GROUPING CALENDAR VARIABLES FOR ELECTRIC LOAD FORECASTING

by

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ABSTRACT

SAURABH SANGAMWAR. Grouping Calendar Variables for Electric Load Forecasting. (Under the direction of DR. TAO HONG)

Human activities are important driving factor of electricity consumption. Human activities can be captured by calendar information. This research uses the hour of a day, days of a week, month of a year and 24 solar terms as calendar variables to classify the data. While using class variables in regression model, complexity of model is directly proportional to the level of the class variables. Additionally, interaction with temperature terms further increases the number of coefficients to be estimated. When there are few training observations, more complexity may lead to overfit the model. Grouping of calendar variable can be one of the solutions to this issue. Previously, many researchers grouped the calendar variables to improve load forecast. This research proposes three heuristic algorithms which are the structured way of finding the optimal grouping pattern instead of selecting it empirically. These heuristic algorithms are faster than enumerating all possible combinations of grouping calendar variables. Additionally, this research studies the number of optimal grouping obtained when model grows. The forecasting accuracy obtained by grouping calendar variable is improved as compared to without grouping calendar variables on validation data and some cases in test data. The experiments were conducted on total system load of ISO New England's and GEFCom2012 publicly available data.

ACKNOWLEDGMENT

When I recall my first interaction with Dr. Tao Hong, during the seminar, his message, “More you spend time, more you learn” Resonated in my ears. Motivated by this and my eagerness to touch base in forecasting, I decided to be a part of his research team.

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CHAPTER 1: INTRODUCTION

In the modern era, electricity has become the basic requirement and necessity of humankind. Electricity cannot be stored in massive amount in any reservoir. It must be produced based on demand. Forecast always supports electricity production, planning, revenue projection, rate design, and energy trading team to understand the consumption behavior, and thus results in decision making. The need for forecasts depends on the requirement of the department, for example, the financial planning department may require a minimum of 1 month to over10 years of forecast [1]. However, the operations department may require a minimum of 15 minutes to 2 weeks of forecast.

There are no reliable standards to categorize the load forecast based on the horizon. Based on specific applications, different institutions have set up different standards for these categories. However, Tao Hong and Shu Fan have categorized load forecast based on the forecasting horizon: - very short-term load forecast (VSTLF), short-term load forecast (STLF), medium-term load forecast (MTLF) and long-term load forecast (LTLF) with cut-off horizon of one day, two weeks, and three years respectively [2].

There are several techniques to forecast electric load. Significant techniques consist of time series such as exponential smoothing, Box- Jenkins, and ARIMA. [3] [4] [5]. In addition to this, multiple linear regression is being used very widely for several horizons [6]. Along with the mentioned time series methods, expert system, neural networks, fuzzy logic, support vector machines, gradient boosting and random forest techniques are also used for electric load forecasting [4] [7] [8] [9] [10] [11]. As mentioned, there are many methods available for electric load forecasting, but it is difficult to conclude that a said method always gives more accurate result than the others. Weather and calendar variables are the widely used predictor variable in electric load forecasting.

Typically, there are multiple seasonal patterns of electricity consumption. Electricity demand is higher in summer and winter as compared to spring and fall. As low and high temperature leads to the need for heating and cooling. Similarly, electricity consumption during the day is higher as compared to that in the night as most of the offices are operated during the day. Consumption pattern during weekdays is different than the weekends. There are several studies that were conducted in the past, for load forecasting, specifically for the holidays [12]. As it has very little training data, and the fact that demand pattern for each holiday is different, depending on the nature of the holidays, such as, long weekends and/or holidays falling on weekdays. It has been observed that the demand pattern of the day before and after the holidays differ based on the nature of these holidays [1].

To model the seasonality, hours, days of the week, months and season are usually used to classify the data in load forecasting models. Previously, it has been observed that the load profile of some weekdays, months and hours are similar [1] [12]. Grouping such calendar variable has improved the load forecast and reduced the degree of freedom of model. Electricity consumption pattern is mainly depending on the outside temperature and human activities. Most of the human activities can be captured by Gregorian Calendar as it is commonly followed calendar. Hence Gregorian calendar is the most commonly used calendar for electric load forecasting models. It is noted that, Xie and Hong have used 24 solar terms, which is an ancient Chinese calendar to classify the load data [13].

This research proposes the study showcasing the effect that the grouping of calendar variables such as, the hour, the day of the week, months and 24 solar terms, may have. Previously, most of the authors used grouping of calendar variables to improve load forecast. However, this research's aim is to improve the forecast, reduce the complexity of the model and reduce the potential issue of overfitting when the model grows. Additionally, this research proposes the new heuristic algorithm to reach the optimal point in a faster way. This also makes new contribution to the research field as this proposes three formal ways to find out the best grouping pattern. To study the performance and implementation of techniques, ISO New England and GEFCom2012 hourly load and temperature data was used.

The rest of the thesis is organized as follows: Chapter 2 discusses the different published journal papers. Chapter 3 introduces the background about the thesis and introduction of data. Chapter 4 explains the algorithms, and chapter 5 shows experimental results.

CHAPTER 2: LITERATURE REVIEW

This chapter briefs about the several research papers in the field of electric load forecasting. To get a specific overview of an electric load forecasting and practices, this chapter is divided into the following three sub-topics:

1. Electric Load Forecasting
2. Variable Selection- Weather and Calendar Variable
3. Methods of Grouping Calendar Variables

2.1 Electric Load Forecasting

In the past, electric load forecasting was mainly studied in two categories: Based on the forecasting horizon, and techniques used to forecast the electric load. In 'Based on the horizon,' more research was focused on Short-term load forecasting as compared to Long-term load forecasting [1]. Also, techniques were mainly studied based on statistical and artificial intelligence techniques. This section discusses research papers on all the above four categories.

Hong,2010[1] has discussed the several research papers in his dissertation. Also, it proposes a robust framework which can be easily related to other forecasts. There were several techniques used for electric load forecasting, but this dissertation provides the benchmark and systematic approach of building short-term load forecasting models. The author used multiple linear regression techniques to develop the models which performed very well as compared to other techniques used. Along with point forecast, one of the emerging techniques, i.e., probabilistic load forecasting is also discussed in this paper. The model developed in this paper, which is popularly known as The Vanilla Benchmark Model has been used as a benchmark model in many researches and forecasting competition such as GEFCom2012 [27].

Eisa and Hassan, 2011 [18] introduced that electric load forecasting is critical because unlike the material product, electricity as a product should be generated as demanded. This paper proposes the methodology which enables us to the decomposition and segmentation of load time series analysis. This methodology is dependent on the case to case scenario. They suggest three bases - region similarity, contour, and proposed related points and their combined forecasts. The case study is conducted on electric load time series data from Kuwait.

Hong, Wilson, and Xie (2014) have proposed the new approach which gives better forecast using hourly information [22]. Three key elements of the proposed approach for long-term load forecasting are predictive modeling, and scenario analysis. Authors used the stepwise selection of parameter for more accurate forecasts, which includes the steps of model selection, length of training data and comparison of other models. Furthermore, they developed probabilistic load forecast through cross scenario analysis. Finally, they used the proposed hourly model for load normalization.

Alfares and Nazeeruddin (2002) present the review and classification of electric load forecasting techniques [23]. Forecasting techniques were classified in nine ways: multiple linear regression, exponential smoothing, iterative reweighted least-square, adaptive load forecasting, stochastic time series, ARMAX (autoregressive moving average models with exogenous inputs) based on genetic algorithm, ANN, fuzzy logic, and expert system. They discussed the methodology, advantage, and disadvantage of each technique.

M. Misisti, Y. Misiti, G. Oppenheim, and JM Poggi showed how disaggregated forecasting (Forecasting using clustering) improve accuracy [24]. Authors have explained the clustering using wavelet and select many clusters and aggregate them stepwise using optimization criterion supervised by predictability. Using optimization function, authors have selected element from one cluster to enter the other and if error decreases, it then calculates the dissimilarity index between the current cluster and each element. If it does not improve, then it disregards any "improvements" and keeps the cluster as it is. Thus, this optimization function has helped to find the best performing cluster based on MAPE-LT error criterion.

Fan and Hyndman (2012) proposed the semiparametric additive model to understand the relationship between load and predictor variable, such as calendar variable, lagged demand observations and historical and predicted temperature [25]. Along with point forecast, the modified bootstrap method is used to find the prediction interval. The proposed methodology has been used by Australian Energy Market Operator (AEMO) to forecast half-hourly electricity demand in Victoria and South Australia. Forecasting horizon for the proposed method was seven days. Also, the performance of the proposed method was validated using out-of-sample test.

Park, El-Sharkawi, Marks II, Atlas, and Damborg (1991) presented an artificial neural network technique for electric load forecasting. Authors have used three months of hourly temperature and load data for the Seattle/Tacoma area for training and testing. They used hourly data to find the peak load of the day, the total load of the day and the hourly load of the day by dividing the data into six sets. Also, authors have concluded that ANN shows higher error on holiday and the next day of the holiday.

2.2 Variable Selection- Weather & Calendar Variables

It is well known that weather and Calendar variables are the most important predictor variable for electric load forecasting [1]. This section has reported the various papers in which weather and calendar variable are used to predict the electric load forecast. Dry bulb temperature, relative humidity, wind speed, wet bulb temperature, dew point temperature, wind direction, temperature humidity index, wind chill index, cooling heating degree days are some of the generally used weather variables. Months of year, days of the week, hours of the day are the most common calendar variables.

Shu Fan, Kittipong Methaprayoon, and Wei-Jen Lee (2009) developed a multiregional short-term load forecasting and applied on the electric utility of Midwest U.S. [28]. The authors analyzed weather and load data characteristic of developing multi region load forecasting system. Thus, they have used the ambient temperature into their proposed multi region load forecasting system to find the optimal region and to apply forecasting technique separately on the separate area. Then aggregating all forecasts gave more accurate results than applying forecasting technique to the complete area.

Hong, Liu, and Wang (2015) used current temperature, previous hour temperature, and an average temperature of the defined period for electric load forecasting [6]. Authors have added the effect of the previous temperature, the average temperature of the defined period along with the interaction effect of month and hour to check the accuracy of the load forecast. Also, authors showed and compared different ways of model selection and data partition which also can be used for load forecasting. Authors have used temperature and calendar variables as essential driving variables for load forecasting.

Ching-Lai Hor, Simon J. Watson, and Shanti Majithia (2005) described the multiple linear regression model to predict monthly demand under the comprehensive range of weather conditions in England and Wales [29]. Authors have used weather variable, gross domestic product, and population growth as predictor variables in multiple linear regression model. Also, authors have proposed three basic model which used different parameterizations of temperature and humidity. Authors have concluded that using humidity factor in models has improved the load forecast during the summer. To address the nonlinear and scattered relationship between temperature and load during the summer and winter, authors proposed degree days, i.e. Heating Degree Days and Cooling Degree Days to quantify how cold and hot the weather is.

Xie and Hong (2018) proposed a unique way to classify the load data [13]. Generally, the Gregorian calendar is used to classify the load data. An hour of a day, days of a week, and months of a year are commonly used calendar variable in forecasting community. Authors have proposed to use 24 solar terms which are based on Sun's position in the zodiac. 24 solar terms are used in China to guide people for their agricultural activities. Authors replaced months predictor variable with solar terms to forecast the electric load, and the proposed technique is used on ISO-New England data to compare the results.

Rahman (1990) discussed the proposed expert system approach which uses the knowledge of expert and relation between load, temperature, wind speed, day type, and hours of the day to predict 7 days of hourly load in advance [30]. Author has divided the variable as weather and non-weather variable. Non- weather sensitive parameters such as the season of the year, seasonal load shape and day of the week influences daily load. Also, the author has used dry bulb temperature, wet bulb temperature, dew point temperature, relative humidity, wind speed, wind direction, and sky cover.

2.3 Grouping of Calendar Variable

Many research papers have considered the grouping of calendar variable to improve electric load forecast accuracy. However, there is no specific or standard grouping, that was proposed in the previous papers as it is mainly data driven. This topic describes the grouping considered by different authors and methods used to group the calendar variable.

Kim, Youn, and Kang (2000), the proposed combination of neural network and fuzzy inference methods for forecasting load of special days in anomalous load condition [14]. Special days consist of public holidays, consecutive holidays and the days before and after the holidays. As the load curve for special days is different for each year and different for each special day, it gets challenging to forecast the load of special days. However, the author found out graphically that if special days grouped by day types and scaled with maximum and minimum loads of each special day, scaled load curve of each special days with a same day of the week are similar to each other. So different ANN models were built based on weekdays, Saturday, Sunday and Monday.

N. Hubele and C. Cheng (1990), reviewed the short-term load forecasting models using statistical decision function [15]. Authors have used hierarchical clustering to subset the data. Authors divided the data into four parts, and four different models were used to forecast the load. As weather conditions of fall and spring are similar, clustering resulted in the same cluster. Then date information was used to divide data into fall and spring. Additionally, the author used a linear discriminant function to classify new observations into an existing group or cluster. So, months were grouped as per seasons, and the day of the week were grouped as Monday, Tuesday-Thursday, Friday, Saturday, and Sunday.

S.Rahman and R. Bhatnagar (1998) grouped months based on four seasons, and four different forecasts were prepared. Also, the author used a calendar variable to select the weather variable while building the model. For instance, the relation of temperature is strong, and the other variable is weak in all season except summer. In summer, there was a strong relation of humidity and temperature. It has been observed that examination of load shapes for different seasons indicated a seasonal influence. Thus, in winter, load shape has two peaks during morning and evening. However, in summer, there is only one peak in the afternoon. During spring and fall, transitional load curve was observed which depends on prevailing weather condition. Thus, the morning load curve of winter was different than the similar day of early spring. It shows that seasonal boundaries also affect the load forecasting process. All days of weeks are considered separately, and holidays are grouped into Saturdays.

Ruzic, Vuckovic, and Nikolic (2003) offered weather sensitive methods for short-term load forecasting [17]. They used temperature instead of dry bulb temperature. Equivalent temperature is calculated by considering the ambient temperature and humidity. They compared the result of the proposed model with ongoing practice in utility. They have analyzed the months and days of week differently.

N. Amjady reviewed time series modeling for short-term load forecasting to predict peak load [3]. Data used in this case study is from Iran. Unlike Christian countries, Friday is the weekend in Iran. So, the load curve of Friday and Saturday is different. Load curve of Sunday to Wednesday is similar. Also, the load curve of the second half of the Thursday is different than the first half because the work for half a day. Furthermore, author has divided the days into hot and cold days based on cut off temperature. Thus, separate models were built for Friday, Saturday, Sunday-Wednesday, and Thursday. Further, it was divided into hot and cold days.

Mogharam and S Rahman (1989) discusses five different technique- MLR, stochastic time series, state space Kalman filter, exponential smoothing and knowledge-based expert system for electric load forecasting [4]. For MLR, authors have created two separate models for summer and winter for 24 hours of future load forecasting. Also, weekends were grouped and model for weekdays and weekends were different. Grouping of hours is different for weekdays and weekends. On weekdays, 12-4AM, 5AM-9AM, 10AM-1PM, 2PM-5PM, 6PM-8PM,9PM-11PM hours were grouped. However, on weekends, 12-4AM, 5AM-8AM, 9AM-12 noon, 1PM-4PM, 5PM-7PM, 8PM-11PM hours were grouped.

Papadakis, Theocharis, Kiartizis, and Bakirtizis (1998) have proposed fuzzy neural networks for short-term load forecasting [7]. Different models were built for each type of the day and for each season. Data were analyzed as per noon and evening break load and morning and afternoon valley load. For each season, four fuzzy models were used to predict the extremal loads for each day type. So total 4*7*4=112 models were used to forecast electric load. Thus, authors have grouped hours to create four parts of a day, i.e., morning, noon, afternoon and evening. All seven days were considered separately, and months were grouped as per season.

Hagan and Behr (1987) used Box and Jenkins time series models to forecast electric load [5]. Authors have divided data based on three parameters i.e., season, day of the week and cloud cover. Days of the year were grouped based on seven seasons mentioned in Table 1. Spring DST and Fall CST are the dates of DST and CST of that year. Also, Tuesday to Thursday was grouped together. Further, the day is divided into two parts as clear (if it's partly cloudy) or partly cloudy (if it's clear).

Table 1. 1: Days of year grouped based on eight seasons

Season	Start Date
Winter	1 Dec
Late Winter -Early Spring	16 Feb
Spring DST	31 May
Late Spring	1 Jun
Summer	1 July
Late Summer-Early Fall	16- Sept
Fall CST	30- Nov

Lamedica, Prudenzi, Sforna, Caciotta, and Cencelli (1996) have designed forecasting method which combination of classification and ANN method for anomalous days load forecast [8]. The proposed approach is a combined approach of supervised and unsupervised learning. The method was tested on data from Italy. Algorithm clustered the load profile into Sundays, Saturdays, Mondays and working days after holidays, working days from Tuesday to Fridays and main holidays such as Christmas, Easter Holidays, and other major holidays. Also, days between weekends and national holidays are classified as Saturdays and Sundays. Working days of August have been classified together with Sunday of late fall; Further, seasonal classifications such as spring-summer as April, May, June, July, and September. The intermediate season comprises of March and October, and the Winter season as January, February, November, and December.

D. Srinivasan, Chang, and Liew (1995) have used combined fuzzy Inference and Neural network model to forecast electric load [12]. The authors have demonstrated that the combined approach has performed well for regular weekdays, but it also performed well for weekends and public holidays. Monday to Friday had similar load profile. However, Sunday and the public holiday has the same. Additionally, morning load of Mondays and evening load of Fridays decreases due to the proximity of the weekend. Along with the temperature, rain forecast is also used. They have used the distance to classify from: one day to another, with far, near, very near and a complete day. All input variables are normalized with the range of 0-1. Also grouped the hours from 12 AM - 6 AM, Morning 6 AM-12 Noon, Afternoon 12 noon-6PM and evening 6 PM to 12 AM.

Pei Zhang, Senior Member, Xiaoyu Wu, Xiaojun Wang, and Sheng Bi (2015) have used load data of residential, commercial, industrial and municipal data which is of about 1.5 TB of data [19]. Author has proposed 5 steps, first is cluster analysis which helped to categorize the user's daily load pattern into the number of clusters. Second association Analysis in which the author has found out the critical variable for each consumer. Third decision tree used classification rules between the first two steps. Fourth model selection step which selects the model for each usage pattern using SVM. The fifth step is to forecast individual customer and then add up to get the system load. Cluster analysis shows that all holidays fall in the separate cluster. There are separate clusters which include most of the weekends, and two separate clusters which include most weekdays. Thus, weekdays are classified into two different groups. Also, there is a separate cluster which includes the first day after a holiday.

Fahiman, Erfanit, Rajasegarar, Palaniswami, and Leckie have explained how the combinations of K-shape clustering and the deep neural network is more accurate than K means and neural network [20]. During the feature selection author has used time cyclic feature in which it reflects the cyclic characteristic of time and type of day in which they used to sin, and cos function to calculate the values. Also segregated working and non-working days by marking 0 and 1 respectively.

Ying Chen have observed that load curve of Tuesday, Wednesday and Thursday are similar, and rest of the days are different [21]. Also, authors have selected weather variable based on calendar variable. For Example, in winter the actual and the temperature felt is different, so wind chill temperature is calculated which gives the felt temperature. However, in summer Humidex is used which is the combined effect of heat and humid. However, for ease of neural network implementation, these parameters were used throughout the year. In this paper, similar day selection criteria were used from ISO New England‘s operation procedure. Similar day needs to have the same weekday index and similar weather to that of tomorrow. The selected day had weekday and day of the year index and shown how similar weather was selected.

CHAPTER 3: BACKGROUND

The benchmark model used in this research is the Multiple Linear Regression (MLR) based model. It uses quantitative and class variable to forecast the load. In this research, several combinations of calendar variables are grouped to forecast the electricity consumption. This research uses MLR based Tao's Vanilla model as the benchmark model. This chapter describes the following topics:

1. Multiple Linear Regression
2. Tao’s Vanilla Benchmark Model
3. Evaluation Measurement
4. Model Evaluation Technique-Sliding Simulation

3.1 Multiple Linear Regression

Multiple linear regression is a statistical technique which models the relationship between the response and two or more predictor variables.

This method uses models, the relationship between them, by fitting a linear equation to the observed data. It assumes that error is normally distributed with mean zero and constant variance.

In this research, the electric load is the dependent variable, and all other is the independent variable. This model incorporates the categorical, and quantitative variables and the correlation between these variables are considered through the interaction effect. This section explains the theoretical background of MLR.

3.2 Tao's Vanilla Benchmark Model

Hong (2010) first introduces Tao's Vanilla benchmark model in his Ph.D. dissertation [1]. It is a multiple linear regression model, and many journal papers and forecasting competition use this as a benchmark model. This research also uses this model as a benchmark model. Further, we added the recency effect to the benchmark model to study the grouping pattern.

Parameters of Vanilla Benchmark:

a) Load: Load is the dependent variable which can be forecasted using different independent variable.

b) Trend: To capture the locally increasing or decreasing trend of demand, the model uses trend as a quantitative variable. The Trend variable is defined by assigning a natural number to each hour in ascending order.

c)Temperature (Temp): Temperature is one of the important predictor variables used in this benchmark model. There is a strong relationship between load demand and temperature which makes it a very significant predictor variable. This model uses 3rd order polynomial of temperature to forecast the load.

d) Calendar Variables: The consumption pattern of the load has different behavior at different times of the day, different days of the week, different months of the year. Along with hours, the day of the week, the month of the year this research uses 24 solar terms as input calendar variables to predict electric load consumption. These calendar variables (Hour, Day, Month, and Solar Terms) are qualitative variables and this model uses those as a seasonal block.

e) Interaction Effect: The temperature variation has a relationship with an hour of the day and month of the year. Also, 24 solar terms can be replaced with months [13]. Thus, the combined effect of temperature and calendar variable can be captured through cross effects.

The components of the benchmarking model are summarized below:

1) Quantitative Variable: Trend, Temp

2) Class Variable: Hour, Day, Month/ Solar Terms

3) Main Effect: Trend, Month/Solar, Temp, Temp2, Temp3

4) Interaction Effect: Day×Hour, Month×Temp, Month×$Temp^2$, Month×$Temp^3$, Hour×Temp, Hour×$Temp^2$, Hour×$Temp^3$

The equation of the regression model is as follows:

$$Load = \beta 0 + \beta 1.Trend + \beta 2.Month + \beta 3.Day + \beta 4.Hour + \beta 5.Day.Hour + \beta 6.Temp + \beta 7.Temp2 + \beta 8.Temp3 + \beta 9.Temp.Month + \beta 10.Temp2.Month + \beta 11.Temp3.Month + \beta 12.Temp.Hour + \beta 13.Temp2.Hour + \beta 14.Temp3.Hour \quad (1)$$

3.3 Evaluation Measurement

The evaluation measurement helps determine the accuracy of the forecasting model. Additionally, parameter estimation and model selection are also selected based on the evaluation measure. There are several ways to measure the performance of forecasting models such as absolute error, mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE):

Absolute Error (AE)= $|(y_t - \hat{y}_t)|$ (2)

Mean Absolute Error (MAE)= $\frac{\sum_{i=1}^{N} |(y_t - \hat{y}_t)|}{N}$ (3)

Root Mean Squared Error (RMSE)= $\sqrt{\frac{\sum_{i=1}^{N} (y_t - \hat{y}_t)|^2}{N}}$ (4)

Mean Absolute Percentage Error (MAPE)= $\frac{100}{N} \sum_{i=1}^{N} |(y_t - \hat{y}_t)|$ (5)

These evaluation measurement techniques are good to compare the series with same units. MAE is easy to interpret as opposed to RMSE, which is quite difficult to interpret. MAE is helpful to interpret average deviation of forecasted values from actual values. MAPE is quite popular among load forecasting community. It is often used to compare the forecast accuracy because it is very intuitive in terms of relative error. Some of the important characteristic of MAPE are scale independent, it gives equal weights to all observations, it is not sensitive to large errors, not sensitive to the sign of the error. For calculation of system load, normally load values are far away from zero and in those case MAPE can be more interpretable. In this research, MAPE is the main criterion for assessing forecast accuracy

3.4 Model Selection- Sliding Simulation

Sliding simulation is well known and a widely used forecast evaluation technique [31]. Sliding simulation better mimics forecasting operations as compared to cross validation. In sliding simulation training window is fixed or changing and it advances forecasting horizon by one year. Variable selection and selection of length of the history are one of the important applications of sliding simulations.

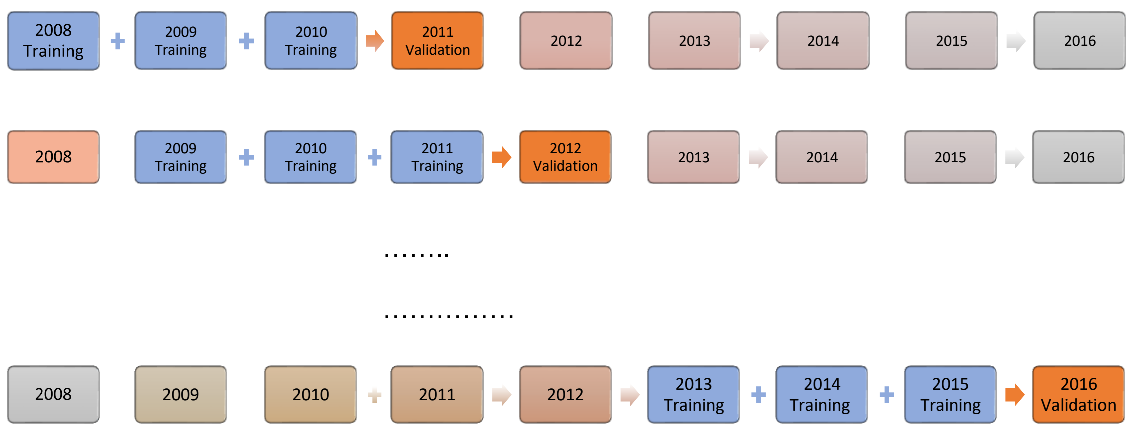

Figure 3. 1: Model Selection Technique-Sliding Simulation (2008-2016)

CHAPTER 4: HEURISTIC ALGORITHM

Hong (2010) discusses and presents the experiments which groups together different weekdays and selects the best grouping pattern [1]. The author also discusses the positive effect of grouping calendar variables which reduces the complexity of model and possibility of overfitting of the model. There is no standard rule on selecting the best grouping pattern of calendar variable. In Chapter 2, the various grouping pattern used in different research have been discussed. But none of these researches have done a comprehensive comparison and concluded the best among all possible grouping patterns. Besides, it varies based on the selection of training data set and validation data set as well. So, the selection of the best grouping pattern can be decided by enumerating each possible combination. But this approach is quite time consuming and cannot be affordable. Thus, the heuristic algorithm is proposed to search for this grouping pattern in fast and efficient way.

The heuristic algorithm searches solution of a problem in a much faster and more efficient way than standard or regular way of finding the solution. It sacrifices the optimality, accuracy, precision, or completeness of speed. Heuristic algorithm can solve the problem individually or it can be used to provide some baseline to start as to what is supported by some optimization algorithm. It is normally used when an approximate solution can be implemented, and the exact solution is quite computationally expensive. It is quite less likely that it will provide with the optimal solution for each problem, but the approximate solution provided by the heuristic algorithm is close to optimal solution. It will be more expensive to go for the exact solution.

This research discusses two heuristic algorithm which can find one of the best groups of calendar variable in a fast and efficient way. This algorithm was applied for grouping of weekdays, the month of the year, an hour of the day and 24 solar terms. Also, this research compared the result of the heuristic algorithm and the traditional way of grouping calendar variable. The result of the heuristic algorithm was compared with the traditional way grouping calendar variable based on the number of iterations it took to reach the optimal point, the time taken by the algorithm and forecasting accuracy.

This section will introduce the stepwise methodology of both heuristic algorithm and the next section discusses the implementation of this algorithm on publicly available data of ISO-New England utility which serves the eight zones and total system load of GEFCom2012 data.

4.1 Benchmark Approach

Literature review of this research has shown that different authors have proposed the different grouping pattern based on calendar variable. No-one has proposed the standard grouping pattern for any calendar variable. This may be because different data set has different load consumption pattern. So similar behaving calendar variables may be different for that data set. Also, it changes with reference to the year. So, selecting grouping pattern will always be dependent on data set, training and validation years.

Benchmark approach will try all possible combination of grouping the calendar variable. In this approach, we will find all possible ways of combining the calendar variable. Considering those combination in class variable of Tao's Vanilla benchmark multiple linear regression model, forecasts will be generated. All these forecasts are compared with actual load consumption to calculate mean absolute percentage error (MAPE). Thus, each possible combination will be assigned with individual MAPE. Those MAPE values are arranged in ascending order to find best performing grouping combination. This is the benchmark approach to calculate MAPE of all possible combinations and select the best combination based on least MAPE.

Number of possible combinations increases exponentially with increase in number of classes in calendar variable. Trying every combination will get time consuming as we start increasing with classes in specific calendar variable. Also, it gets even more time consuming if the model is very big, so processing time to perform each iteration increases and so does the total time.

It is important to note that hereafter Sunday will be represented with 1, Monday will be represented as 2 and so on for 7 days of week. January will be represented with 1, February with 2 and so on for 12 months of year. Hour will be represented as per the 24 hours of day. 24 solar terms will be represented based on [13].

4.2 Heuristic Algorithm 1- Sequential Grouping

Hong has proposed a heuristic algorithm in his book to find the best grouping pattern of weekdays [1]. Table 4.1 shows the calculation of number of possible ways of grouping the week days. There are 877 ways we can grouping the 7 weekdays. So, it would be very time consuming to try each possible combination and select the best out of it. Thus, the author proposed the heuristic algorithm by grouping two days, i.e., instead of considering those two different days consider them as one day and forecast for the validation period. So, there will be only 7 ways of grouping those weekdays. If forecast accuracy by grouping weekdays is better than considering every weekday differently, then that grouping pattern is the best grouping pattern to forecast electric load.

The idea behind testing each weekday that is adjacent to each other is that the consumption pattern of adjacent weekdays is similar and grouping them together will help predict the more accurate load forecast. It also reduces the degree of freedom of the model. Also, this heuristic algorithm has reduced the possibility of trying 877 possible combinations to 7 combinations and found the approximate solution which can improve the load forecast.

Similar approach can be applied to other calendar variables such as hour of the day, the month of the year and 24 solar terms and it will take 23, 11 and 23 iterations respectively to group two adjacent variables and can reduce the complexity of the model.

Table 4.1 Total possible combinations of grouping weekdays

No of Classes	No of Combination
1	1
2	63
3	301
4	350
5	140
6	21
7	1
Total	877

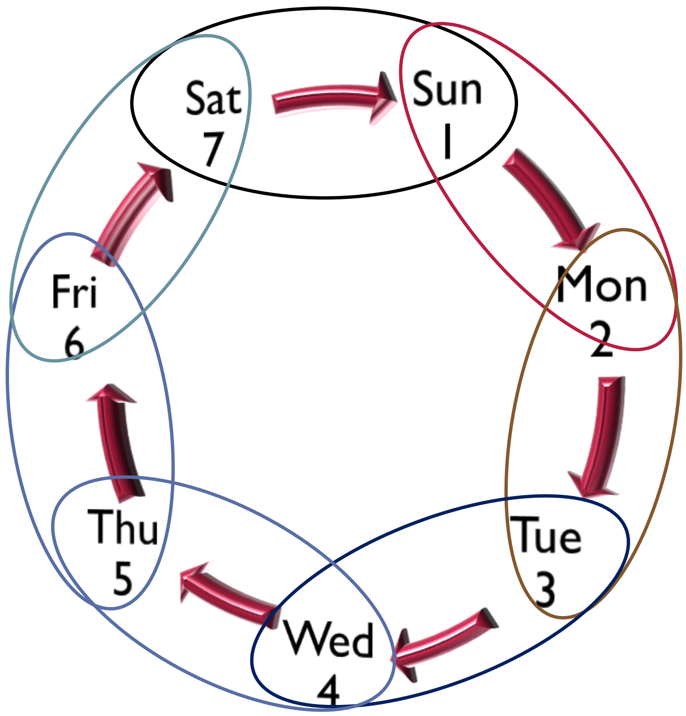

Figure 4. 1: Representation of Heuristic Algorithm 1-Sequential Grouping

4.3 Heuristic Algorithm 2- Branch and Bound Method

In the above-mentioned algorithm, it groups the two calendar variables which are adjacent to each other and rest are considered as different. But there is possibility that in one group it may consist of three calendar variables. However, this possibility was not considered in above algorithm. So, there can be different ways of grouping other calendar variables instead of only grouping adjacent calendar variables. This section will address this issue.

As it's quite computationally expensive to try each combination of grouping calendar variable. This algorithm proposed that first divide the calendar variables into only two parts i.e., instead of considering the 7 classes for day of week or 12 classes for month of the year or 24 classes for hour of the day or 24 classes for solar terms we will initially consider there will be only two classes for each calendar variable. For example, in case of grouping days of the week, instead of assigning each day with 1 to 7 we will consider week can be divided only in two days. Then we will try all possible ways of keeping actual classes of calendar variable in two classes. For example, in case of days of the week, in the first class there can only be one-week day and rest all weekdays can be considered as other day. Also, it can be possible that first class can be represented by two different weekdays days and rest other weekdays will be represented as other day and so on. Thus, this algorithm will find out all possible combination of grouping all classes of calendar variable into two classes and forecast year ahead load with each possible combination. Then all forecasts are compared with actual load to calculate the mean absolute percentage error (MAPE). The combination with least MAPE is considered for further break down. We consider that best combination has similar feature among them or it also can be seen in the other way that days, months or hours in the first part has similar feature as compared to variables in second parts.

Best performing combination of dividing calendar variable into two classes can be divided further 3 classes into two ways. One possible way can be, try all possible ways of dividing first class into two classes and keep second class as it is. Restricting second class as it is, that's where we are reducing the combination which are not necessary. Also, another way can be by dividing second class into further two classes and now keeping first class as it is. So, the number of combinations will depend on the configuration of parent class. For example, let’s consider best performing group when dividing calendar variables in two parts is 3 and 4 i.e., any three days of week in first class and other 4 days in second class. Now, while dividing two class into 3 class, 3 days of first class can be divided in further two classes in one way (keeping other 4 days of second class as it is) and total combinations can be calculated as $\binom{3}{1}$ = 3 ways. However, 4 days of second class (now keeping 3 days of first class as it is) can divided in two ways and total combination can be calculated as $\binom{4}{1} + \binom{4}{2}$= 10 ways. We will calculate the forecast of all 10+3=13 combination and forecast having best accuracy i.e., less MAPE value among 13 values will be considered as best way of dividing the calendar variable in three parts. Thus, this combination will be selected as the base group to divide further in four classes in the same way as explained above. We will do this branch and bound method until the maximum possible grouping ways that would be n-1, is reached, where n is total number of classes of that calendar variable.

This algorithm will try a smaller number of iterations as compared to trying all possible combinations. When calculating the forecast of all possible combinations grouping the calendar variables into two classes will have same iterations of benchmark method and method explained in this section. Further dividing in more classes, benchmark method will have lot more combinations because it selects each combination from actual classes of calendar variable. However, this approach finds the all possible combinations from best performing group among dividing two classes. For instance, in case of days of week, 7 days of week can be divided into two classes in three ways:

1. Keep any one day of week in first class and rest six days of week in second class. Thus, there will be $\binom{7}{1}$=7 ways of grouping them.

2. Keep any two days of week in first class and rest five days of week in second class. Thus, there $\binom{7}{2}$=21 ways of keeping two days in first class and rest five days in second class.

3. Keep any three days of week in first class and rest four days of week in second class. thus, there will be $\binom{7}{3}$=35 ways of keeping three days in first class and rest four days in second class.

If we further divide days of week to keep four days of week in first class and the rest three days of week in second class, then that combination will be same as that of 3rd case. So, benchmark method and heuristic algorithm will have same techniques and possible combinations when dividing the calendar variables into two classes. So, benchmark method and heuristic algorithm 2 will try 7+21+35=63 combinations and generate 63 forecasts to find the best performing combination among these 63. However, now in case of considering three classes instead of two, benchmark method will try all possible ways of grouping 7 days of week in three classes and that combinations can be $(\binom{7}{1} * \binom{6}{1})/2=21$, $(\binom{7}{1} * \binom{6}{2}) = 105$, $(\binom{7}{2} * \binom{5}{2})/2=105$, and $(\binom{7}{1} * \binom{6}{3})/2=70$. So total combination tried by benchmark model will be 21+105+105+70=301 and among 301 forecasts it will select the best based on least MAPE. Now, heuristic algorithm will handle this case differently. Let's assume that the best configuration i.e., having least MAPE among 63 combination is any 3 days of the week in first class and rest 4 days of the week in other class. To calculate possible combination of dividing the calendar variables in three classes, heuristic algorithm will calculate dividing 3 days of the week in two parts and keeping rest 4 days of the week of second class as it is. So possible combinations will be $\binom{3}{1} = 3$. Second possibility is to divide the 4 days of week in second class into further two classes while keeping first class as it is. So total possible combinations will be $\binom{4}{1}+(\binom{4}{2})/2=$ 4+3=7. So heuristic algorithm will try 7+3=10 combinations and select the best configuration for further division. Thus, benchmark model with 301 iterations and heuristic algorithm will try only 10 iterations to select best among them. Further, this approach will select best performing group among all division down the line and finally will select best performing i.e., having least MAPE will be considered as best grouping pattern for that model. Also, finally it also compares all results with no grouping of calendar variables.

Below figure 4.2 is schematic diagram for Heuristic 2 algorithm which explains stepwise procedure for execution.

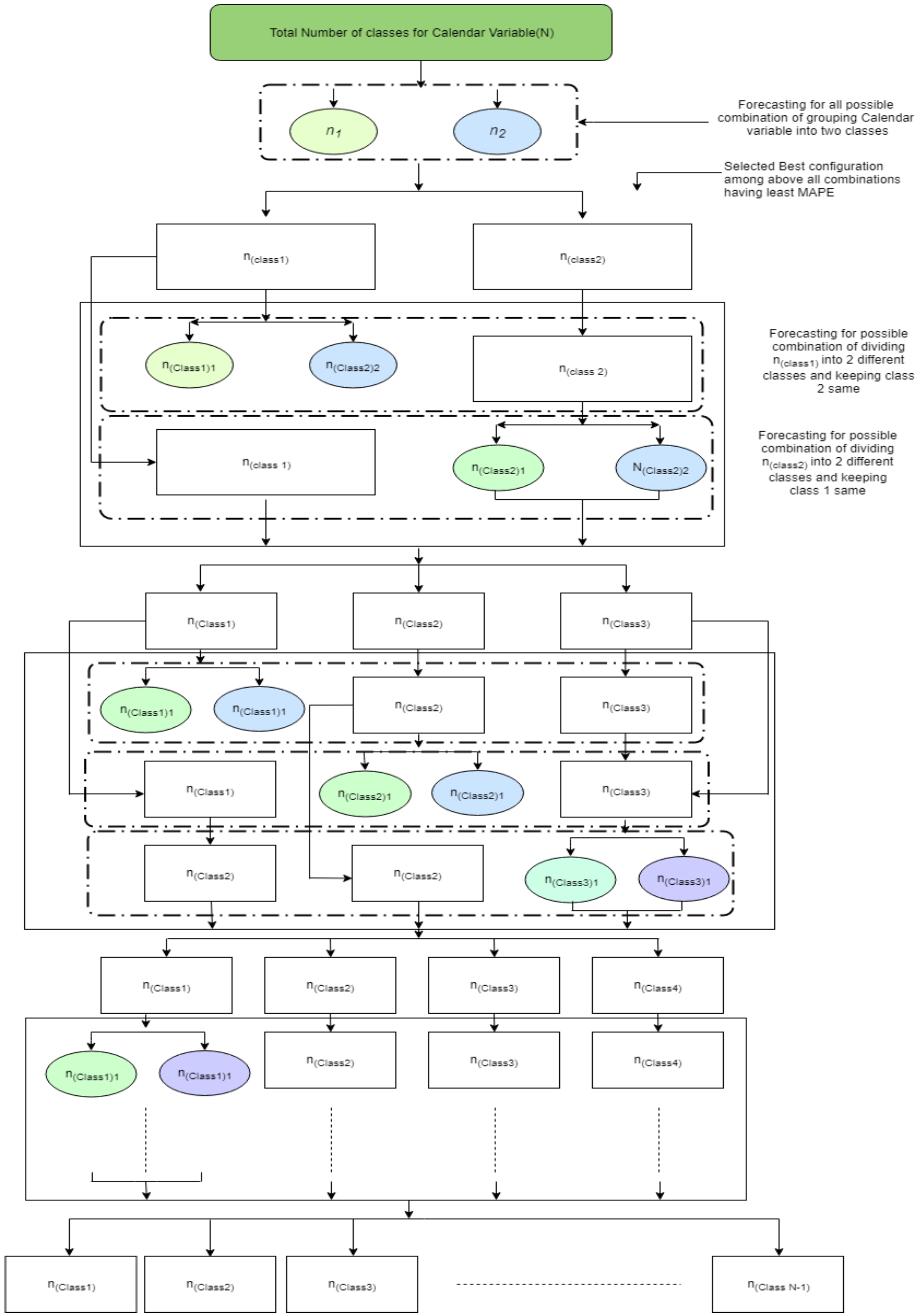

Figure 4. 2: Representation of Heuristic Algorithm 2-Branch and Bound Method

4.4 Heuristic Algorithm 3- Modified Branch and Bound Method

It can be easily found that heuristic algorithm 2 will try a smaller number of iterations as compared to benchmark model. Benchmark model will give global minimum while heuristic algorithm will give local minimum. The local minimum may or may not be equal to global minimum. However, local minimum will be very near to global minimum and that can be acceptable because cost of computation for benchmark method is very high as compared to heuristic algorithm 2.

Similarity between the heuristic algorithm 2 and benchmark method is that both would find all possible combination of grouping calendar variables in two classes. In case of days of week those combinations are 63 and in case of grouping months that combinations are 2047. Using high computation software, 2047 combinations will not take that much of time. However, in case of 24 hours of the day or 24 solar terms of year grouping hours or solar terms in two classes will try 8388607 i.e. around 8.38 million combination just to find the best combination when dividing calendar variable in two classes. Table 4.3 shows the calculation of number of combinations. This number almost double the all possible combination of grouping months which is around 4.17 million. It is computationally high and not an efficient approach to find the best grouping configurations. Heuristic algorithm 3 -Modified Branch and Bound method is proposed to handle this kind of issue.

Table 4.2: Total possible combinations of grouping months of the year

No of Classes	No of Combination
1	1
2	2047
3	86526
4	611501
5	1379400
6	1325652
7	627396
8	159027
9	22275
10	1705
11	66
12	1
Total	4215596

Table 4.3: Possible combinations of grouping hours in two classes

Class 1	Class 2	No. of Combinations
1	23	24
2	22	276
3	21	2024
4	20	10626
5	19	42504
6	18	134596
7	17	346104
8	16	735471
9	15	1307504
10	14	1961256
11	13	2496144
12	12	1352078
Total		8388607

Heuristic algorithm 2 and Heuristic algorithm 3 is similar to each other, except in the first step i.e., to find the best configuration of grouping the calendar variable into two classes. As discussed above it is computationally very expensive, once the classes of calendar variable start increasing. This approach modifies the first step of heuristic algorithm 2 i.e., it proposes another way to find the best configuration of grouping the calendar variable into two classes that is lesser computationally expensive as compared to heuristic algorithm 2. It suggests to first try all possible ways of assigning only one value to first class and rest others in second class and forecast for all combination.

Thus, every time one value will enter in the first class and in the next iteration it will be replaced with another value of the calendar variable. So, we will try all possible combinations and after comparing with actual consumption best configuration will be selected based on least MAPE. So best configuration will have one value in first class and (n-1) values in second class where n is classes in which that calendar variable is divided (n=7 for week, n=12 for months, n=24 for hour and n=24 solar terms). Now, fix the value in first class and try adding one more value in first class from (n-1) values of second class. So now we will try n-1 ways and n-1 forecast will be compared with actual and configuration with least MAPE is selected. Hence now in first class there will be 2 values and n-2 values in second class. This procedure will further be tried for n-2 times. Thus, total number of possible combinations will be $(n(n+1)/2)-1$ and best configuration will be selected which having least MAPE. Once this best configuration is achieved for dividing the calendar variable into two classes. Further the similar technique as of heuristic algorithm 2 will be applied to further stepwise splitting of the classes. First class of variables further divided into two classes keeping second class as it is, and second class can be divided into two classes. Thus, try all possible combinations and forecast for each combination. Best forecast with combination is selected for further split. Thus, we will get the best configuration of dividing calendar variable into three classes and this configuration can be used to further split into four classes. This process will continue till n-1 which is the last possible way of splitting the classes and in last combination it will have a group with only two values and all other classes consist of only one value of calendar variable. Below Figure 4.3 process flow explains for the modification for the case hours.

To further explain the Heuristic algorithm 3 - Modified Branch and Bound Method, this section will be explaining the approach by taking the example of grouping the days of the week. So, algorithm will try all possible combination of grouping only one value in first class and other 6 values in second class. So, there will be 7 iterations and 7 forecasts will be generated. More accurate forecast among them is selected and corresponding configuration will be selected. Let’s assume that keeping Thursday (weekday=4) in first class and all others in second class is more accurate than any other combination. So, for next trial, each value from second class is considered along with Thursday such as Thursday and, Sunday in group 1 and rest in other group. In next iteration Thursday and, Monday in group 1 and rest in the other group and so on. So, algorithm will try 6 possible combination keeping Thursday constant throughout. After all trials, let's assume that grouping Thursday and Wednesday together gives best result and hence in the next iterations we would group Thursday, Wednesday and each weekday trying 5 combinations. The one with best MAPE will be selected. Thus, algorithm will find the best configuration of keeping three weekdays in first class and rest other weekdays in other class. Thus, it will try until there will be 2 weekdays in second class. So, there will be 7+6+5+4+3+2=27 iterations. It will find the best configurations of grouping week days in two classes. As mentioned earlier Heuristic algorithm tried 63 trial to find best and Heuristic algorithm tried only 27 iterations. Once best configuration is obtained from the method, similar approach of Heuristic algorithm 2 is applied further to find best grouping pattern.

Figure 4. 3: Process flow of Modified Heuristic Algorithm 2 (Heuristic Algorithm 3)

CHAPTER 5. THE EXPERIMENT

In this Section, the proposed heuristic algorithms are applied to ISO New England and GEFCom2012 dataset to compare the performance and improvement of benchmark and heuristic algorithm. ISO-New England serves the eight zones under them and aggregated load of eight zones are represented with ISONE data set. Also, total system load of 20 zones of GEFCom2012 is also used for implementation of these heuristic algorithm. MLR based Tao's Vanilla Benchmark model is used to forecast for every combination. ISO New England's data was used to find the best configuration with same model and rolling validation year and GEFCom2012 data set was used to study the grouping pattern when model grows. Hour, day and month are class variables in this multiple linear regression. Sunday will be represented with 1, Monday will be represented as 2 and so on for 7 days of week. January will be represented with 1, February with 2 and so on for 12 months of the year. Hour will be represented as per 24 hours of day. 24 solar terms will be represented based on [13].

This section discusses the implementation of Benchmark Model, Heuristic Model 2 and Heuristic Model 3 for each calendar variable i.e., day of week, month of year, hour of day and 24 solar months. Sliding simulation is one of the widely used forecast evaluation technique. Equal length of history is used to evaluate the coefficient of independent variable. Three years of predefined length is used as training period and load of next year is forecasted. For example, load of year 2011 is forecasted using training period of year 2008 to year 2010. Then forecasting origin is forwarded with one year. Now, 2009 to 2011 is used to forecast load of 2012 and so on.

To study the effect of grouping calendar variables on different year and same model, this research used ISO New England data. Tao's vanilla benchmark model was used to forecast the load of a year and previous three years of data is used as a training data and forecasting window moves forward by each year keeping training period constant. To find out the scope of improvement by grouping the calendar variable the forecasting error found by no grouping and grouping was compared. It shows that if perfect grouping pattern identified then the possible improvement in forecasting error. Also, to inspect the effect of grouping calendar variables when model grows on same validation period, GEFCom2012 data was used. The best grouping patterns found in the validation period is directly used to forecast the load of test period.

5.1 Data

This research uses publicly available nine years (2008-2016) of hourly load and temperature data of ISO New England [32]. ISO New England serves eight load zones in six states. This case study uses system total load which is sum of load from eight zones. To adjust the load data for Daylight-saving time (DST), at beginning hour of DST, zero reading is replaced by average of adjacent two hours and at end hour of DST, load value is divided by two. Three years of data is used for training and next year as validation and another next year as test data Also, to avoid the holiday effect on model all US federal holidays have been removed from dataset. Also, to study the effect of grouping with growing model, we used GEFCom2012 data to these experiments.

Following figures 5.1 and 5.2 shows the time series plot of hourly load and temperature data.

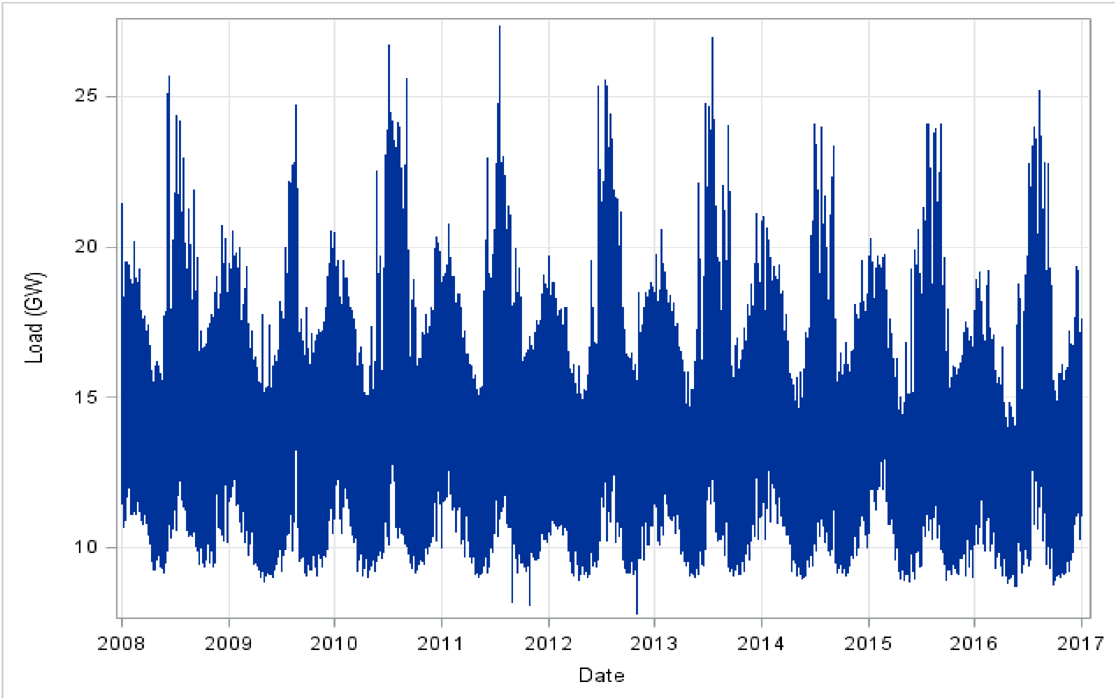

Figure 5. 1: Time series plot of hourly load (GW) for ISO-New England (2008-2016)

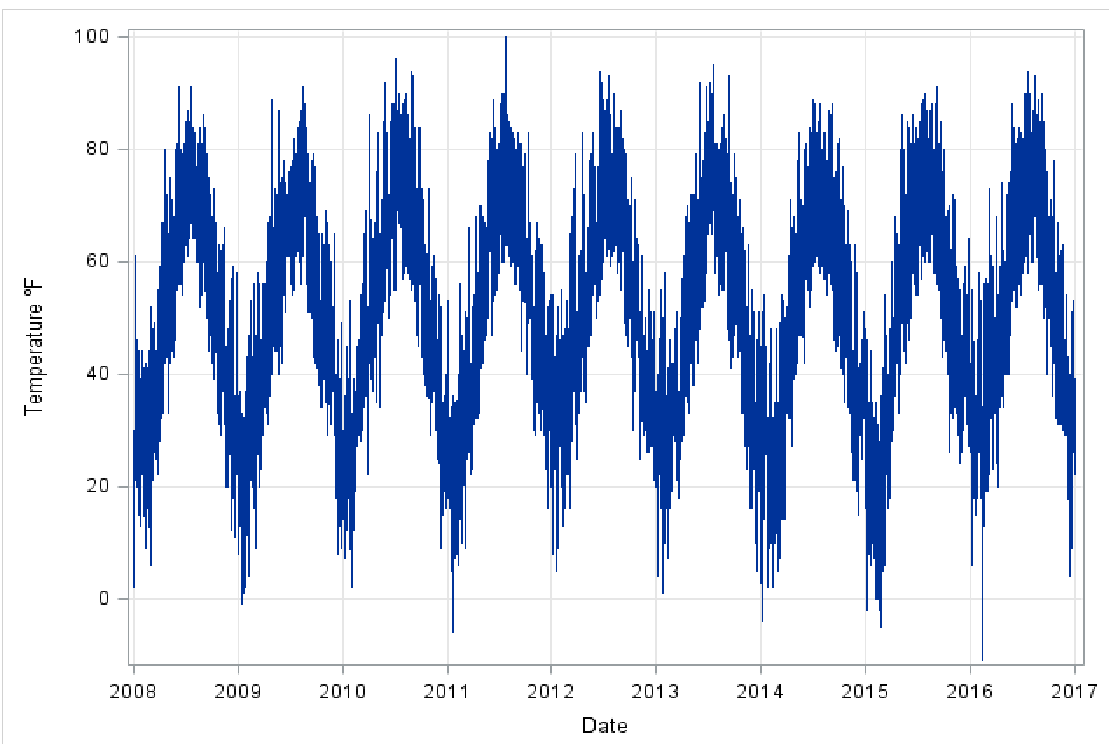

Figure 5. 2: Time series plot of hourly temperature (^{0}F) for ISO-New England (2008-2016)

5.2 Seasonality

This research uses hour of the day, day of the week, month of the year and solar month of the year as a calendar variable or seasonal block. Since temperature is one of the important predictor variables in Tao's Vanilla Benchmark model, seasonal behavior of both temperature and load should be studied based on the calendar variable. This section discusses relationship of load and temperature.

5.2.1 Hours of a day

Temperature changes during the day based on sunrise and sunset. This can lead to the seasonality between temperature throughout the day. Since there strong relation between temperature and load then this should be observed in hourly time series plot of a day. Also, figure 5.3 shows the temperature vs load scatter plot by each hour of the day. As there is temperature difference on each hour of the day throughout the year, figure shows that it also reflects in load level as well. Also, there is a difference in load profile of summer and winter days. Normally, it is observed that there are two peaks in winter days; one in the morning and one in the afternoon. However, there is only one peak value is observed during the summer days. Generally, this peak value is observed during the noon. Thus, interaction of hour with temperature and its polynomial terms is included in the model.

5.2.2 Day of the week

Human activity during the week is also one of the important factors in electricity consumption. Human activities are different throughout the week [1]. Normally, offices function during the weekdays and are shut during the weekends. Hence, load profile on weekends are different than that of the weekdays. However, the temperature is not correlated with the weekdays, thus interaction of the day of week with temperature is not significant. Few of the authors have proposed several grouping methods for days of the week. Weekends and Tuesday-Thursday are grouped together to forecast electric load in [33]. However, Tuesday-Thursday are grouped together, and other days are kept separate for electric load forecasting in [34]. Another way which is commonly followed by forecasters is to consider all days of week separately [35]. In this research, we tried all possible ways of grouping the days of the week.

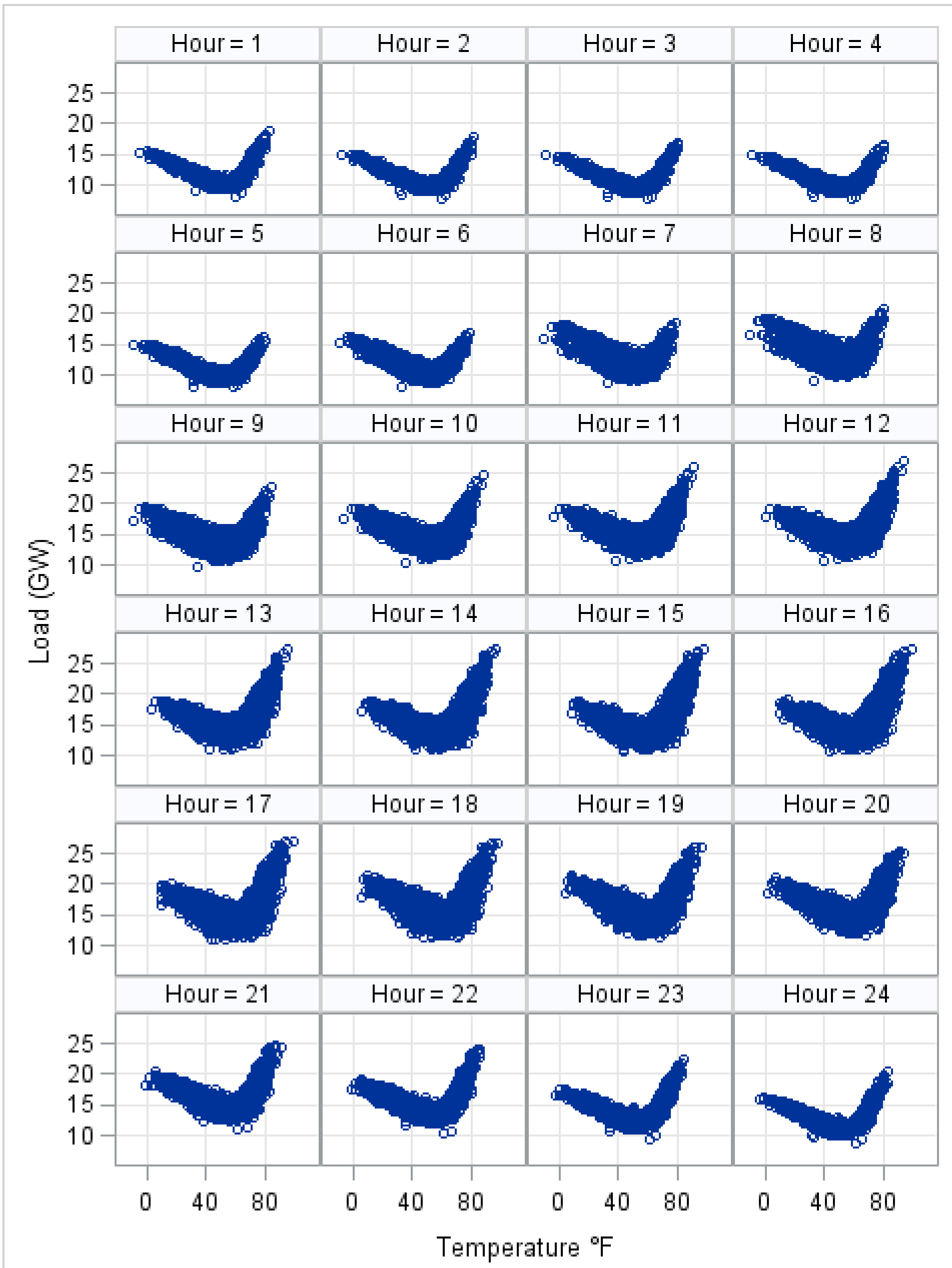

Figure 5. 3: Load-Temperature Scatter Plot for each hour of data

5.2.3 Month of the Year

There is a variation in temperature during the year and there is strong relationship between the month and the temperature. Figure 5.4 shows scatter plots of load vs temperature pattern for each month during the year. It's been observed that there are two peak loads in winter and one peak load in summer. To consider the variation of temperature throughout the year, month is used as class variable and interaction of month with temperature is considered.

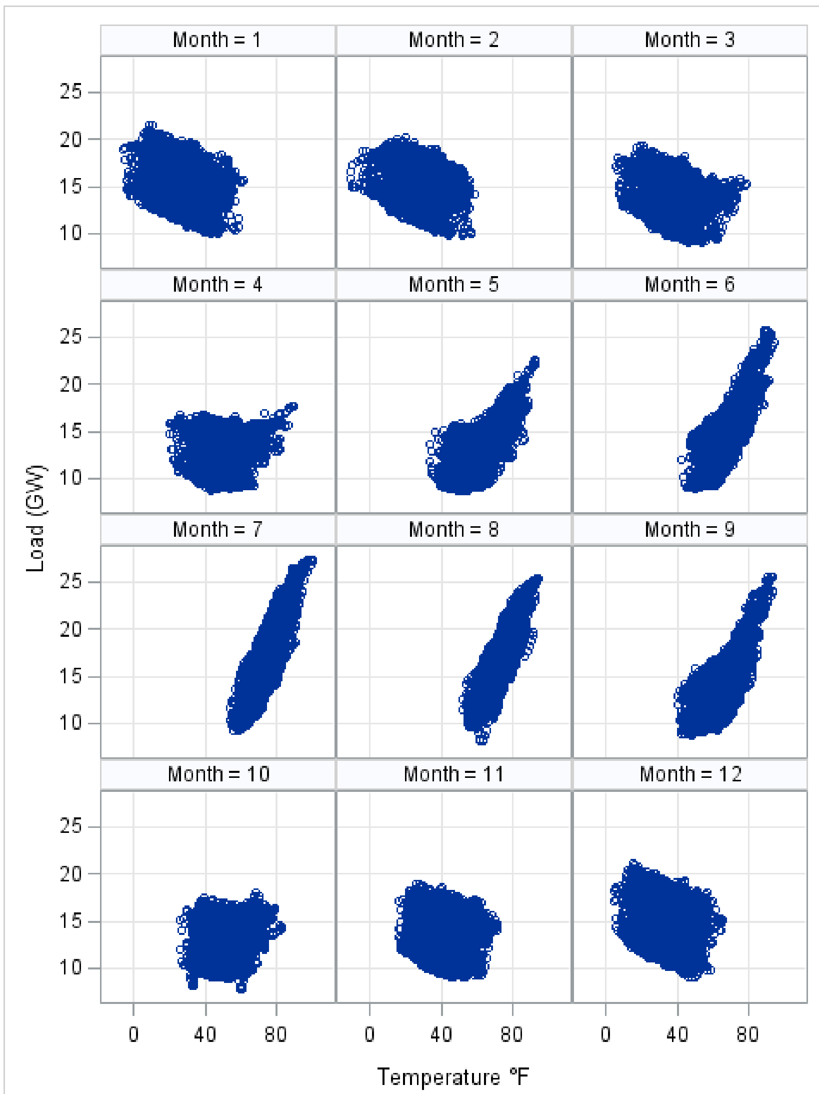

Figure 5. 4: Load-Temperature Scatter Plot for each month of the year

5.2.4 Solar Months of the Year

Gregorian calendar is the most common calendar used worldwide for daily activities and for electric load forecasting to classify the months. Gregorian calendar divides a year in 12 months based on the Moon's orbit around the earth. Xie and Hong (2018) proposed 24 solar terms to divide the year in 24 parts [13]. These 24 solar terms were originally from the ancient China to guide people for their agriculture activities. Figure 5.5 shows the temperature vs load curve for each solar term throughout the year.

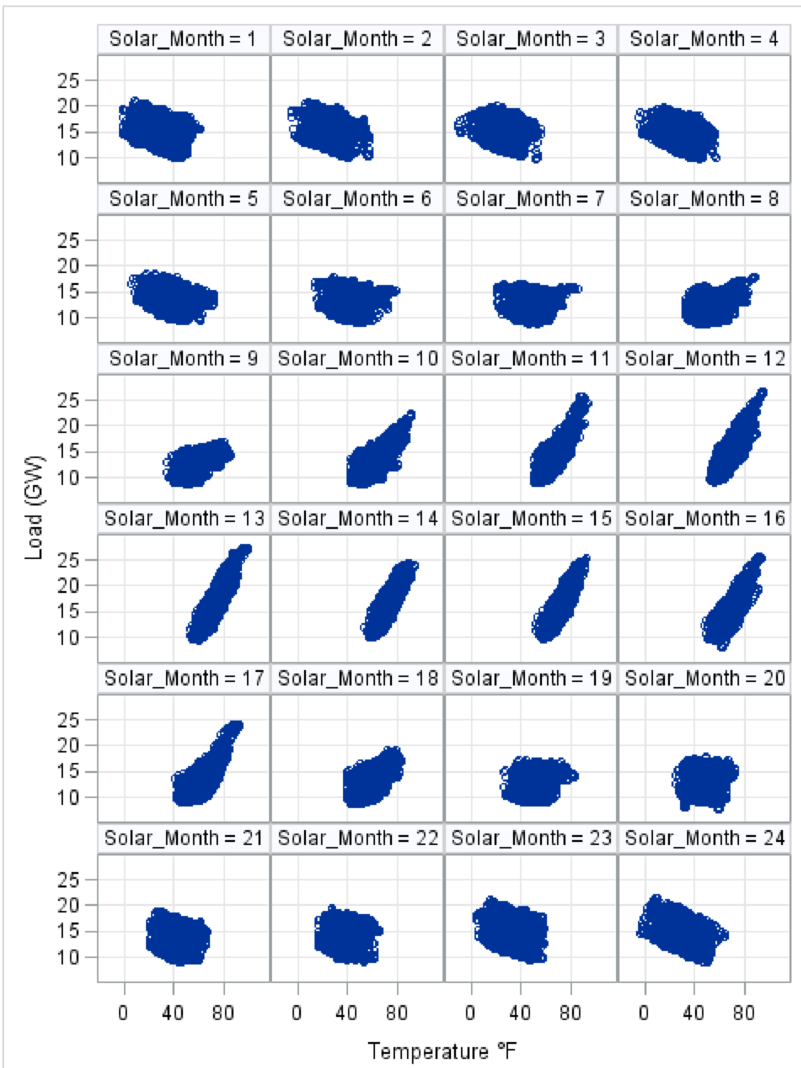

Figure 5. 5: Load-Temperature Scatter Plot for each solar month

5.3 Days of a week

As per the benchmark approach, forecast of all possible combinations of grouping calendar variable are compared with actual consumption, selecting the most accurate forecast and best grouping combination. Table 4.1 shows the calculation of number of possible combinations based on number of classes. Table 5.1 shows the MAPE and iterations it took to find the combinations of grouping calendar variable among each class and best grouping configuration.

For Heuristic algorithm 1 adjacent days of week are grouped together. In this approach only two classes are grouped together, and errors are calculated. Number of possible combinations will always be fixed for calendar variable.

Heuristic algorithm 2 is applied to ISO New England and GEFCom2012 data to find the best grouping pattern in a faster way. To evaluate the proposed algorithm the forecasting accuracy of model with grouping calendar variables compared with forecasting accuracy of the model without grouping any calendar variables. Also, best grouping pattern found in validation data is directly used in test data forecast load of test data. Another scope of comparison is number of groups formed by optimal solutions. No grouping model will have maximum number of grouping and heuristic algorithm will have minimum number of grouping. Heuristic Algorithm 3 is faster than Heuristic 2 and provides almost similar results.

Results obtained in table 5.1 are using Tao's benchmark model to ISO New England's data. To study the final number of groups when model grows, recency effect is applied to benchmark model [6]. First, average temperature of last 24 hours (T_{ave}), square and cube of temperature (T_{ave}^2, T_{ave}^3) and their interaction with class variable month and hour is added to model to check the number of groups. Then, stepwise one lag of temperature, two lag of temperature, three lags of temperature and so on along with their square, cube and interaction with month and hour is also included. It does not follow any specific trend of reduction or increasing the number of groups. Lags are denoted by "h" and daily average is denoted by "d". General formulation is explained below:

$$T_{t,d} = \frac{1}{24}\sum_{h=24d-23}^{24d} T_{t-h} \quad \text{, where d= 1, 2, 3. . ..11.} \tag{6}$$

$$Y_t = \beta_0 + \beta_1\, Trend + \beta_2\, Month + \beta_3\, Day + \beta_4 Hour + \beta_5 Day \;\times hour + f(T_t) + \sum_d f(T_{(t,d)}) + \sum_h f(T_{t-h}) \tag{7}$$

where $\mathrm{f}(T_t) = \beta_6 T_t + \beta_7 T_t^2 + \beta_8 T_t^3 + \beta_9 T_t M_t + \beta_{10} T_t^2 M_t + \beta_{11} T_t^3\, M_t + \beta_{12} T_t H_t + \beta_{13} T_t^2\, H_t + \beta_{14} T_t^3\, H_t$

Table 5.1 -Table 5.4 shows the result of ISO New England data set based on different performance matric for grouping days of a week. Figure 5.6 shows the possible improvement by in forecasting accuracy by grouping weekdays with same Tao's vanilla benchmark model.

Table 5. 1 Comparison of performance of heuristic Algorithms on validation data for grouping days of week (ISO New England)

Performance Metric -MAPE (%)-Validation Data					
Validation Year	**No Grouping**	**Benchmark Approach**	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
2011	3.0730	3.0717	3.0726	3.0717	3.0717
2012	2.8478	2.8455	2.8455	2.8455	2.8455
2013	2.9594	2.9580	2.9580	2.9580	2.9580
2014	3.1598	3.1580	3.1580	3.1580	3.1580
2015	3.4548	3.4540	3.4542	3.4542	3.4540
2016	3.1963	3.1907	3.1947	3.1907	3.1907

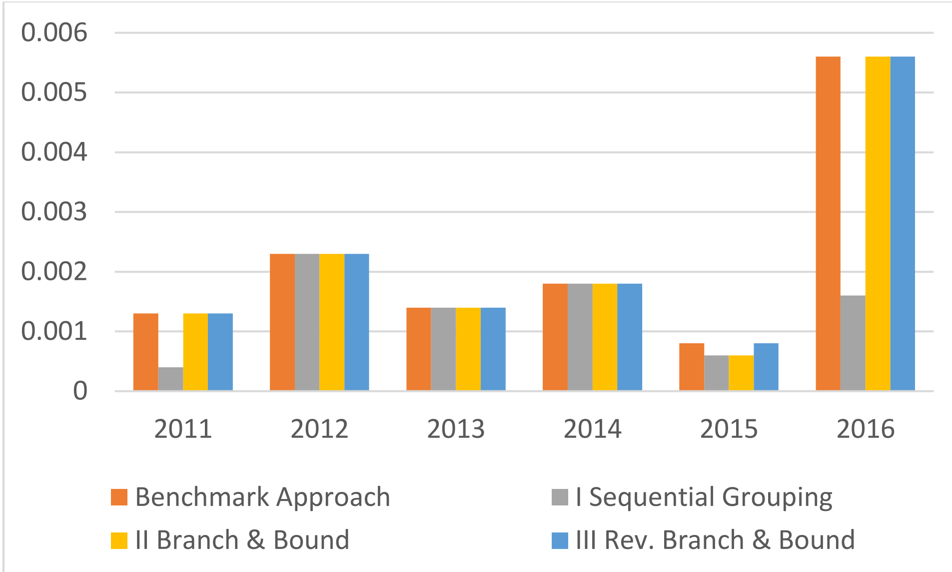

Figure 5. 6 Difference in MAPE as compared to 'No Grouping' for days of a week (ISO New England)

Table 5. 2.: Number of iterations to reach best combination of grouping days of a week (ISO New England)

Performance Metric -Iterations					
Validation Year	**No Grouping**	**Benchmark Approach**	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
2011	1	877	7	108	72
2012	1	877	7	108	72
2013	1	877	7	108	72
2014	1	877	7	108	72
2015	1	877	7	108	72
2016	1	877	7	108	72

Table 5. 3 Number of groups formed by best combination of grouping days of a week (ISO New England)

Performance Metric -No. of Groups					
Validation Year	No Grouping	Benchmark Approach	I Sequential Grouping	II Branch & Bound	III Rev. Branch & Bound
2011	7	6	6	6	6
2012	7	6	6	6	6
2013	7	6	6	6	6
2014	7	6	6	6	6
2015	7	5	6	6	5
2016	7	6	6	6	6

Table 5. 4 Number of groups formed by best combination of grouping days of a week when model grows (Heuristic Algorithm 3)

d	h	2011	2012	2013	2014	2015	2016
0	0	6	6	6	6	5	6
1	0	6	6	6	6	5	6
	1	6	6	6	6	5	6
	2	6	6	6	6	5	6
	3	6	6	6	6	5	6
	5	6	6	6	6	5	6
	7	6	5	6	6	5	6
	9	6	6	6	5	5	6
	11	6	6	6	5	5	6

To study the same grouping pattern on test data set, the best grouping pattern of validation year is used to forecast the test year. Test year is next year to the validation year and 3 previous years of data is used as training year. Table 5.5 shows the result of test year and Table 5.6 shows the grouping pattern used to forecast the result. Grouping pattern in table 5.6 is best grouping pattern in the validation year.

Table 5. 5 Comparison of performance of heuristic Algorithms on test data for grouping days of Week (ISO New England)

Performance Metric -MAPE (%)-Test Data					
Test Year	**No Grouping**	**Benchmark Approach**	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
2012	2.8478	2.8473	2.8455	2.8473	2.8473
2013	2.9594	2.9595	2.9595	2.9595	2.9595
2014	3.1598	3.1618	3.1618	3.1618	3.1618
2015	3.4548	3.4542	3.4542	3.4542	3.4542
2016	3.1963	3.1908	3.1947	3.1947	3.1908
2017	5.1908	5.1933	5.1933	5.1933	5.1933

Table 5. 6 Grouping pattern of days of a week used to forecast on test data (ISO New England)

Performance Metric -Grouping Pattern				
Test Year	**Benchmark Approach**	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
2012	(3,5)	(3,4)	(3,5)	(3,5)
2013	(3,4)	(3,4)	(3,4)	(3,4)
2014	(4,5)	(4,5)	(4,5)	(4,5)
2015	(3,4)	(3,4)	(3,4)	(3,4)
2016	(3,4,5)	(3,4)	(3,4)	(3,4,5)
2017	(3,4)	(3,4)	(3,4)	(3,4)

To study the effect of the grouping when model grows and to check the potential of improvement, GEFCom2012 data was used. In this case, validation and test year is same but model grows. Parameters of d and h shows the number of average temperature and lag of temperature along with their polynomial forms and interaction with calendar variables. Like ISO New England's data, heuristic algorithm was implemented on GEFCom2012 validation data and tested on next year. Table 5.7- Table 5.9 show the results of GEFCom2012 data. Figure 5.7 shows the improvement in the forecast accuracy on test data as compared to no grouping.

Table 5. 7 Comparison of performance of heuristic Algorithms on validation data for grouping days of a Week (GEFCom2012)

Performance Metric -MAPE (%)-Validation Year-2006				
Model Configuration	**No Grouping**	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
d=0, h=0	4.8344	4.8261	4.8256	4.8256
d=1, h=0	4.0629	4.0552	4.0549	4.0549
d=1, h=1	3.8796	3.8715	3.8715	3.8715
d=1, h=2	3.7751	3.7676	3.7676	3.7676
d=1, h=3	3.7184	3.7110	3.7110	3.7110

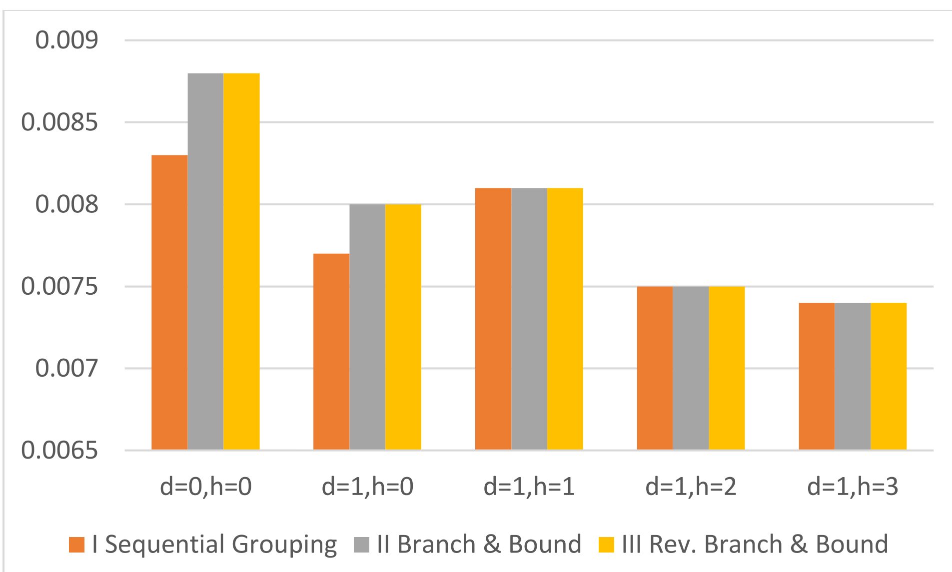

Figure 5. 7 Difference in MAPE as compared to 'No Grouping' for days of a week (GEFCom2012)

Table 5. 8 Comparison of performance of heuristic Algorithms on test data for grouping days of a Week (GEFCom2012)

Performance Metric -MAPE (%)-Test Year-2007				
Model Configuration	**No Grouping**	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
d=0, h=0	5.1050	5.1030	5.1021	5.1021
d=1, h=0	4.4317	4.4310	4.4319	4.4319
d=1, h=1	4.3187	4.3177	4.3177	4.3177
d=1, h=2	4.2440	4.2432	4.2432	4.2432
d=1, h=3	4.1980	4.1965	4.1965	4.1965

Table 5. 9 Grouping pattern of days of a week used to forecast on test data (GEFCom2012)

Performance Metric -Grouping Pattern			
Model Configuration	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
d=0, h=0	(3,4)	(3,4,5)	(3,4,5)
d=1, h=0	(4,5)	(3,4,5)	(3,4,5)
d=1, h=1	(4,5)	(4,5)	(4,5)
d=1, h=2	(4,5)	(4,5)	(4,5)
d=1, h=3	(4,5)	(4,5)	(4,5)

5.4 Months of the year

Table 4.2 shows the calculation of all possible combination of grouping months. As it will be time consuming to try all combinations and select best out of them, we tried all possible combinations and selected best out of them to compare the result with heuristic algorithm. Result obtained through the benchmark model is global minimum and results obtained through heuristic algorithms are local minimum. It can be inferred that often heuristic algorithms reach global minimum. But local minimum is not that far from global minimum and can be easily acceptable as it saves us from hugely computationally expensive approach.

Also, MAPE of 'without grouping calendar variable' is considered as a benchmark and it is compared with best outcome of each heuristic algorithm. There is improvement of 1% to 10% also there they reduced the complexity of model. Table 5.10 -Table 5.12 shows the comparison of each techniques on validation period of ISO New England data.

Table 5. 10 Comparison of performance of heuristic Algorithms on validation data for grouping months of a year (ISO New England)

Performance Metric -MAPE (%)					
Validation Year	**No Grouping**	**Benchmark Approach**	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
2011	3.0730	2.9055	3.0568	2.9055	2.9055
2012	2.8478	2.7059	2.8089	2.7407	2.7180
2013	2.9594	2.8771	2.9407	2.8952	2.8952
2014	3.1598	3.1142	3.1471	3.1142	3.1188
2015	3.4548	3.2605	3.4121	3.2802	3.2653
2016	3.1963	3.0750	3.1599	3.0852	3.0852

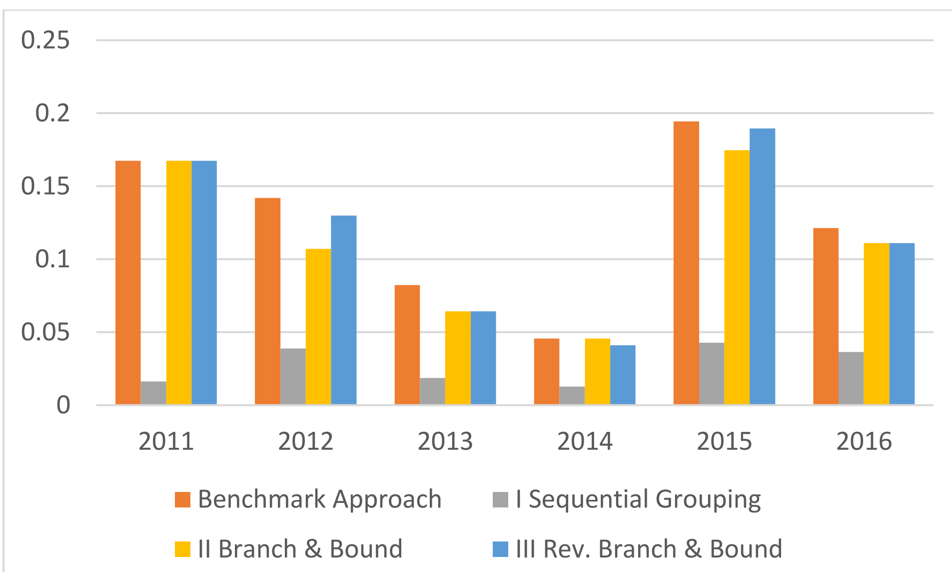

Figure 5. 8 Difference in MAPE as compared to 'No Grouping' for months of a year (ISO New England)

Table 5. 11 Number of iterations to reach best combination of grouping months of a year (ISO New England)

Performance Metric -Iterations					
Validation Year	No Grouping	Benchmark Approach	I Sequential Grouping	II Branch & Bound	III Rev. Branch & Bound
2011	1	4,173,964	12	2866	434
2012	1	4,173,964	12	2684	361
2013	1	4,173,964	12	2722	290
2014	1	4,173,964	12	2725	350
2015	1	4,173,964	12	2721	378
2016	1	4,173,964	12	2680	248

Table 5. 12 Number of groups formed by best combination of grouping months of a year (ISO New England)

Performance Metric -No. of Groups					
Validation Year	No Grouping	Benchmark Approach	I Sequential Grouping	II Branch & Bound	III Rev. Branch & Bound
2011	12	7	11	7	7
2012	12	8	11	7	9
2013	12	7	11	8	8
2014	12	9	11	9	8
2015	12	6	11	6	6
2016	12	8	11	9	9

As explained in section 5.3, we also did the experiments for grouping months to check the number of groups when model grows. Implemented same technique mentioned in section 5.1. Table 5.13 shows the number of groups obtained for each model.

Table 5. 13 Number of groups formed by best combination of grouping months of a year when model grows (Heuristic Algorithm 3)

d	h	2011	2012	2013	2014	2015	2016
0	0	7	9	8	8	6	9
1	0	6	7	5	7	7	9
	1	6	7	6	8	7	9
	2	6	7	6	8	6	9
	3	6	7	6	8	6	9
	5	6	8	8	8	6	9
	7	7	8	8	9	6	9
	9	7	8	6	9	7	10
	11	7	9	8	7	7	9

As explained earlier in section 5.3, grouping pattern found in validation year is directly used in test year. Table 5.14 shows the results and Table 5.15 shows the grouping pattern used to predict the load.

Table 5. 14 Comparison of performance of heuristic Algorithms on test data for grouping months of a year (ISO New England)

Performance Metric -MAPE (%)-Test Data					
Test Year	**No Grouping**	**Benchmark**	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
2012	2.8478	3.1108	2.8364	3.1108	3.1108
2013	2.9594	3.0430	2.9408	3.0447	3.0048
2014	3.1598	3.2542	3.1602	3.2521	3.2521
2015	3.4548	3.5423	3.4868	3.5423	3.4800
2016	3.1963	3.3353	3.1831	3.3603	3.4468
2017	5.1908	5.1378	5.1925	5.1686	5.1686

Table 5. 15 Grouping pattern of months of a year used to forecast on test data (ISO New England)

Performance Metric -Grouping Pattern			
Test Year	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
2012	(3,4)	(7,8); (6,9); (4,10,11); (2,12)	(7,8); (6,9); (4,10,11); (2,12)
2013	(3,4)	(6,9); (1,11); (2,10)	(3,4); (6,9);(2,11)
2014	(1,12)	(6,8); (2,3); (1,12); (10,11)	(6,8); (2,3); (1,12); (10,11)
2015	(4,5)	(4,5); (3,6); (1,12)	(4,5); (1,12); (6,10); (3,11)
2016	(7,8)	(4,11); (7,8,12); (6,9);(1,2,3)	(6,10); (4,11); (1,2,3); (7,9,12)
2017	(3,4)	(3,5); (7,8); (1,12)	(3,5); (7,8);(1,12)

Like days of a week, all heuristic algorithm was applied to GEFCom2012 data set. Table 5.16– Table 5.18 shows the results on GEFCom2012 data. Figure 5.9 shows scope of improvement by grouping months of a years when model grows.

Table 5. 16 Comparison of performance of heuristic Algorithms on validation data for grouping months of a year (GEFCom2012)

Performance Metric -MAPE (%)-Validation Year-2006				
Model Configuration	**No Grouping**	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
d=0, h=0	4.8344	4.6394	4.3124	4.3124
d=1, h=0	4.0629	3.8898	3.5783	3.5783
d=1, h=1	3.8796	3.7249	3.4565	3.4565
d=1, h=2	3.7751	3.6291	3.3929	3.3980
d=1, h=3	3.7184	3.5721	3.3476	3.3551

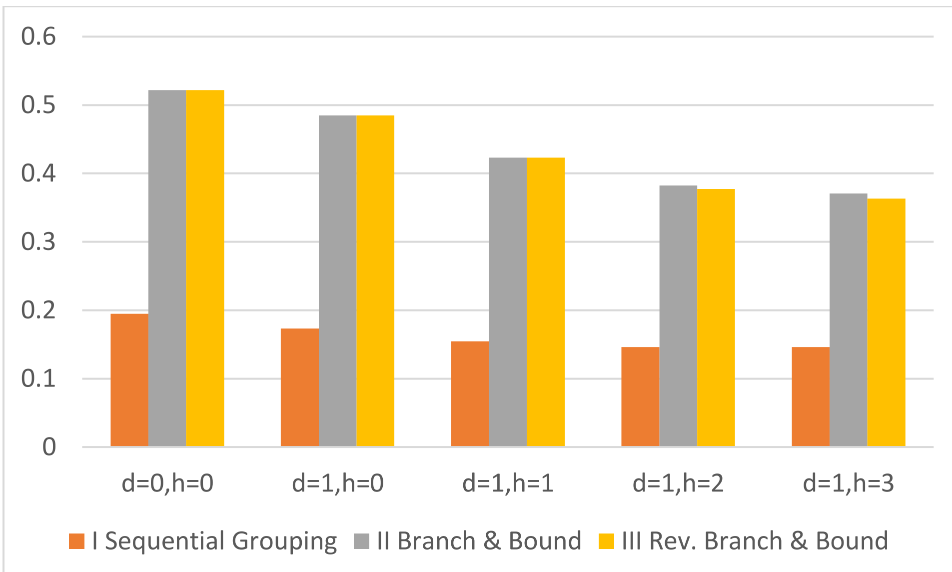

Figure 5. 9 Difference in MAPE as compared to 'No Grouping' for months of a year (GEFCom2012)

Table 5. 17 Comparison of performance of heuristic Algorithms on test data for grouping months of a year (GEFCom2012)

Performance Metric -MAPE (%)-Test Year-2007				
Model Configuration	**No Grouping**	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
d=0, h=0	5.1050	5.0995	5.3940	5.3940
d=1, h=0	4.4317	4.4134	4.8007	4.8007
d=1, h=1	4.3187	4.3017	4.3839	4.3839
d=1, h=2	4.2440	4.2295	4.3146	4.6284
d=1, h=3	4.1980	4.1863	4.2751	4.5843

Table 5. 18 Grouping pattern of months of a year used to forecast on test data (GEFCom2012)

Performance Metric -Grouping Pattern			
Model Configuration	**I Sequential Grouping**	**II Branch & Bound**	**III Rev. Branch & Bound**
d=0, h=0	(1,12)	(3,10); (1,12); (7,8); (2,11); (6,9)	(3,10); (1,12); (7,8); (2,11); (6,9)
d=1, h=0	(1,12)	(1,12); (7,8); (4,5); (2,6,10,11)	(1,12); (7,8); (4,5); (2,6,10,11)
d=1, h=1	(1,12)	(5,10); (7,8); (6,9); (2,11); (1,12)	(5,10); (7,8); (6,9); (2,11); (1,12)
d=1, h=2	(1,12)	(5,10); (7,8); (6,9); (2,11); (1,12)	(1,12); (7,8); (4,5); (2,6,10,11)
d=1, h=3	(1,12)	(5,10); (7,8); (6,9); (2,11); (1,12)	(1,12); (7,8); (4,5); (2,6,10,11)

5.5 Hour of the day.

There are 24 hours of the day and to calculate all the possible combinations of grouping 24 hours would be very time consuming. Table 4.3 shows calculation for grouping hours in just two classes. It is almost the double the total combinations of grouping months. Additionally, there are another 23 possible ways we can create classes and their possible calculation would be very high. So, considering the scope of this thesis we decided not to include the benchmark approach for grouping the hours. We directly applied the heuristic algorithm for grouping hours. Table 5.19 -Table 5.21 shows the outcome of all heuristic algorithm on validation period of ISO New England

Table 5. 19 Comparison of performance of heuristic Algorithms on validation data for grouping hours of a day (ISO New England)

Performance Metric -MAPE(%)			
Validation Year	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
2011	3.073	3.0718	3.0723
2012	2.8478	2.8477	2.8477
2013	2.9594	2.9594	2.9601
2014	3.1598	3.1598	3.1603
2015	3.4548	3.4545	3.4545
2016	3.1963	3.1961	3.1946

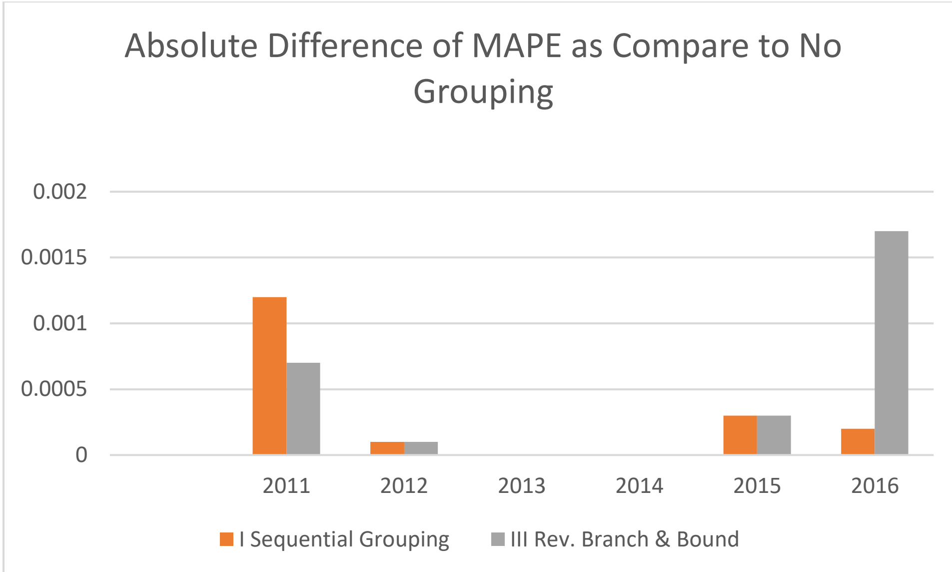

Figure 5. 10 Difference in MAPE as compared to 'No Grouping' for hours of a day (ISO New England)

Table 5. 20 Number of iterations to reach best combination of grouping hours of a day (ISO New England)

Performance Metric -Iterations			
Validation Year	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
2011	1	24	92778
2012	1	24	87771
2013	1	24	92430
2014	1	24	87665
2015	1	24	87409
2016	1	24	73059

Table 5. 21 Number of groups formed by best combination of grouping hours of a day (ISO New England)

Performance Metric -No. of Groups			
Validation Year	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
2011	24	23	23
2012	24	23	23
2013	24	23	23
2014	24	23	23
2015	24	23	23
2016	24	23	23

After analysis, it can be inferred that the grouping hours is not that effective for hourly load forecasting. Results shows that it is sometimes worse than considering all hours separately. Also, the results which are better than benchmark has grouped only two hours. So, complexity doesn't reduce that much, as compared to that in case of month of the year.

Table 5. 22 Number of groups formed by best combination of grouping hours of a day when model grows (Heuristic Algorithm 3)

d	h	2011	2012	2013	2014	2015	2016
0	0	23	23	23	23	23	23
1	0	23	23	23	23	23	23
	1	23	23	23	23	23	23
	2	23	23	23	23	23	22
	3	23	23	23	23	23	23
	5	23	23	23	23	23	22
	7	23	23	23	23	23	22
	9	23	23	23	21	23	20
	11	23	23	23	22	22	20

Table 5.23 shows the result of test data and Table 5.24 shows the grouping pattern used to predict the load which is found in validation data.

Table 5. 23 Comparison of performance of heuristic Algorithms on test data for grouping hours of a day (ISO New England)

Performance Metric -MAPE (%)-Test Data			
Test Year	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
2012	2.8478	2.8485	2.8585
2013	2.9594	2.9602	2.9602
2014	3.1598	3.1607	3.1607
2015	3.4548	3.4558	3.4558
2016	3.1963	3.1961	3.1961
2017	5.1908	5.1911	5.1883

Table 5. 24 Grouping pattern of hours of a day used to forecast on test data (ISO New England)

Performance Metric -Grouping Pattern		
Test Year	**I Sequential Grouping**	**III Rev. Branch & Bound**
2012	(11,12)	(10,14)
2013	(15,16)	(15,16)
2014	(15,16)	(15,16)
2015	(11,12)	(11,12)
2016	(13,14)	(13,14)
2017	(13,14)	(13,16)

Table 5.25 shows the validation and test results of GEFCom2012 data sets. Also, table 5.27 shows the best grouping pattern found in the validation set and same grouping pattern used in test data.

Table 5. 25 Comparison of performance of heuristic Algorithms on validation data for grouping hours of a day (GEFCom2012)

Performance Metric -MAPE (%)-Validation Year-2006			
Model Configuration	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
d=0, h=0	4.8340	4.8330	4.814
d=1, h=0	4.0630	4.0611	4.0615
d=1, h=1	3.8800	3.8793	3.8793
d=1, h=2	3.7750	3.7743	3.7733
d=1, h=3	3.7180	3.7144	3.7118

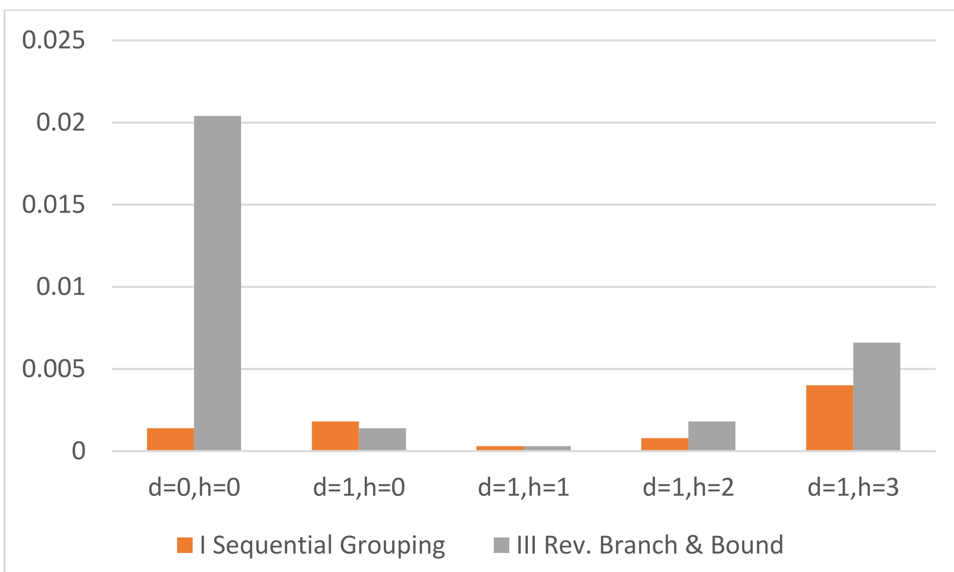

Figure 5. 11 Difference in MAPE as compared to 'No Grouping' for hours of a day (GEFCom2012)

Table 5. 26 Comparison of performance of heuristic Algorithms on test data for grouping hours of a day (GEFCom2012)

Performance Metric -MAPE (%)-Test Year-2007			
Model Configuration	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
d=0, h=0	5.1050	5.1051	5.1226
d=1, h=0	4.4317	4.4338	4.4338
d=1, h=1	4.3187	4.3178	4.3178
d=1, h=2	4.2440	4.2471	4.2412
d=1, h=3	4.1980	4.1949	4.1967

Table 5. 27 Grouping pattern of hours of a day used to forecast on test data (GEFCom2012)

Performance Metric -Grouping Pattern		
Model Configuration	**I Sequential Grouping**	**III Rev. Branch & Bound**
d=0, h=0	(13,14)	(9,16);(13,14);(10,17)
d=1, h=0	(13,14)	(13,14)
d=1, h=1	(15,16)	(15,16)
d=1, h=2	(15,16)	(15,16);(14,17)
d=1, h=3	(15,16)	(15,16);(14,17)

5.6 24 Solar Terms

As explained in the earlier section, we are directly applying heuristic algorithms. In this case, as proposed by Xie and Hong 2018, just replaced the class variable month with solar terms in MLR based Tao's Vanilla benchmark model and forecasts are generated [13]. Using 24 solar terms improved the accuracy of benchmark model and grouping them further improved the accuracy. On top of that, it reduces the complexity of model.

Table 5.28 – Table 5.30 shows the results obtained by applying heuristic algorithm on ISO New England data set. Figure 5.12 shows the scope of improvement by grouping 24 solar terms in perfect grouping pattern is chosen. Also, table 5.1 shows the number of groups formed when model grows. There is no specific trend can be obtained when model grows.

Table 5. 28 Comparison of performance of heuristic Algorithms on validation data for grouping 24 solar terms of a year (ISO New England)

Performance Metric -MAPE (%)			
Validation Year	No Grouping	I Sequential Grouping	III Rev. Branch & Bound
2011	2.9846	2.9689	2.7453
2012	2.7577	2.7327	2.5791
2013	2.9090	2.8774	2.6858
2014	3.0631	3.0329	2.9368
2015	3.4122	3.3768	3.0415
2016	3.2596	3.2237	3.0299

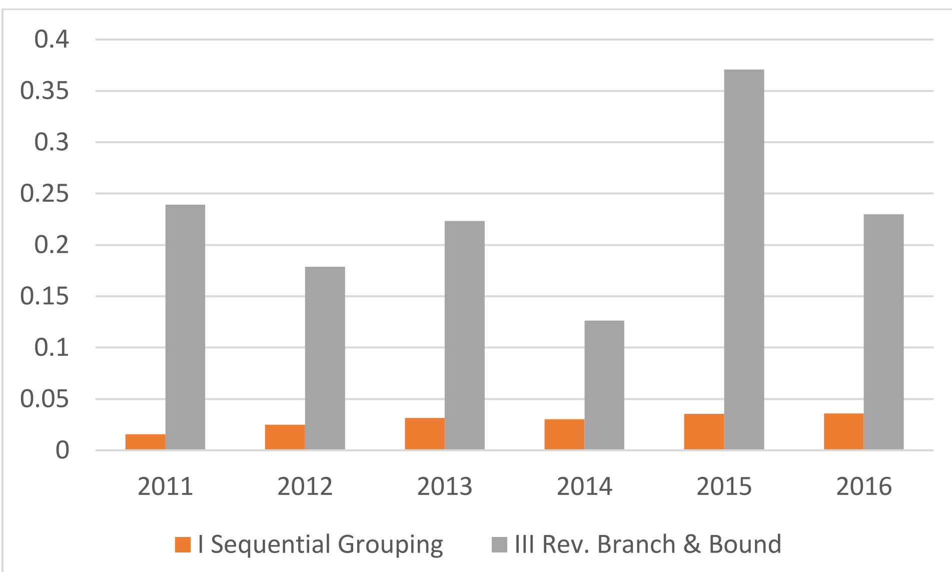

Figure 5. 12 Difference in MAPE as compared to 'No Grouping' for 24 solar terms of a year (ISO New England)

Table 5. 29 Number of iterations to reach best combination of grouping 24 solar terms of a year (ISO New England)

Performance Metric -Iterations			
Validation Year	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
2011	1	24	8942
2012	1	24	42177
2013	1	24	10376
2014	1	24	158493
2015	1	24	13105
2016	1	24	12524

Table 5. 30 Number of groups formed by best combination of grouping 24 solar terms of a year (ISO New England)

Performance Metric -No. of Groups			
Validation Year	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
2011	24	23	10
2012	24	23	12
2013	24	23	11
2014	24	23	10
2015	24	23	9
2016	24	23	12

Table 5. 31 Number of groups formed by best combination of grouping 24 solar terms of a year when model grows (Heuristic Algorithm 3)

d	h	2011	2012	2013	2014	2015	2016
0	0	10	12	11	10	9	12
1	0	11	14	10	11	9	14
	1	9	14	11	11	9	12
	2	8	14	11	11	8	12
	3	8	12	12	12	8	15
	5	9	12	12	12	8	13
	7	10	12	13	13	9	13
	9	11	11	12	14	9	13
	11	9	12	13	12	10	13

Table 5. 32 shows effect of grouping the 24 solar terms on test year on ISO New England data set. To study the same grouping pattern on test data set, the best grouping pattern of validation year is used to forecast the test year. Test year is next year to the validation year and 3 previous years of data is used as training year. Table 5.32 shows the result of test year of grouping 24 solar terms and Table 5.33 shows the grouping pattern of 24 solar terms used to forecast the result.

Table 5. 32 Comparison of performance of heuristic Algorithms on test data for grouping 24 solar terms of a year (ISO New England)

Performance Metric -MAPE (%)-Test Data			
Test Year	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
2012	2.7577	2.7351	3.0241
2013	2.9090	2.9063	3.0192
2014	3.0631	3.061	3.1057
2015	3.4122	3.4133	3.414
2016	3.2596	3.2716	3.2588
2017	5.1385	5.1434	5.1297

Table 5. 33 Grouping pattern of 24 solar terms of a year used to forecast on test data (ISO New England)

Performance Metric -Grouping Pattern		
Test Year	**I Sequential Grouping**	**III Rev. Branch & Bound**
2012	(19,20)	(7,8,9,20);(1,2,3,23);(11,16,17,18);(5,22); (4,24);(6,10,21);(13,15);(19);(12);(14)
2013	(1,24)	(1,24);(10,11,19);(4,13,16,21);(5,9,20); (6,8);(17,18);(14,15);(3,22);(2);(23);(7);(12)
2014	(22,23)	(13,22,23);(12,14);(3,5,15,16,21);(10,11,17) (6,18,20);(7,19);(1,24);(8);(2);(9);(4)
2015	(15,16)	(4,22,24);(1,2,23);(7,8,9);(15,17);(3,6,12,20); (5,13,16,21);(10,18);(19);(11);(14)
2016	(22,23)	(11,12,18,19);(4,14,16,22,24);(2,3,5,6,7); (20,21);(13,15);(1,17,23);(8);(9);(10)
2017	(2,3)	(12,17);(3,4,21);(11,20);(2,14,22);(13,15,16); (1,24);(10,18);(5,7);(6,9);(23);(8):(19)

Table 5.34 -Table 5.36 shows the results of GEFCom2012 dataset including the grouping pattern used to the load on test year.

Table 5. 34 Comparison of performance of heuristic Algorithms on validation data for grouping 24 solar terms of a year (GEFCom2012)

Performance Metric -MAPE (%)-Validation Year-2006			
Model Configuration	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
d=0, h=0	4.9936	4.8537	4.1680
d=1, h=0	4.5410	4.2003	3.4981
d=1, h=1	4.3320	3.9983	3.3439
d=1, h=2	4.2986	3.8915	3.2696
d=1, h=3	4.2970	3.8369	3.2196

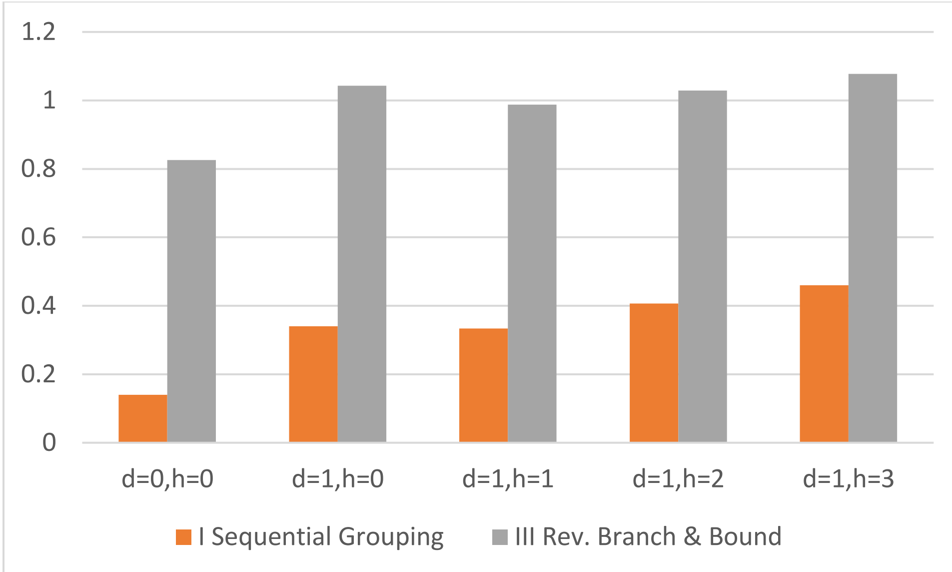

Figure 5. 13 Difference in MAPE as compared to 'No Grouping' for 24 solar terms of a year (GEFCom2012)

Table 5. 35 Comparison of performance of heuristic Algorithms on test data for grouping 24 solar terms of a year (GEFCom2012)

Performance Metric -MAPE (%)-Test Year-2007			
Model Configuration	**No Grouping**	**I Sequential Grouping**	**III Rev. Branch & Bound**
d=0, h=0	5.0550	5.0015	5.3189
d=1, h=0	4.6074	4.4244	4.4095
d=1, h=1	4.5225	4.3432	4.2787
d=1, h=2	4.4657	4.2892	4.2123
d=1, h=3	4.4282	4.2563	4.1701

Table 5. 36 Grouping pattern of 24 solar terms of a year used to forecast on test data (GEFCom2012)

Performance Metric -Grouping Pattern		
Model Configuration	**I Sequential Grouping**	**III Rev. Branch & Bound**
d=0,h=0	(2,3)	(11,17);(5,6);(7,8);(12,13);(14,15,16);(9,19); (10,18);(1,24);(3,21);(2,4,20,22)(23);
d=1,h=0	(2,3)	(14,15,16);(1,3,24);(21,23);(2,4,20,22); (9,10,18);(6,7);(5,8);(11,17);(12,13);(19)
d=1,h=1	(2,3)	(14,15,16);(1,3,24);(21,23);(2,4,20,22); (9,10,19);(5,6,7);(11,17);(12,13);(18);(8)
d=1,h=2	(2,3)	(14,15,16);(1,3,24);(21,23);(2,4,20,22); (9,10,19);(5,6,7);(11,17);(12,13);(18);(8)
d=1,h=3	(2,3)	(14,15,16);(1,3,24);(21,23);(2,4,20,22); (9,10,19);(5,6,7);(11,17);(12,13);(18);(8)

CHAPTER 6: CONCLUSION

The electric load forecast plays an important role in production and planning of electricity. Along with weather variable, calendar variable is one of the important predictor variables in electric load forecasting. Load profile can be studied based on calendar variable and it varies based on consumption pattern and ambient temperature of that area. Since there can be similarities amongst the load profile with respect to calendar variable, grouping calendar variables could be explored in improving the prediction capability of model. Grouping of calendar variable that have similar load profile can improve the load forecast. Also, grouping reduces the degree of freedom, complexity and potential overfitting issue of the model.

This research proposes three unique heuristic algorithms for grouping calendar variable. These heuristic algorithms are more efficient and faster than trying each combination. Additionally, the thesis has compared the performance of all calendar variable separately and grouping the calendar variable. For all calendar variable, the forecast by grouping calendar variable technique was more accurate than the forecast by considering all calendar variable separately on validation period. However, when same grouping pattern is used on test data then there is very small improvement is seen and sometimes it is worse that no grouping. This can be referred as the overfitting.

We have used Tao's Vanilla Model to forecast the electric load [1]. In normal practices, all calendar variables are considered separately. Thus, keeping all calendar variable separately was a benchmark model. We used publicly available ISO New England and GEFCom2012 data so that work can be reproduced, and results can be compared. Experiments were conducted for calendar variables such as weekdays, months, hour and 24 solar terms. The validation was conducted on the year ahead horizon for six consecutive years (2011-2016).

To get the best grouping pattern which has least forecasting error measure (MAPE), we first calculated MAPE for all possible combination of grouping calendar variables for weekdays and months. There were 877 and around 4.17 million possible combination of grouping weekdays and months respectively. After trying all combinations, grouping pattern with lowest MAPE was selected as the best grouping pattern and yielding the global minimum. This pattern has the lower degree of freedom and more accurate load forecast as compared to forecast obtained by considering all calendar variable separately. The forecasting accuracy obtained by grouping the calendar variables can be interpreted as the scope of improvement by grouping the calendar variables and at the same time reducing the complexity of model as compared to no grouping, provided the best grouping pattern need to be picked. Selecting best grouping pattern on previous year is not the perfect grouping pattern on next year. The investigation of the reason behind this can be considered as future work.

The proposed heuristic algorithms were evaluated by comparing performance of various models based on grouping of weekdays, month, hour and 24 solar terms in separate setup. In the case of weekdays, optimal grouping pattern was identified as grouping any two or three weekdays among Tuesday, Wednesday, and Thursday. This grouping was identified by trying 7 to 108 combinations instead of all 877 possible combinations. On the other hand, in the case of grouping months, grouping was reduced to 6 to 9 groups instead of 12 resulting in an improvement in MAPE values from 1% to 5.5% on validation period. Like weekdays, heuristic algorithm tried 12 to 450 combinations to find one of the best-performing groups. The number of iterations depends on the selection of the heuristic algorithm.

In some cases, one of the heuristic algorithms was able to catch the global minimum. In case of grouping weekdays, all three algorithms were able to capture global minimum more than once among 6 validation years. Additionally, in case of grouping months, Heuristic algorithm 2 and heuristic algorithm 3 were able to capture global minimum for validation year 2011 and 2014. However, in other cases, grouping pattern identified by heuristic was very near to the global minimum. Among the three heuristic algorithms, each have their pros and cons. Heuristic algorithm 1 only consider grouping adjacent calendar variables but in case of grouping weekdays and grouping hours it is most affordable algorithm. To group months, one can try both heuristic algorithm 2 and heuristic algorithm 3 to select best among them. As explained in section 5.4, heuristic algorithm 3 suits best to group 24 solar terms. Based on the need, one must select a suitable heuristic algorithm.

As there are 24 hours and 24 solar terms, calculating MAPE of all possible combinations of grouping hours and 24 solar terms for six years would have been computationally highly time-consuming. So, in the case of grouping hours and 24 solar terms we directly applied the heuristic algorithm. When forecasting year in advance, hourly electricity load, grouping hour is less effective as compared to grouping other calendar variables. However, in the case of 24 solar terms, MAPE values were improved in the range of 4% to 10% and grouping reduced to groups of 9 to 12 resulting in reduction of complexity. Also, it is simple, readily applicable, more accurate, reduce the issue of overfitting when model grows and more robust than without grouping calendar variables.

When dealing with regression model consisting class variable, the complexity of model is directly proportional to the number of levels of this class variables. Also, interaction of class variable with temperature variables increases the calculation of estimating the parameters. Thus, model having more complexity may overfit. When forecasters need to find the trade-off between growing model and issue of overfitting, grouping calendar variables could be a good solution to this problem. This research further proposed the formal ways to find out the optimal grouping pattern, instead of using empirical ways to group the calendar variable.

However, even if forecasting accuracy is improved on validation period but it is not necessary it will improve on test period. So, selection of grouping pattern for test period can be found out by doing cross- validation and selecting common grouping pattern. This may also avoid the issue of overfitting which was observed in sliding simulation. Further, sequential grouping can group the adjacent three or four calendar variables. Grouping adjacent calendar variable may have less chance of overfitting the model. These works can be considered as future work as it requires more investigation. Also, this research can be used to infer that using calendar variables as it is for electric load forecasting may not be best way as calendar variables was designed to organize the days of social, administrative, religious or commercial purpose.

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