Indian Institute of Management Calcutta

Working Paper Series

WPS No. 832 /August, 2019

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Mid-term Electricity Demand Forecasting: A Parsimonious Model

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ABSTRACT:

This paper presents a year-ahead electricity demand forecasting model. We intend to predict hourly demand to be catered by the power grid. Year-ahead forecast of hourly demand is relevant in the present context of ever-increasing capacity of power plants based on renewable energy (RE). While RE are desirable owing to their marginal cost of production, they are intermittent, which in turn increases the complexity in production planning of NRE. Moreover, lack of an effective and economical mode of energy storage technology renders NRE irreplaceable in catering large baseload. The proposed model takes into consideration trend and seasonality due to hourly, daily, and time of the year effects on electricity demand. We test our model in four regions (Austria, Germany, France, and Arizona in the USA) with a significant share of RE. We compare the results of our proposed model with a set of benchmark models for these regions. Empirical results suggest that our model outperforms the benchmark models while predicting hourly demand a year in advance. This work aids in decision making on investments for capacity addition (or closure) for the year ahead by power-producing firms based on non-renewable energy sources. This work places itself on the setting of co-existence of RE and NRE firms and thus is a contribution to the extant literature.

Keywords:

Mid-term forecasting, renewable energy, non-renewable energy, Smoothing, electricity demand

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Introduction:

Over the past decade, governments of most nations have realized the peril of increased levels of greenhouse gases (GHG), substantiated by consistently high levels of carbon dioxide (CO_2) on a global scale (408 ppm as of 5th of February 2018 (Global Greenhouse Gas Reference Network, 2018)) and corresponding changes to the weather/climate. One of the major actions that governments have sought is incentivizing power plants based on renewable energy sources (RE) like solar, wind, tidal, etc. in forms of subsidies or feed-in-tariff (FIT). Encouragement to RE is further augmented by falling prices of the installation, more prevalent for solar-based power plants, owing to the technological up-gradation. Moreover, RE firms benefit from a lower marginal cost of production when compared to NRE firms. As a result, the world has witnessed a surge in the number of power plants based on renewable energy. In 2016, RE constituted more than 66% of the installed (additional) power capacity (Vaughan, 2017). An increase in the number of RE has, on an average, led to lowering of wholesale prices owing to the merit order effect (Sensfuß, Ragwitz, & Genoese, 2008), which in turn have reduced the revenue of NRE firms. The uncertainty of production, owing to incoming RE, could also lead to instances of supply overshooting demand, which could, in turn, deem the wholesale prices negative. A case in point being the negative wholesale prices in California on 11th March 2017 owing to the excess production from solar-based RE (Monthly Electric Utility Sales and Revenue Report with State Distributions , 2017). Power plants based on non-renewable sources of energy, unlike RE based plants, are steady and reliable. These plants are, however, declining with many coal-based pants being rendered non-operational due to financial losses especially in countries like India, China, Germany, etc. where there has been an influx of RE based power plants in a big way. For instance, as per a report by the Central Electricity Authority in India, the thermal power plant's utilization in India may drop to 48% by 2022 (Sengupta, 2016). These losses are primarily a result of the entry of RE firms which have a lower marginal cost of production.

NRE firms are at wane but have not yet become obsolete as they are more reliable. Of late, there have been instances of the government of nations like USA championing the cause of NRE (Grunwald, 2017), though it would not be enough given the global apprehension about the global warming effects. On a global level, there has been a larger entry of firms into RE even though there has been evidence of not all RE firms doing well (Livsey, 2017). Thus, to stay in the competition, it becomes pertinent for NREs to forecast demand that they can cater to, accurately to ensure profitable bidding in the day-ahead energy market. Accurate mid-term forecasting would additionally also enable them to make a sound decision on their capacity. Thus, mid-term forecasting has assumed greater significance in the context of an increasing share of renewable energy in the overall electricity supply. While welcome as a cleaner source of energy, renewable energy contributes to greater challenges to demand-supply matching in a grid owing to its supply being intermittent. Studies indicate an increase in volatility in the grid, owing to a higher share of renewable energy and its detrimental impact on the performance of conventional NREs. Although there are many existing forecasting models, most of them are specific to a given dataset and restrict themselves for short-term forecasting to cater to day-ahead market bidding. Not many articles look into forecasting as a tool to enable management to take an informed decision on the investments in light of the changing landscape (Hahn, Meyer-Nieberg, & Pickl, 2009). Moreover, most of the existing articles do not take into account variability in demand for NRE owing to the intermittent nature of the RE supply.

In this paper, we endeavor to arrive at a better forecasting model which could forecast hourly demand a year-in-advance with better accuracy than existing models. We forecast demand which is characterized by a trend, multiple levels of seasonalities (intra-day, intra-week and intra-year seasonalities being the significant ones) and stochastic randomness. As mentioned before, most of the models developed so far are specific to a particular region and are STLF. Moreover, these models seldom contribute to making strategic decisions on investments and generation planning. We intend to bridge this gap by developing a model which would provide a reasonable fit irrespective of the location. Results obtained suggest that the proposed model forecasts demand with reasonable accuracy in spite of it being mid-term forecasting. Moreover, unlike most of the work reported in the literature, our model is based on univariate time series and does not include weather or/and economic factor data and still performs better than the benchmark models.

The subsequent section presents an extensive, though not exhaustive, review of the work pursued by researchers so far. We have tried to cover most of the prevalent methodologies adopted in forecasting demand for electricity. The third section explains the methodology adopted in this paper. Results and corresponding implications are explained in the fourth section. This is followed by the conclusion and future scope of research.

Literature Review:

This paper mainly focuses on forecasting hourly demand a year in advance, which is of immense importance for the power plants given the rise in investments in power plants based on renewable sources of energy (RE) with a negligible marginal cost of production. To the best of the author's knowledge, this work has not been pursued before in the literature. Load forecasting can be classified based on lead time or the method used for forecasting or time-window for which the aggregate demand is forecasted, that is the granularity of the forecast.

Lead time for forecasting can be defined as the length of time between making the demand forecast and realizing the actual demand. On the basis of lead time, load forecasting can be classified into short-term load forecasting (STLF), mid-term load forecasting (MTLF) and long-term load forecasting (LTLF) (Hahn, Meyer-Nieberg, & Pickl, 2009). STLF model predicts loads up to one week ahead, whereas the lead time of MTLF ranges from a week to a year (Kyriakides & Polycarpou, 2007). LTLF models generally forecast demand to be realized more than a year in the future. Usually, most of the articles on STLF, forecast demand an hour or a day- ahead. STLF models predominantly aid in operational decisions like the chalking out the scheduling of the generation system or deciding on the bidding amount, whereas MTLF aid the plants in short term planning such as designing contracts especially pertaining to the energy exchange (González-Romera, Jaramillo-Morán, & Carmona-Fernández(2006), (Hong & Fan(2016)). LTLF models, on the other hand, aid in taking strategic decisions like those pertaining to capacity addition and deletion, and so on. Granularity in forecasting can be defined as the time window for which the aggregated demand is forecasted, for example, for for a given minute, total demand in a given time frame of thirty minutes or an hour or a week or a month or a year and so on. Most of the load forecasting models so far try to cater to aggregate demand over a time frame that ranges from a quarter of an hour to a year. In this paper, we forecast demand on an hourly basis. For the sake of convention, demand for the first hour refers to the total demand from 12:00 hours to 1:00 hour.

Based on the methodology, forecasting models can be broadly classified into statistical methods or the parametric methods and methodologies based on artificial intelligence (Al-Hamadi & Soliman, 2005). Another branch of methodology could be based on heuristic/meta-heuristic methods. Statistical methods are those which are based on sound statistical foundations. Few examples of the same would be methodologies based on auto-regression (AR), auto-regressive moving average (ARMA) models, auto-regressive integrated moving average (ARIMA) models, regression models, and so on. Methodologies based on machine learning techniques or those based on fuzzy logic come under the ambit of artificial intelligence. There is a substantial number of forecasting models in the literature which are based on evolutionary algorithms or meta-heuristics like the ant-colony optimization, genetic algorithm, etc.

The literature on load forecasting over the years has been dominated by short-term load forecasting techniques wherein a day ahead (or a time-slot ahead) hourly demand is predicted to aid managers in their bids to be placed in the day-ahead market (or spot market). Over the years, various types of models have come to the fore for forecasting. One of the seminal paper on STLF was by Taylor J. (2003). The author discusses the application of the ARIMA model and proposes a variant of the same for better accuracy. They take into account two levels of seasonality, namely intra-day and intra-week, by using a multiplicative seasonal ARIMA model in conjunction with Holt-Winter's exponential smoothing formulation. Their work proves the merit of taking into consideration multiple levels of seasonalities vis-à-vis just one, since the forecasting errors (Mean Absolute Percentage Error being the metric) is ***significantly*** less. Taylor J. (2010) further improve upon their earlier work by considering an additional level of seasonality, seasonality owing to intra-year effects, which improves the accuracy of the forecasting even further as compared to their earlier work. Hagan & Behr (1987) improve upon Box and Jenkins transfer function model (Box, Jenkins, & Reinsel, 1994) by non-linearizing the transfer function to aptly fit the non-linear relation between the load and temperature. Most of the applications of ARIMA and ARMA models mentioned above is on the premise of the availability of adequate data points. However, with the advent of neural nework based fuzzy logic, researchers have found a way around it. Barak & Sadegh (2016) develop a hybrid forecasting model that can deal with data shortage. Their algorithm is based on ARIMA and adaptive neuro inference fuzzy system (ANFIS). Their methodology ensues a three-stage approach, wherein at the first stage ARIMA model is used to forecast the linear pattern in the data, residuals of which are fed into ANFIS for the second stage. In the third stage, they are combined to provide the final forecast. AdaBoost model is used in the second stage owing to lack of sufficient data points. This methodology could be useful for forecasting in developing countries where existing data and resources for data collection could be inadequate. Electricity demand is generally non-linear by nature and thus, accurate forecasting for the same calls for special treatment for this chaotic nature. Wang, Chi, Wu, & Lu (2011) cater to it by employing a two-step approach. First, they employ delay embedding theorem to account for the non-linear structure of the demand and then use weighted largest Lyapunov exponent forecasting method (WLLEF) to predict the chaotic nature of the demand. The weights for WLLEF are determined by Particle Swarm Optimization (PSO) algorithm. Their model inherently also takes into account the seasonality impact on the demand by decomposing the demand at a given time as a product of trend and seasonality for that time slot. Our methodology makes use of the same. Zhu, Wang, Zhao, & Wang (2011) use a combination of the combined model of Moving Average (to iron out seasonal effects and obtain a trend) and PSO (to take into account seasonality effects). Dudek (2016) pre-processes the data to develop patterns that mimic the daily load curves. Thus, they can eliminate the non-stationarity in the data. Then, the NN is trained to best fit the pattern, given the input data. Most of the papers that we discussed on STLF, forecast for a granularity which is similar to the lead time of their model, since as the name suggests they are 'short term'!

Most of the MTLF and LTLF models forecast demand at an aggregate level, that is overall demand for the forecasting period. In comparison to STLF, application of LTLF and MTLF has been limited. However, most of the MTLF and LTLF models are multivariate and often do not take into consideration economic factors for demand forecasting. Kucukali & Baris (2010) used only one variable, namely Gross Domestic Product (GDP), to forecast yearly demand for Turkey. They proposed that GDP alone was enough to predict the demand for subsequent years. Akay & Atak (2007) use Grey Prediction with Rolling Mechanism (GPRM) to predict the yearly demand for the subsequent year. They find the results to be more robust and accurate, given the volatile nature of the demand. Most of the articles that we discussed so far in this section have a forecasting model that has the same lead time and granularity level. However, though we came across very few articles, there exists another set of literature that forecast at shorter granularity levels than the lead time. Al-Hamadi & Soliman (2005) forecast the hourly load patterns for a typical week of a year, a year in advance. They make use of the strong correlation of daily load behavior with the yearly load behavior to forecast the demand. In addition to the correlation between the hourly load with weekly load, they also take into consideration the trend, that is the growth rate, of demand over the years. The approach proposed by them can be utilisd for mid-term or long-term lead times to predict at an hour granularity. Though granularity is at an hourly level, it is the average demand for a typical hour of a week. For instance, they forecast average demand in the first hour for the second week of the upcoming year and so on. Hong, Wilson, & Xie (2014) develop a comprehensive model to predict monthly peak demand and monthly demand a year in advance. Their model consists of a linear regression model that looks at the various correlation between the meterological parameters and the hourly demand patters, which in turn is augmented by the economic factors like the gross state product. The output from the regression model acts as an input to the probabilistic forecasting model, which looks at different scenarios with assigned probabilities.

Thus, some articles on LTLF and MTLF try to foresee demand for the coming year or quarter or month on an aggregate level, that is demand on an average on a day of the month or the week of the month or the month of the year, so as to aid plants in their capacity related decision. Another stream of literature that predict demand on an hourly basis a year in advance do so by taking into consideration the error in the forecast that happened a time-period in advance. This paper uniquely places itself in the forecasting literature in two ways. Firstly, we predict demand for electricity using a univariate model and secondly, our LTLF model doesn't use the error in forecasting a time period in advance. To the best of our knowledge, there aren't any attempts to predict demand, at an hour granularity, a year-in advance. Such a forecast could help the management make informed investment decisions and plan their generation. A summary of the various types of forecasting model has been elucidated in Table 1. This paper tries to cater to the gap represented by the cell-shaded green.

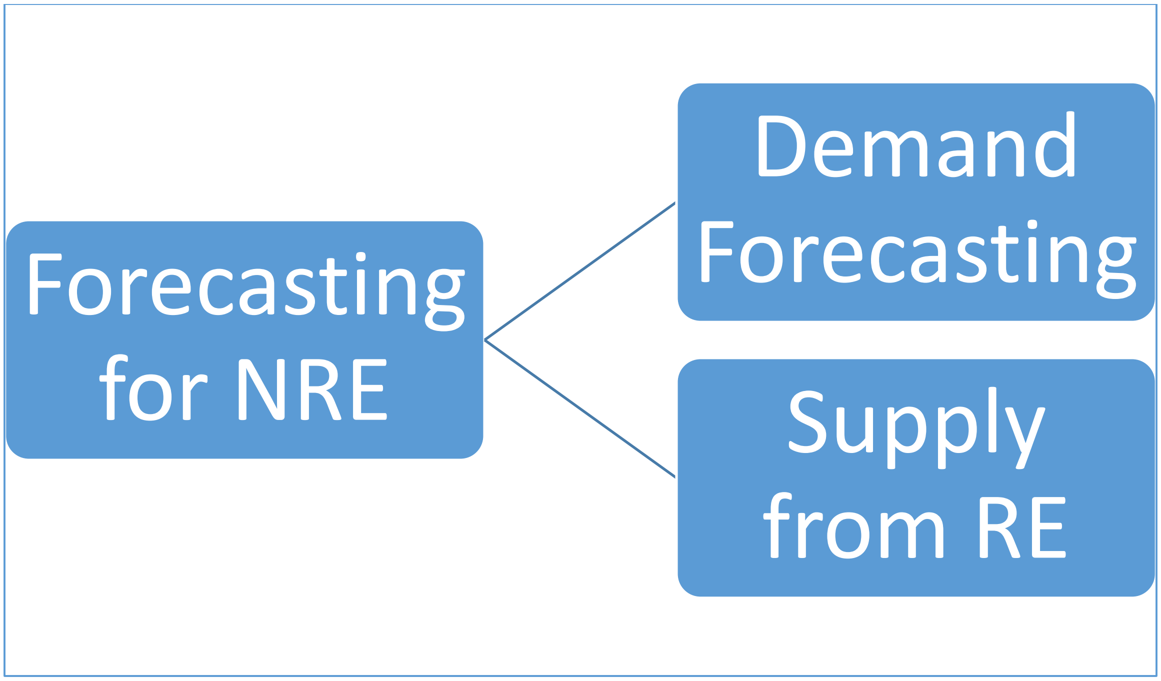


Figure 1: Problem Definition

Table 1: Summary of the classification of the forecasting model

			Granularity				
			Half an Hour	Hourly	Hour of a Week	Monthly	Yearly
Lead Time	STLF	Half an Hour	Taylor J. (2003)				
		Day	Taylor J. (2010)	Hagan & Behr (1987)			
	MTLF	Month				Zhu, Wang, Zhao, & Wang (2011)	
	LTLF	Year			Al-Hamadi & Soliman (2005)	Hong, Wilson, & Xie (2014)	Akay & Atak (2007)

Table 2: Literature Review Summary

A summary of the literature discussed in the above paragraphs and a few more on

Author	Granularity	Prediction Lead Time	Method	Variables	Evaluation
Kucukali & Baris (2010)	Yearly	Year	Fuzzy Logic	GDP	MAPE(0.041)
Akay & Atak (2007)	Yearly	Year	Grey Prediction with Rolling Mechanism	Time	MAPE(0.037)
Wang, Chi, Wu, & Lu (2011)	Half Hourly	Day	Weighted Lyapunov Exponent forecasting method + PSO	Time	MAPE(0.025)
Zhu, Wang, Zhao, & Wang (2011)	Monthly	Month	Hybrid (MA+Combined+PSO)	Time	MAPE(0.088)
Azadeh, Ghaderi, & Sohrabkhani (2008)	Monthly	Month	ANN/Time Series Simulation/DOE	Time	MAPE(0.018)
Azadeh, Ghaderi, Tarverdian, & Saberi (2007)	Monthly	Month	GA+ANN	Price, number of customers, Time	MAPE(0.037)
Taylor (2010)	Half Hourly	Day	ARMA, Holt-Winter's Exponential Smoothing, Exponential Smoothing	Time	MAPE(0.016, 0.016, 0.017)*

forecasting of demand for electricity has been enlisted in table 2. Granularity in table 1 and table

			method for triple seasonality		
Taylor J. (2003)	Half Hourly	Day and Half an hour	Holt-Winter's exponential smoothing funtion with multiplicative seasonal ARIMA model	Time	MAPE(0.012)*
Hagan & Behr (1987)	Hourly	Day	Non-liner variant of Box-Jenkins transfer function model	Time, Temperature	MAPE(0.0373, average value for MAPE of Summer, Fall Winter, Spring)

2 refers to the time window for which the demand has been aggregated, which in turn is forecasted whereas lead time refers to duration between the forecast made and realization of the demand. In this paper, our primary contribution is the extension of the multiplicative model ($Y = Trend \times Seasonality$) to include seasonality at three different levels, namely hour of the day, day of the week and week of the year. The proposed model has shown robustness for geographical location, unlike most of the models proposed so far in literature which function the best for the given region. We forecast, a year in advance, demand for each hour of a day of a year based on the past data, and hence, our model caters to mid-term forecasting unlike most of the literature discussed above. Moreover, we deviate from common perception for the need of multivariate forecasting models for non-short term forecasting as our methodology is univariate and predicts the demand with reasonable certainty and by making it univariate, we also eliminate the errors owing to the forecasting the weather for the upcoming year.

Methodology:

Figure 1 shows a typical time series for electricity demand. Point 1 in x-axis refers to a time window between 00:00 hours to 1:00 hours on 1st January 2006, point 2 refers to 1:00 hour to 2:00 hours on 1st January 2006 and so on. The red line in the figure represents the trend line for the demand, which captures the trend at which demand has grown over the years. A closer look at Figure 1

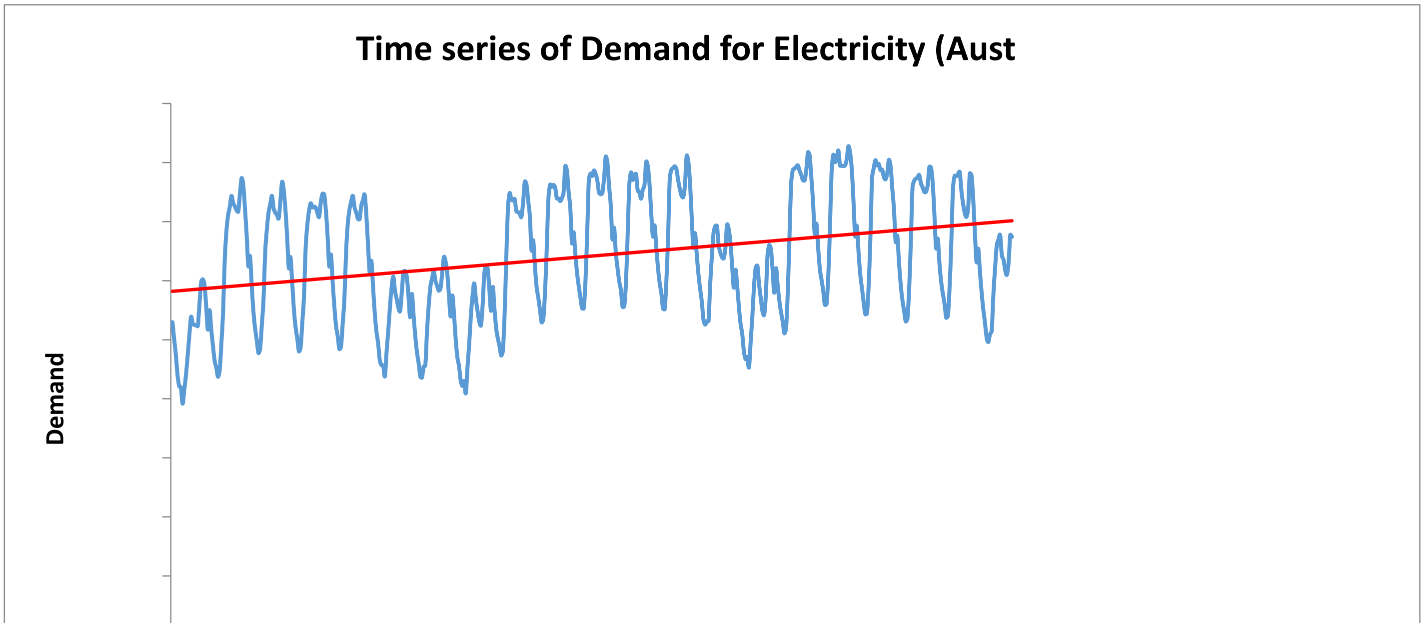


Figure 2: A typical time series of Electricity Demand

shows that a typical time series for electricity demand can generally be broken into four components. We discuss the same in the following paragraphs.

Firstly, the demand follows a trend over the years, as can be seen in Figure 1. The red trend line in Figure 1 suggests that the demand has only been increasing over the years. However, the demand for a typical hour of a day of a year may not have been increasing at the same rate. One can attempt to look at each typical day separately and predict it for the upcoming year. Although, we may now possess the computational capabilities to pursue the method, it would become a tedious job and may prove to be a devil in disguise owing to two reasons. Firstly, we would need to look at 8760 (24×365) data points separately, which given the limited availability of dataset for certain regions could be cumbersome and leave us with only inadequate points for forecasting. Secondly, and most importantly, a typical day of a year, may not be the same for all years since they may fall on different days of the week. As would be discussed later, since we have seasonality indices pertaining to each hour of a day of a week of a month, we are essentially taking care of the effects for every type of a day. Thus, in a way, we are averaging out any seasonality effects that a typical hour of a day may bring into the picture and then extract the trend from the de-seasonalised data. Other three components of the time series comprise of seasonality owing to the effect of time of the day, day of the week and week of the year. On any given day, demand would be mostly low at the dusk as compared to mornings when most of the people are working. Demand for a given hour on different days may be different; however, the correlation between demands at two different hours of a day would most likely remain the same over different days. This can be seen in Figure 2, which depicts demand in electricity for two consecutive days in Austria, wherein time stamp 1 refers to demand between 00:00 hours and 1:00 hour on 1st January 2016 and so on. As can be seen, the form of the graph for both the days is similar even though demand on the second day is higher than on the first.

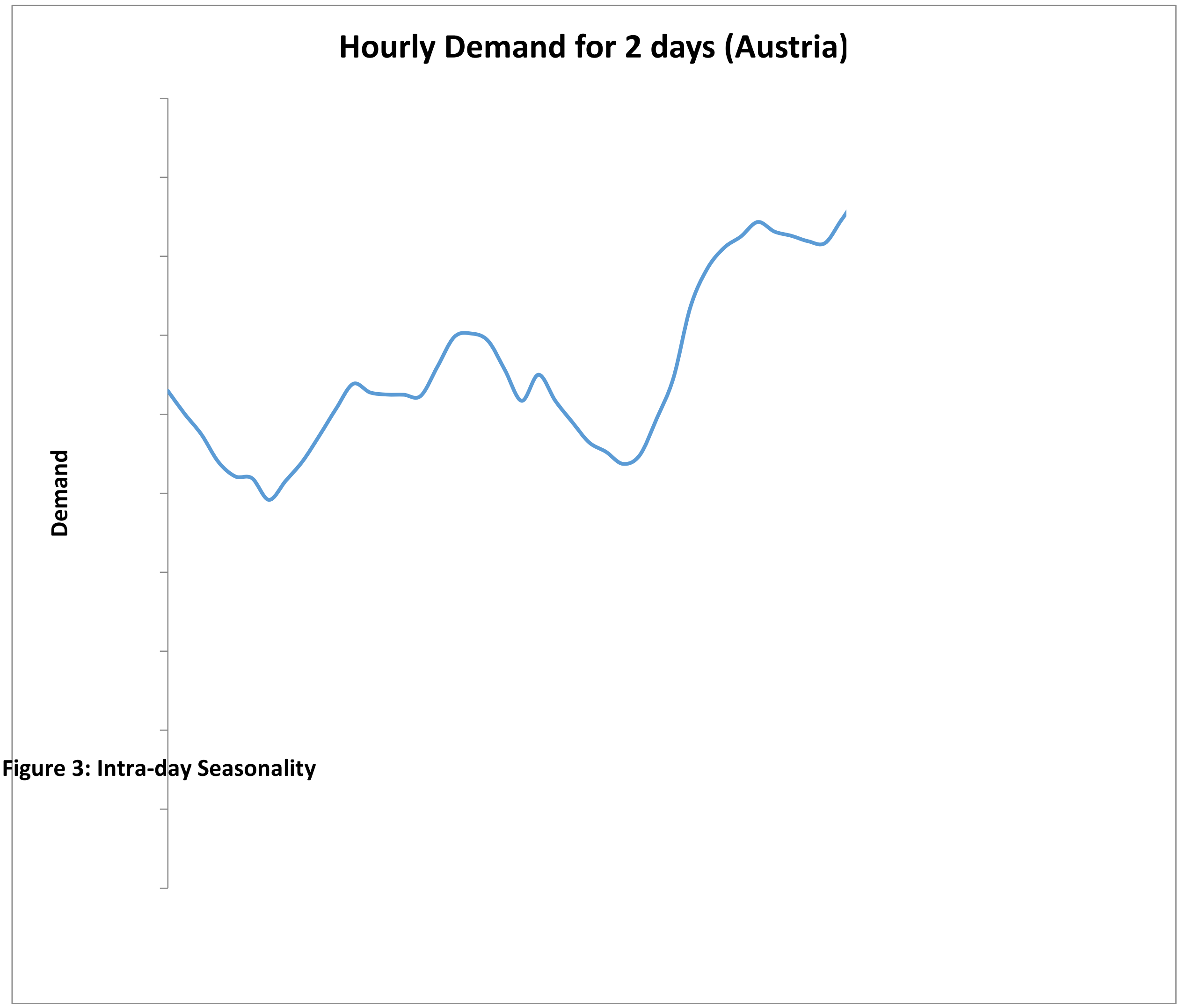


Figure 3: Intra-day Seasonality

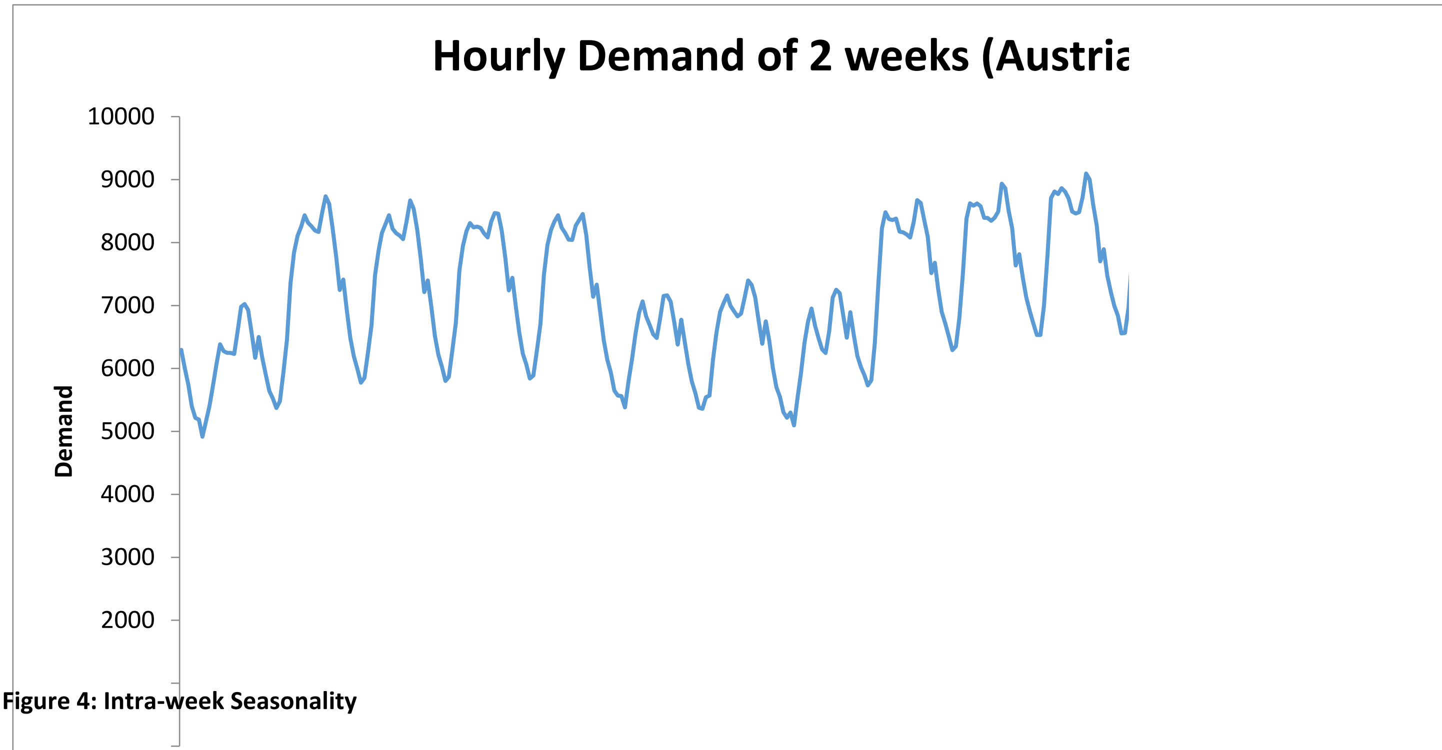


Figure 4: Intra-week Seasonality

The second level of seasonality that we observed in the four datasets is the seasonality owing to the day of the week. For instance, weekends would have a lower demand for electricity than on the weekdays. Figure 3 elucidates the same. The x-axis refers to an hour (in chronological order) of a day of a week of the year. The graph represents two consecutive weeks of the year 2006, wherein a value 1 against day refers to Sunday, 2 to Monday and so on. As can be seen in Figure 2, the form of the graph remains the same for different days. Also, on closer inspection of Figure 2, one can see that the form of the graph is quite similar for the weeks. The third level of seasonality is concerning week of the year, which is more granular than the seasons in a year. Three levels of seasonality have also been discussed in the literature. Taylor J. (2010) is the closest to the work that we envisage in this paper wherein they forecast real-time electricity demand. We, however, try to forecast demand a year in advance and use a different model which is simpler in execution. We then compare performance of our model with benchmark models in terms of MAPE. We consider hourly demand data for Arizona, Austria and France. Using data of five years, we predict the demand for the sixth year.

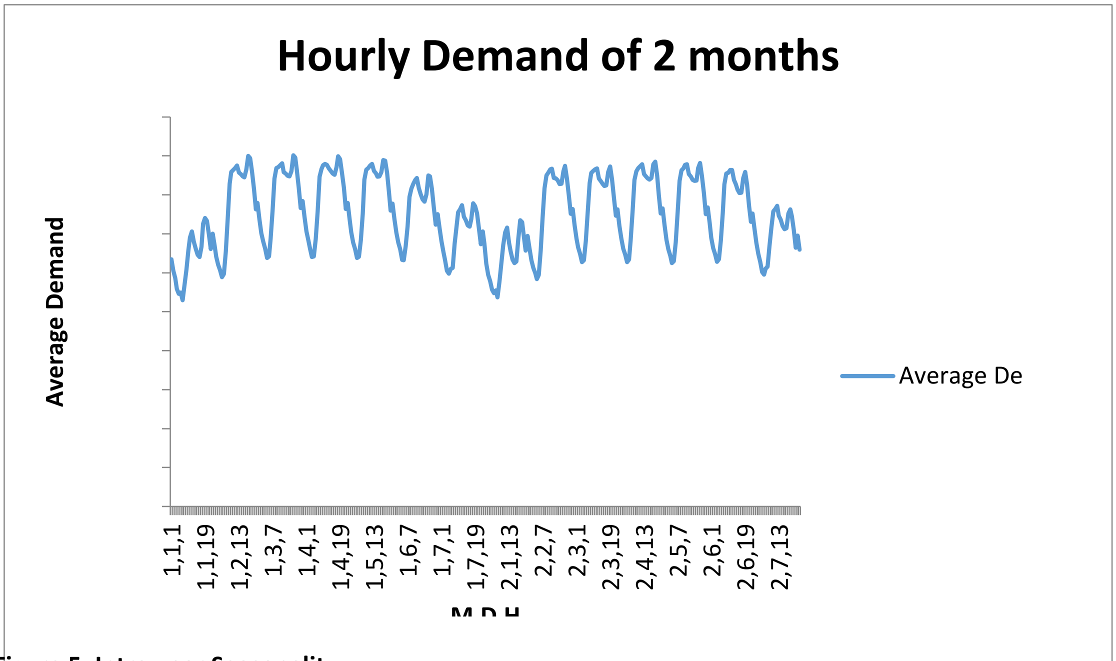


Figure 5: Intra-year Seasonality

We use a multiplicative model to forecast the demand taking into consideration the aforementioned four components of the time series data for the respective region selected. We use a bottom-up approach to arrive at the respective seasonality indices and top-down approach to forecast the demand. We make use of Moving Average (MA) to de-seasonalise data at each step.

Results:

Our various findings and evaluation of the model are based on Mean Absolute Percentage Error (MAPE) which defined as:

$$MAPE = \sum \frac{|A_t - F_t|}{A_t}$$

where, A_t is the actual demand realized and F_t is the demand predicted for the time period t. On the model defined we tried to compare the results for various combinations. The variants with corresponding MAPE are tabulated in Table 2.

Table 2: Comparison of MAPE for Forecasting under different scenarios

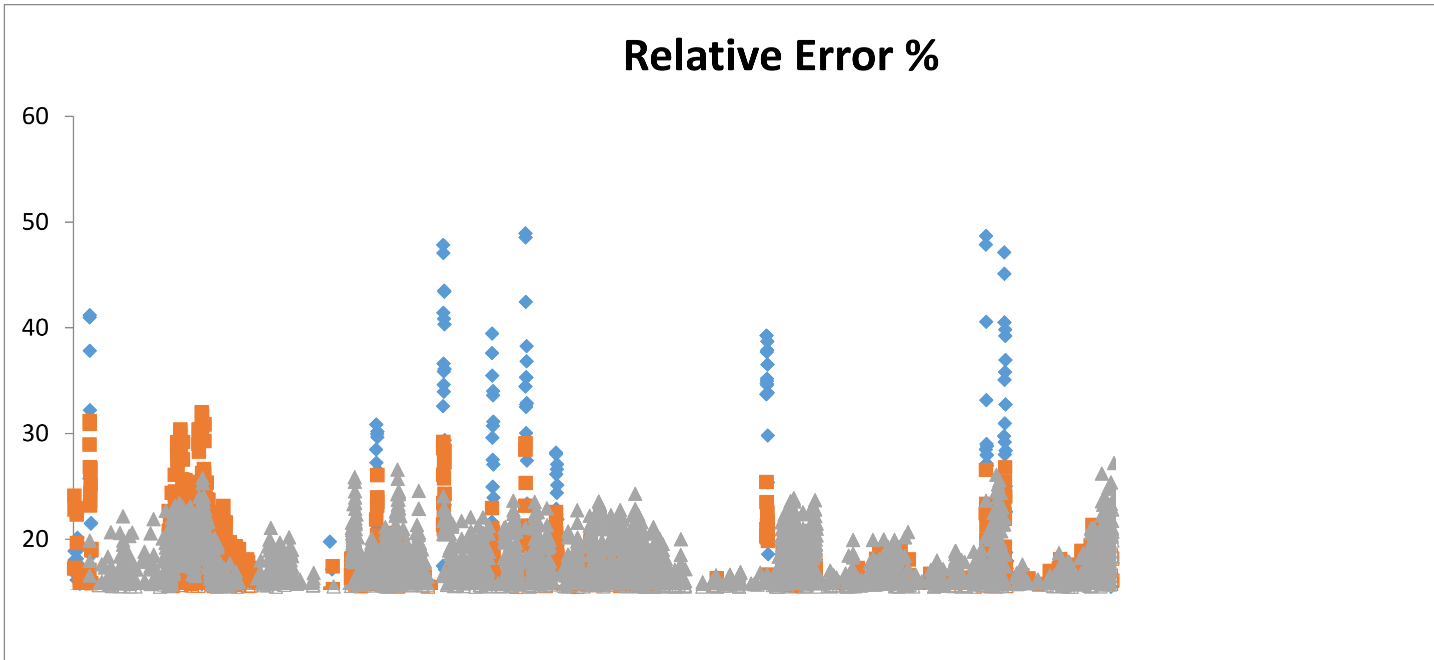
Variant (All Seasonalities included)	MAPE (%)			
	France	Austria	Arizona	Ontario
Trend of all years	7.07	7.10	7.30	5.50
Trend of last year	5.81	4.40	5.40	5.44
No trend	6.06	13.45	15.2	6.52

We next compare our model with some of the benchmark models. The summary for the same is provided in Table 3.

Table 3: Comparison of MAPE for different models including the benchmark model

Model No.	Model Description	MAPE (%)		
		France	Austria	Arizona
1	Proposed Model (Last year trend)	5.81	4.4	5.4
2	No trickle down seasonality	9.25	8.38	10.22

3	Probabilistic model based on k-means clustering (k=20)	13.25	13.47	15.23



Conclusion:

Forecasting literature in operations management has been limited to contributions in terms of techniques. However, seldom these techniques have found utility in practice. This paper concerns the forecasting of hourly demand for electricity with a lead time of a year, as a tool relevant to practice. We propose (CMA) a multiplicative model wherein seasonality indices are evaluated by smoothing the data using moving average. Since, there has been no literature on MTLF for forecasting hourly demand, we extend two well-known STLF models, namely Holt-Winters (HW) and Holt-Winters-Taylor (HWT) exponential smoothing method for MTLF and use them as benchmarks. Most of the forecasting models in literature are devised for a particular geography and evaluated on the same. A model is considered robust when it performs consistently across different geographies and conditions. We thus, select six

European countries varying in demographic, geographic and economic factors to compare our model with the benchmark models and to also evaluate robustness. In comparison to the HWT method, the CMA method has no terms to initialize and entails lesser computational effort. We also find that our proposed model performs much better than the benchmark models and is more robust. Our model is of utmost importance to regulators or plant managers who need to take a decision on capacity addition or deletion. It is under this premise that it becomes necessary to take into account the impact of seasonal cycles on the accuracy of forecasts. Discounting impact of seasonality on demand could lead to overestimating or underestimating the need for the capacity addition. In such scenarios, data granularity matters and thus MTLF model proposed in this paper could aid the managers. The granularity in the MTLF has an impact in the investment decisions. Thus, it is imperative to pursue MTLF at a granular level especially in recent times wherein there has been an influx of intermittent energy sources in the electricity grid. Parsimony and computationally less intensity of the model proposed also enables the manager to take a decision on the go. Such models also benefit regulators in estimating time of use tariffs well in advance so as to influence consumer demand effectively and flatten the load curve. This is of immense importance in the current times wherein there has been an advent in the number of power plants based on renewable sources of energy like the sun or wind whose supply at the best is intermittent.

In this paper we also discussed the need to take into consideration the sequence of de-seasonalisation. Another factor which also needs to be accounted for is the interaction between different seasonal cycles. Our model does not take into account special days separately. While it is pertinent to treat them seperately for STLF, it does not have a huge impact for MTLF. With the advent of artificial neural network and machine learning based heuristics all these have become redundant. However, a simple model like CMA with appropriate consideration could perform better. Moreover, such models could be the 'white' box in the hand of decision makers to make informed decisions. Availability of hourly data now makes it possible to forecast hourly demand a year in advance.

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