency model is implemented for each day of the year on rolling basis adding to the model the actual hourly loads of the previous day. The hourly forecast is then summed to get the energy of the day.

Table 10: One day ahead Ex Post Daily Energy Forecasting Results for the prediction year

	Zones	Direct Green	Recency TA	Proposed Model
REGULAR ZONES - GEFCom2012	1	4.86	4.10	4.60
	2	4.18	3.81	4.13
	3	4.18	3.81	4.13
	5	6.53	6.29	6.27
	6	4.19	3.80	4.13
	7	4.18	3.81	4.13
	8	4.96	4.72	4.79
	10	4.34	3.80	4.04
	11	4.68	4.21	4.35
	12	4.54	3.83	4.13
	13	4.65	4.16	4.34
	14	5.70	4.97	5.34
	15	4.56	4.23	4.60
	16	5.28	4.66	4.83
	17	3.20	2.83	3.00
	18	4.04	3.51	3.55
	19	4.50	3.97	4.03
	20	3.55	3.24	3.35
	21	3.53	3.00	3.21
Average		**4.51**	**4.04**	**4.26**

Zones	Direct Green	Recency TA	Proposed Model
NH	2.29	1.95	2.14
VT	3.04	2.84	2.93
WCMASSS	3.27	2.33	2.53
ME	3.36	3.24	3.30
NEMASS	2.95	2.49	2.69
CT	2.68	2.08	2.29
RI	2.82	2.10	2.30
SEMASS	2.90	2.24	2.36
ISONE	2.25	1.65	1.83
Average	**2.84**	**2.33**	**2.49**

The results are congruous to the results of the year ahead forecasting as in section 5.2.1.1 although the accuracy of all three models are much better than their respective year ahead forecast. This is obvious as one step ahead forecasting utilizes the information of the actual load of previous step for training the model. The recency TA model fares best among the three outperforming the proposed model by 5.4% and 6.9% for GEFCOM 2012 and ISONE datasets respectively.

5.2.2.2 Daily Peak Load

The performance of three models on One day-ahead daily peak module is quite similar to One year ahead daily peak module. The recency model outperforms the three models standing at an average MAPE of 4.84% and 2.81% for GEFCom 2012 and ISONE datasets which is better by 5.6% and 4.6% from proposed model in the respective zone.

Table 11: One day ahead Ex Post Daily Peak Load Forecasting Results for the prediction year

	Zones	Direct Green	Recency TA	Proposed Model
REGULAR ZONES - GEFCom2012	1	6.06	4.92	5.84
	2	4.86	4.38	4.70
	3	4.86	4.38	4.70
	5	7.35	6.30	7.27
	6	4.90	4.30	4.70
	7	4.86	4.38	4.70
	8	5.74	5.10	5.38
	10	5.34	5.03	5.18
	11	5.42	4.94	5.62
	12	5.04	4.42	5.20
	13	5.44	5.02	5.28
	14	5.59	6.25	5.66
	15	5.00	5.57	4.96
	16	5.78	5.31	5.89
	17	3.78	3.67	3.95
	18	5.04	4.62	4.94
	19	5.07	5.55	5.24
	20	4.20	4.27	4.00
	21	3.90	3.46	3.79
Average		**5.17**	**4.84**	**5.11**

Zones	Direct Green	Recency TA	Proposed Model
NH	2.67	2.80	2.66
VT	2.50	3.12	2.56
WCMASSS	3.16	2.75	3.13
ME	3.15	3.00	3.16
NEMASS	3.60	3.43	3.61
CT	2.79	2.53	2.83
RI	3.36	2.63	3.13
SEMASS	3.14	2.81	2.90
ISONE	2.55	2.24	2.50
Average	**2.99**	**2.81**	**2.94**

5.2.2.3 Daily Minimum Load

The results of the daily minimum model are in contrary to the other two modules. The proposed model outperforms the recency TA model too. This was expected since, as discussed before, the minimum load is less influenced by the temperature of the hour or the preceding hours but rather than the hours with least human activities. Hence the proposed model performs better by

1% and 16% over the recency TA model on GEFCom2012 data track and ISONE dataset respectively.

Table 12: One day ahead Ex Post Daily Min. Load Forecasting Results for the prediction year

	Zones	Direct Green	Recency TA	Proposed Model
REGULAR ZONES - GEFCom2012	1	6.79	6.06	5.70
	2	5.36	4.62	4.60
	3	5.36	4.62	4.60
	5	9.39	8.10	8.09
	6	5.45	4.63	4.62
	7	5.36	4.62	4.60
	8	6.74	5.79	6.05
	10	6.73	4.83	4.98
	11	7.00	5.90	4.82
	12	7.34	5.81	4.99
	13	6.73	5.66	5.84
	14	9.66	8.10	7.96
	15	7.14	5.95	6.34
	16	7.78	6.27	6.27
	17	5.68	4.27	4.50
	18	6.72	5.64	5.35
	19	7.82	5.94	6.05
	20	5.04	4.11	4.32
	21	5.25	4.09	4.18
Average		**6.70**	**5.53**	**5.47**

Zones	Direct Green	Recency TA	Proposed Model
NH	3.12	2.62	2.24
VT	3.17	4.00	2.52
WCMASSS	4.16	3.78	2.76
ME	4.55	3.94	4.46
NEMASS	3.67	2.33	2.54
CT	4.19	2.66	2.58
RI	3.50	2.91	2.44
SEMASS	3.49	3.56	2.13
ISONE	3.24	2.16	1.72
Average	**3.68**	**3.10**	**2.60**

5.3 Ex-ante Load Forecasting

Since the weather variables are hard to be predicted for a forecasting horizon of a year and even sometimes a day, hence an ex-ante forecasting is studied for the three models. This section uses monte-carlo simulation technique [19] to add noise to the temperature series of the forecasting period. Thus, the hourly temperature T, modifies to T`, where T`= T+T*p%, where p is the percentage number randomly generated from the Uniform or Normal distribution. For uniform distribution the interval parameter U(a, b) has been set from (0,0) to (-10 to10), thus making 11 scenarios. For the normal distributed noises, N (μ, σ), the parameters mean (μ) and standard deviation (σ) are varied from 0 to 5 and 1 to 9 (with an increment of 2 at each level) respectively thus making 30 scenarios. This basically conjures up some situations for ex-ante forecasting of the daily load. The performance of the proposed model is evaluated for the three modules of daily load forecasting and compared them with two benchmark models.

5.3.1 One year ahead forecasting

For one year ahead forecasting, the noises are generated and added to all the hourly temperatures of the prediction year. Then the models are tested for 11 scenarios of uniformly distributed anomalies and 30 scenarios of normally distributed anomalies. For Uniformly distributed anomalies, the average MAPE (%) of all the respective zones of each dataset is presented for all three models. But for the normal distributed anomalies, average MAPE (%) of each dataset for the best two models, that are, recency model and proposed model, are presented.

5.3.1.1 Daily Energy

In this section, the performance of proposed model is evaluated for the ex-ante daily load forecasting of daily energy module. It can be inferred from the table no.14 and 15 that with high level of uniformly distributed anomalies and normally distributed anomalies, the proposed model performs better than the Recency TA model. In case of uniformly distributed, this level is U (-5, 5) and U (-9, 9) for GEFCom2012 and ISONE dataset respectively.

While for normally distributed anomalies, the noise p% with $N(\mu, \sigma^2) > N(2, 7^2)$ is the cut off found when the proposed model outperforms the recency model for ISONE zone. It can be observed that for GEFCom2012 dataset, the noise p% with $\sigma^2 > 3$ is the cut off, but we could not find the cutoff of μ within the level of noise induced, but can be extrapolated at $N(6, 3^2)$ level.

Table 13: Sensitivity analysis of the models on uniformly distributed anomalies in temperature data. This table shows the results in MAPE (%) for all three models with color formatted cells.

	GEFCom2012			ISONE		
U(a, b)	Direct Green	Recency TA	Proposed	Direct Green	Recency TA	Proposed
(0,0)	5.19	**4.71**	4.96	3.41	**2.85**	3.08
(-1,1)	5.20	**4.73**	4.96	3.41	**2.86**	3.07
(-2,2)	5.22	**4.77**	4.98	3.42	**2.87**	3.07
(-3,3)	5.27	**4.85**	5.00	3.45	**2.89**	3.07
(-4,4)	5.33	**4.95**	5.04	3.49	**2.92**	3.07
(-5,5)	5.42	**5.08**	**5.08**	3.55	**2.96**	3.08
(-6,6)	5.54	5.22	**5.14**	3.63	**3.00**	3.10
(-7,7)	5.68	5.39	**5.20**	3.74	**3.06**	3.12
(-8,8)	5.84	5.57	**5.28**	3.86	**3.12**	3.15
(-9,9)	6.03	5.78	**5.36**	4.02	3.19	**3.18**
(-10,10)	6.25	6.00	**5.44**	4.19	3.26	**3.21**

Table 14: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for GEFCom2012 dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY TA MODEL

μ \ σ	**1**	**3**	**5**	**7**	**9**
0	**4.77**	**5.11**	5.68	6.44	7.40
1	**5.04**	**5.37**	5.97	6.76	7.76
2	**5.62**	**5.92**	6.49	7.29	8.29
3	**6.47**	**6.71**	7.24	8.00	8.99
4	**7.49**	**7.70**	8.16	8.88	9.82
5	**8.65**	**8.81**	9.22	9.87	10.78

PROPOSED MODEL

μ \ σ	**1**	**3**	**5**	**7**	**9**
0	5.00	5.15	**5.39**	**5.73**	**6.14**
1	5.27	5.42	**5.65**	**5.97**	**6.38**
2	5.85	5.98	**6.18**	**6.48**	**6.86**
3	6.66	6.76	**6.94**	**7.20**	**7.55**
4	7.65	7.73	**7.87**	**8.11**	**8.43**
5	8.77	8.83	**8.95**	**9.16**	**9.46**

Table 15: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for ISONE dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY TA MODEL

μ \ σ	**1**	**3**	**5**	**7**	**9**
0	**2.88**	**3.00**	**3.21**	3.49	3.84
1	**3.05**	**3.17**	**3.38**	3.68	4.06
2	**3.43**	**3.53**	**3.73**	4.02	4.39
3	**3.93**	**4.01**	**4.19**	**4.47**	4.84
4	**4.53**	**4.60**	**4.76**	**5.02**	5.38
5	**5.19**	**5.26**	**5.42**	**5.66**	6.00

PROPOSED MODEL

μ \ σ	**1**	**3**	**5**	**7**	**9**
0	3.09	3.16	3.28	3.44	**3.65**
1	3.29	3.35	3.46	3.62	**3.82**
2	3.68	3.74	3.83	3.97	**4.15**
3	4.21	4.25	4.34	**4.47**	**4.64**
4	4.84	4.87	4.95	**5.07**	**5.23**
5	5.54	5.57	5.65	**5.76**	**5.91**

It may be noted that for normally distributed anomalies, the best two performing models are Recency TA model and the proposed model across all noise levels and hence for the sake of simple presentation, the results of Direct Green model have not been included in table 14 and table 15.

5.3.1.2 Daily Peak Load

The daily peak module has similar results as the daily energy for uniformly distributed anomalies. The cut off level when the proposed model outperforms the recency model is U (-4, 4) here. For normally distributed anomalies above level of N (5, 0^2), the proposed model performs the best in case of GEFCom2012 dataset. In case of ISONE dataset, proposed model outperforms Recency Model above the noise level of N (1, 1^2). It may be noted that for normally distributed anomalies, the best two performing models are Recency TA model and the proposed model across all noise levels and hence for the sake of simple presentation, the results of direct Green model are not included in table 17 and table 18.

Table 16: Sensitivity analysis of the models on uniformly distributed anomalies in temperature data. This table shows the results in MAPE (%) for all three models with color formatted cells.

	GEFCom2012			ISONE		
U(a, b)	Direct Green	Recency TA	Proposed	Direct Green	Recency TA	Proposed
(0,0)	5.91	**5.56**	5.73	3.51	**3.14**	3.32
(-1,1)	5.93	**5.57**	5.74	3.52	**3.16**	3.32
(-2,2)	5.96	**5.64**	5.77	3.54	**3.21**	3.32
(-3,3)	6.02	**5.78**	5.81	3.57	**3.29**	3.33
(-4,4)	6.15	5.99	**5.88**	3.63	3.40	**3.34**
(-5,5)	6.32	6.28	**5.96**	3.70	3.54	**3.36**
(-6,6)	6.56	6.64	**6.06**	3.80	3.71	**3.39**
(-7,7)	6.85	7.08	**6.17**	3.91	3.91	**3.43**
(-8,8)	7.18	7.59	**6.28**	4.05	4.14	**3.46**
(-9,9)	7.55	8.19	**6.41**	4.23	4.38	**3.51**
(-10,10)	7.96	8.86	**6.54**	4.42	4.66	**3.55**

Table 17: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for GEFCom2012 dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY MODEL TA

μ \ σ	1	3	5	7	9
0	**5.61**	6.27	7.91	10.54	14.11
1	**5.71**	6.63	8.50	11.32	15.04
2	**6.13**	7.26	9.33	12.29	16.15
3	**6.88**	8.14	10.36	13.43	17.41
4	7.87	9.24	11.56	14.75	18.84
5	9.07	10.51	12.93	16.21	20.40

PROPOSED MODEL

μ \ σ	1%	3%	5%	7%	9%
0	5.77	**5.96**	**6.28**	**6.74**	**7.32**
1	5.85	**6.03**	**6.36**	**6.81**	**7.40**
2	6.23	**6.40**	**6.70**	**7.13**	**7.69**
3	**6.88**	**7.03**	**7.30**	**7.69**	**8.22**
4	**7.72**	**7.86**	**8.11**	**8.47**	**8.96**
5	**8.72**	**8.84**	**9.07**	**9.41**	**9.88**

Table 18: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for ISONE dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY MODEL TA

μ \ σ	1	3	5	7	9
0	**3.20**	3.51	4.15	5.10	6.34
1	**3.40**	3.82	4.55	5.58	6.91
2	3.83	4.29	5.08	6.18	7.56
3	4.40	4.89	5.72	6.87	8.30
4	5.08	5.58	6.44	7.62	9.11
5	5.83	6.34	7.23	8.45	9.97

PROPOSED MODEL

μ \ σ	1	3	5	7	9
0	3.32	**3.40**	**3.54**	**3.74**	**3.97**
1	3.42	**3.49**	**3.63**	**3.83**	**4.06**
2	**3.72**	**3.77**	**3.89**	**4.06**	**4.28**
3	**4.17**	**4.20**	**4.29**	**4.42**	**4.61**
4	**4.71**	**4.73**	**4.79**	**4.91**	**5.06**
5	**5.32**	**5.33**	**5.38**	**5.47**	**5.61**

5.3.1.3 Daily Minimum Load

For this module, the results show that the proposed model outperforms the two models at all level noises for uniformly distributed anomalies. For Normally distributed anomalies, the higher level above $N(1,0^2)$, worsens the performance of the proposed model in case of GEFCom2012 data track, while for ISONE, the proposed model remains the best stake. It may be noted that for normally distributed anomalies, the best two performing models are Recency TA model and the proposed model across all noise levels and hence for the sake of simple presentation, the results of direct Green model have not been included in table 20 and table 21.

Table 19: Sensitivity analysis of the models on uniformly distributed anomalies in temperature data. This table shows the results in MAPE (%) for all three models with color formatted cells.

U(a, b)	GEFCom2012 Direct Green	GEFCom2012 Recency TA	GEFCom2012 Proposed	ISONE Direct Green	ISONE Recency TA	ISONE Proposed
(0,0)	7.29	6.21	**5.98**	4.34	3.79	**3.26**
(-1,1)	7.32	6.24	**5.97**	4.34	3.81	**3.26**
(-2,2)	7.38	6.32	**5.97**	4.37	3.84	**3.26**
(-3,3)	7.52	6.47	**5.99**	4.43	3.91	**3.28**
(-4,4)	7.70	6.68	**6.02**	4.54	3.99	**3.30**
(-5,5)	7.94	6.97	**6.06**	4.67	4.10	**3.33**
(-6,6)	8.21	7.33	**6.11**	4.85	4.22	**3.36**
(-7,7)	8.53	7.74	**6.16**	5.06	4.36	**3.39**
(-8,8)	8.89	8.23	**6.23**	5.30	4.50	**3.43**
(-9,9)	9.28	8.79	**6.30**	5.56	4.66	**3.48**
(-10,10)	9.70	9.44	**6.38**	5.85	4.83	**3.53**

Table 20: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for GEFCom2012 dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY MODEL TA

μ \ σ	**1**	**3**	**5**	**7**	**9**
0	6.05	6.87	8.54	11.17	15.01
1	**6.26**	7.03	8.68	11.33	15.23
2	**6.71**	7.41	8.98	11.61	15.59
3	**7.36**	8.00	9.46	12.03	16.05
4	**8.20**	8.74	10.10	12.60	16.63
5	**9.18**	**9.63**	10.87	13.31	17.33

PROPOSED MODEL

μ \ σ	**1**	**3**	**5**	**7**	**9**
0	**6.00**	**6.14**	**6.39**	**6.73**	**7.14**
1	6.26	**6.43**	**6.71**	**7.07**	**7.50**
2	6.80	**6.98**	**7.25**	**7.61**	**8.05**
3	7.54	**7.73**	**8.00**	**8.35**	**8.79**
4	8.49	**8.67**	**8.94**	**9.29**	**9.73**
5	9.60	9.78	**10.04**	**10.39**	**10.82**

Table 21: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for ISONE dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY TA MODEL

μ \ σ	**1**	**3**	**5**	**7**	**9**
0	3.85	4.15	4.63	5.23	5.97
1	3.87	4.15	4.61	5.22	5.97
2	4.04	4.28	4.71	5.30	6.05
3	4.36	4.54	4.92	5.47	6.18
4	4.81	4.93	5.23	5.72	6.40
5	5.36	5.42	5.64	6.06	6.69

PROPOSED MODEL

μ \ σ	**1**	**3**	**5**	**7**	**9**
0	**3.27**	**3.36**	**3.51**	**3.72**	**3.96**
1	**3.39**	**3.50**	**3.67**	**3.88**	**4.12**
2	**3.66**	**3.77**	**3.94**	**4.15**	**4.39**
3	**4.07**	**4.17**	**4.32**	**4.52**	**4.76**
4	**4.56**	**4.66**	**4.80**	**4.99**	**5.21**
5	**5.14**	**5.23**	**5.36**	**5.54**	**5.75**

5.3.2 One day ahead forecasting

For one year ahead forecasting, the noises are generated and added only to the 24-hourly temperatures of the day ahead. This process is iterated for each day of the prediction year. Then the models are evaluated for 11 scenarios of uniformly distributed anomalies and 30 scenarios of normally distributed anomalies. For Uniformly distributed anomalies, the average MAPE (%) of all the respective zones of each dataset is presented for all three models. But for the normal distributed anomalies, average MAPE (%) of each dataset for the best two models, that are, recency model and proposed model, are presented This is done for the sake of simple presentation of data.

5.3.2.1 Daily Energy

The study of the table no. 22 suggests that the proposed model performs best at noise level of U (-7, 7) and U (-8, 8) for GEFCom2012 and ISONE dataset respectively. While for normally distributed anomalies with σ > 7 for GEFCom2012 data track, the performance of proposed model has been found better. For ISONE dataset, the cut off is the noise level above N $(3,7^2)$. For GEFCom2012 dataset, noise level with $\sigma^2>5$, we found the proposed model outperforms. The cutoff of noise level of μ we can be extrapolated at N $(6, 3^2)$ when proposed model outperforms. This is similar to the year ahead ex-ante forecasting.

Table 22: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for GEFCom2012 dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY MODEL TA

μ \ *σ*	**1**	**3**	**5**	**7**	**9**
0	**4.11**	**4.46**	5.05	5.85	6.83
1	**4.46**	**4.80**	5.40	6.20	7.21
2	**5.14**	**5.44**	6.00	6.79	7.78
3	**6.07**	**6.32**	6.82	7.54	8.39
4	**7.16**	**7.37**	7.66	8.46	9.35
5	**8.25**	**8.54**	8.91	9.37	10.33

PROPOSED MODEL

μ \ *σ*	**1**	**3**	**5**	**7**	**9**
0	4.30	4.48	**4.77**	**5.17**	**5.66**
1	4.65	4.81	**5.08**	**5.45**	**5.92**
2	5.33	5.46	**5.68**	**6.01**	**6.45**
3	6.26	6.35	**6.53**	**6.81**	**7.20**
4	7.36	7.41	**7.54**	**7.79**	**8.14**
5	8.56	8.59	**8.69**	**8.90**	**9.21**

Table 23: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for ISONE dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY MODEL TA

μ \ σ	1	3	5	7	9
0	**2.34**	**2.46**	**2.67**	**2.96**	**3.31**
1	**2.46**	**2.59**	**2.80**	**3.11**	**3.48**
2	**2.80**	**2.91**	**3.11**	**3.41**	**3.78**
3	**3.29**	**3.37**	**3.55**	**3.83**	4.21
4	**3.86**	**3.93**	**4.10**	4.36	4.72
5	**4.49**	**4.56**	**4.72**	4.97	5.31

PROPOSED MODEL

μ \ σ	1	3	5	7	9
0	2.96	3.04	3.19	3.39	3.63
1	2.99	3.08	3.23	3.44	3.69
2	3.24	3.30	3.43	3.62	3.85
3	3.64	3.67	3.76	3.92	**4.13**
4	4.14	4.15	4.21	**4.33**	**4.51**
5	4.72	4.72	4.75	**4.84**	**4.99**

Table 24: Sensitivity analysis of the models on uniformly distributed anomalies in temperature data. This table shows the results in MAPE (%) for all three models with color formatted cells.

	GEFCom2012			ISONE		
U(a, b)	Direct Green	Recency TA	Proposed	Direct Green	Recency TA	Proposed
(0,0)	4.51	**4.04**	4.26	2.84	**2.33**	2.49
(-1,1)	4.52	**4.06**	4.26	2.85	**2.33**	2.48
(-2,2)	4.56	**4.11**	4.28	2.86	**2.34**	2.48
(-3,3)	4.61	**4.19**	4.30	2.89	**2.36**	2.49
(-4,4)	4.69	**4.31**	4.34	2.93	**2.40**	2.50
(-5,5)	4.78	4.44	**4.38**	2.99	**2.44**	2.51
(-6,6)	4.89	4.60	**4.44**	3.06	**2.49**	2.53
(-7,7)	5.03	4.78	**4.50**	3.14	2.55	**2.56**
(-8,8)	5.11	4.97	**4.57**	3.23	2.62	**2.59**
(-9,9)	5.29	5.18	**4.65**	3.34	2.69	**2.62**
(-10,10)	5.50	5.42	**4.73**	3.47	2.77	**2.66**

It may be noted that for normally distributed anomalies, the best two performing models are Recency TA model and the proposed model across all noise levels and hence for the sake of simple presentation, the results of direct green model are not included in Table no 23 and 24.

5.3.2.2 Daily Peak Load

The analysis of this module suggests that when uniformly distributed anomalies are introduced, the cutoff for proposed model surpassing the recency TA model is around U (-3,3) level for both datasets. For normally distributed anomalies, ISONE dataset has the cutoff of noise level above N (0, 1^2). For GEFCom2012, it can be inferred that at anomalies with $\sigma^2 > 1^2$ level the proposed model outperforms the recency model. The cut off level when performance of the proposed model outdoes the recency model can be extrapolated at N (6, 1^2).

Table 25: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for GEFCom2012 dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY TA MODEL

μ \ σ	1	3	5	7	9
0	**4.93**	5.75	7.59	10.29	13.82
1	**5.09**	6.17	8.19	11.04	14.72
2	**5.62**	6.88	9.02	12.00	15.81
3	**6.46**	7.82	10.05	13.14	16.66
4	**7.53**	8.95	10.94	14.45	18.49
5	**8.67**	10.25	12.65	15.56	20.05

PROPOSED MODEL

μ \ σ	1	3	5	7	9
0	5.15	**5.38**	**5.75**	**6.24**	**6.83**
1	5.35	**5.55**	**5.90**	**6.37**	**6.94**
2	5.87	**6.06**	**6.36**	**6.78**	**7.31**
3	6.66	**6.82**	**7.08**	**7.44**	**7.93**
4	7.62	**7.75**	**7.99**	**8.31**	**8.75**
5	8.71	**8.82**	**9.02**	**9.32**	**9.73**

Table 26: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for ISONE dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY TA MODEL

μ \ σ	1	3	5	7	9
0	**2.85**	3.14	3.74	4.62	5.79
1	3.02	3.40	4.10	5.07	6.33
2	3.39	3.83	4.60	5.62	6.95
3	3.92	4.39	5.18	6.27	7.64
4	4.55	5.04	5.86	6.98	8.39
5	5.27	5.76	6.60	7.76	9.21

PROPOSED MODEL

μ \ σ	1	3	5	7	9
0	2.96	**3.04**	**3.19**	**3.39**	**3.63**
1	**2.99**	**3.08**	**3.23**	**3.44**	**3.69**
2	**3.24**	**3.30**	**3.43**	**3.62**	**3.85**
3	**3.64**	**3.67**	**3.76**	**3.92**	**4.13**
4	**4.14**	**4.15**	**4.21**	**4.33**	**4.51**
5	**4.72**	**4.72**	**4.75**	**4.84**	**4.99**

Table 27: Sensitivity analysis of the models on uniformly distributed anomalies in temperature data. This table shows the results in MAPE (%) for all three models with color formatted cells.

U(a, b)	GEFCom2012 Direct Green	GEFCom2012 Recency TA	GEFCom2012 Proposed	ISONE Direct Green	ISONE Recency TA	ISONE Proposed
(0,0)	5.17	**4.84**	5.11	2.99	**2.81**	2.94
(-1,1)	5.22	**4.86**	5.11	3.00	**2.83**	2.94
(-2,2)	5.30	**4.95**	5.12	3.01	**2.87**	2.95
(-3,3)	5.42	**5.12**	5.17	3.04	**2.94**	2.96
(-4,4)	5.59	5.38	**5.22**	3.09	3.05	**2.97**
(-5,5)	5.80	5.72	**5.30**	3.16	3.18	**3.00**
(-6,6)	6.07	6.13	**5.38**	3.25	3.33	**3.02**
(-7,7)	6.38	6.63	**5.48**	3.35	3.51	**3.05**
(-8,8)	6.73	7.19	**5.60**	3.48	3.72	**3.09**
(-9,9)	7.11	7.83	**5.72**	3.63	3.94	**3.13**
(-10,10)	7.52	8.54	**5.85**	3.80	4.18	**3.17**

5.3.2.3 Daily Minimum Load

Similar to year ahead ex-ante forecasting the results of this module imply that the proposed model outperforms the two models at all level noises for uniformly distributed Anomalies. For Normally distributed anomalies, the higher level above N $(1, 4^2)$, worsens the performance of the proposed model in case of GEFCom2012 data track, while for ISONE, the proposed model remains the best at all level of noise taken up in the study.

Table 28: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for GEFCom2012 dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY TA MODEL

μ \ σ	1	3	5	7	9
0	5.60	6.37	8.09	10.72	14.50
1	5.85	6.59	8.25	10.91	14.76
2	**6.34**	7.02	8.59	11.25	15.15
3	**7.05**	7.63	9.10	11.71	15.46
4	**7.93**	8.40	9.52	12.29	16.27
5	**8.82**	**9.31**	10.52	12.70	17.00

PROPOSED MODEL

μ \ σ	1	3	5	7	9
0	**5.49**	**5.65**	**5.93**	**6.29**	**6.73**
1	**5.81**	**5.99**	**6.27**	**6.64**	**7.08**
2	6.40	**6.58**	**6.85**	**7.21**	**7.65**
3	7.21	**7.38**	**7.65**	**7.99**	**8.41**
4	8.20	**8.37**	**8.62**	**8.94**	**9.35**
5	9.34	9.51	**9.74**	**10.05**	**10.44**

It may be noted that for normally distributed anomalies, the best two performing models are Recency TA model and the proposed model across all noise levels and hence for the sake of simple presentation, the results of direct Green model are not included in Table no 28 and 29.

Table 29: Sensitivity analysis of the models in case of normally distributed anomalies in temperature data for ISONE dataset. This table shows the MAPE (%) with bold fonts indicating the better MAPE (%) of the two.

RECENCY TA MODEL

μ \ σ	1	3	5	7	9
0	3.16	3.45	3.90	4.48	5.17
1	3.13	3.41	3.86	4.43	5.12
2	3.28	3.50	3.91	4.47	5.14
3	3.58	3.75	4.10	4.61	5.25
4	4.02	4.12	4.39	4.85	5.45
5	4.56	4.60	4.79	5.17	5.73

PROPOSED MODEL

μ \ σ	1	3	5	7	9
0	**2.61**	**2.70**	**2.86**	**3.08**	**3.33**
1	**2.69**	**2.80**	**2.98**	**3.20**	**3.46**
2	**2.95**	**3.06**	**3.23**	**3.44**	**3.70**
3	**3.34**	**3.44**	**3.60**	**3.79**	**4.03**
4	**3.83**	**3.92**	**4.06**	**4.25**	**4.47**
5	**4.39**	**4.48**	**4.61**	**4.78**	**5.00**

Table 30: Sensitivity analysis of the models on uniformly distributed anomalies in temperature data. This table shows the results in MAPE (%) for all three models with color formatted cells.

	GEFCom2012			ISONE		
U(a, b)	Direct Green	Recency TA	Proposed	Direct Green	Recency TA	Proposed
(0,0)	6.70	5.53	**5.47**	3.68	3.10	**2.60**
(-1,1)	6.70	5.55	**5.46**	3.68	3.12	**2.60**
(-2,2)	6.73	5.60	**5.46**	3.72	3.16	**2.61**
(-3,3)	6.82	5.73	**5.48**	3.79	3.23	**2.62**
(-4,4)	6.97	5.94	**5.51**	3.90	3.32	**2.65**
(-5,5)	7.18	6.22	**5.55**	4.03	3.43	**2.68**
(-6,6)	7.44	6.58	**5.60**	4.20	3.55	**2.71**
(-7,7)	7.76	7.01	**5.65**	4.40	3.69	**2.75**
(-8,8)	8.11	7.52	**5.72**	4.61	3.84	**2.79**
(-9,9)	8.51	8.08	**5.79**	4.85	3.99	**2.84**
(-10,10)	8.95	8.71	**5.87**	5.11	4.16	**2.89**

6. CONCLUSION

Daily load forecasting is an important aspect for a reliable and profitable operation of modern power utilities. The utilities value it for resource planning and decision making in the energy market. The study in this research involves modeling the hourly temperatures to forecast the three modules of daily load forecast: Daily Energy, Daily Peak Load, and Daily Minimum Load. This study was also motivated by a real business problem of developing daily load curves in case of missing hourly load data or converting monthly load consumption into daily load curves. So, this research uses daily series of historic daily energy, daily peak load and the daily minimum load for modeling of the respective modules. This kind of multi-frequency study is unique in the field of load forecasting. Most of the earlier research in the field of load forecasting at the daily resolution is focused on daily peak load. Typically, these researches have used the maximum temperature of the day as the key parameter for modeling. In this research, we explored the twenty-four dimensions of the daily temperature, found the relevant subsets of the hourly temperatures for daily load forecasting. The proposed model for daily energy module was generated from a detailed study of hourly temperatures and finding the best subset of hourly temperatures for capturing maximum temperature hours and minimum temperature hours. The proposed model for daily peak module uses the reduced space of daytime to get the average temperature, grouped maximum, and minimum temperatures. The proposed model for daily minimum module uses the grouped temperature of minimum load hours along with the average temperature of reduced space and grouped maximum temperature. Hence, the optimum groups of hourly temperatures relevant to the daily load are captured. Most of the time, this group carries the maximum or the minimum temperature of the day, but the group also has the temperature of peer hours. Hence the group negates any false impact of the extreme values of the daily temperature curve.

To evaluate the performance of the proposed models, two benchmark models have been employed. One is a direct daily load forecasting model based on Tao's Vanilla model using maximum, minimum and average temperature of the day, which we have referred to as the direct Green Model. The other is based on temporal aggregation of the hourly load forecasts. The hourly load forecasting employed in this benchmark models the recency effect of hourly temperature as proposed in [13] using hourly temperature as well as hourly load. This model has proven superiority over the benchmark model by a 12% to 15% on average for the GEFCom2012 dataset and is also high in computational requirement. Hence, this model is a high-end benchmark , that we call here Receny TA, is used here to understand how far off is the performance of the proposed model that uses daily load series instead of hourly load series.

To conduct this experiment, two real-world datasets have been used which are available publicly. One is the data track used in the GEFCom2012 competition and the other dataset is the load and weather history of nine zones of ISO, New England. By analyzing the performance of these three models for the three modules of the daily load forecast, it is shown that the adopted model performs much better than the Direct Green model for all three modules. But when compared to the Recency TA model for daily energy module, the proposed model lags by approximately 5.4% and 7.5% on GEFCom2012 and ISONE dataset respectively. For daily peak module, the proposed model lags by 4.3% and 5.2%. But for the daily minimum load, the proposed model outperforms the recency TA model by 2.2% and 15.1% for GEFCOM2012 and ISONE dataset respectively. This is quite understandable as recency model works on capturing the fundamental relationship between the load and the temperatures of preceding hours, while the minimum load is more driven by hours with minimum human activities. Hence, the minimum load is observed neither in the coolest temperature hours in summers nor in the highest temperature hours in winters, rather it is observed during the hours with least human activities which are the post-midnight hours before the dawn.

In real business, ultimately the ex-ante forecast is what matters. The information on weather data are unforeseen and hence liable to vary from what presumed. Hence, it is imperative to evaluate the models in case of any variation in the values of the regressors, that is, the temperature. To conduct this study, we added noise that follows a normal or uniform distribution into the temperature series of the forecasting year. The ex-ante forecast study revealed that the proposed model is a more reliable model in case of a high level of uncertainty in the temperature data. For the summary purpose, we can say that for daily energy module, any variation (p%) in temperature data above U(-5,5) or $N(5,3^2)$ level results in proposed model outperforming the recency model, while this level is U(-8,) or $N(4,7^2)$ for ISONE data. For daily peak load module, even at a low level of variations of around U(-4,4) or $N(3,3^2)$, the proposed model outdoes the recency model for GEFCom2012 dataset, while for ISONE the level is even lower at U(-4,4) or $N(0,1^2)$. Also the proposed model performs very consistent across all zones for daily peak load forecasting. For daily minimum load, the proposed model for the GEFCom2012 dataset is outperformed at a high level of $N(1, 4^2)$ of noise while for ISONE the proposed model remains the most resilient of the three at all level of noises under the study.

The subsets of the hourly temperatures have been obtained from a profound analysis of the temperature curve and load curve of each dataset. The group of hours can vary from one dataset to other. One of the most important findings of this study is that the temperatures of specific hours are more influential than the critical temperatures of the day such as the highest and lowest temperature of the day. With most of the earlier research using maximum or the minimum temperature of the day for daily load forecasting, it is distinctive to use hour-based temperatures. Besides, the proposed methodology of grouping the relevant hourly temperatures also emerges out to be a resilient as well a practical and interpretable methodology of predicting the three modules of daily load as demonstrated empirically.

Taking this study further, this methodology can be deployed and assessed in hierarchical load forecasting for obtaining hourly or monthly load series by way of disaggregating and aggregating and reconciling the independent load series. Also, on the side of improving the proposed methodology, the twenty-hour dimension can be subjected to various dimension reduction technique such as Principal Component Analysis (PCA) to get the best dimension of daily temperatures for daily load forecasting. It would also be interesting to explore other technique of dimension reduction for this purpose.

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