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Mid-Term Forecasting of Electricity Demand with Multiple Seasonal Cycles

Subhasis Mishra[1], Megha Sharma[2], Balram Avittathur[2]

[1]Independent Researcher, Bengaluru, India
[2]Indian Institute of Management Calcutta, Kolkata, India
Email: subhasism15@iimcal.ac.in, megha@iimcal.ac.in, balram@iimcal.ac.in

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Abstract

The increasing penetration of intermittent renewable energy sources such as solar and wind has heightened the need for electricity demand forecasts that are both granular and available well in advance. While existing studies focus either on short-term hourly forecasting or on mid- to long-term forecasting at aggregated levels, the problem of forecasting hourly electricity demand a year in advance remains largely unexplored. This paper proposes a parsimonious, univariate mid-term load forecasting (MTLF) model based on centered moving averages that captures three levels of seasonality typically present in hourly electricity demand, *i.e.*, hour of the day, hour of the week, and hour of the year. The proposed approach requires no parameter initialization, and is computationally simple and easy to interpret, making it well suited for practical decision-making. Using real-life demand data from six European countries with diverse demographic and economic characteristics, we compare the performance of the proposed model with extensions of the Holt-Winters and Holt-Winters-Taylor exponential smoothing methods. The results show that the proposed model consistently outperforms the benchmark methods in terms of accuracy and robustness, achieving mean absolute percentage errors ranging from 3.27% to 5.52%. Overall, the paper highlights the value of granular mid-term forecasting in improving renewable energy utilization, supporting capacity planning, and informing regulatory decisions in modern electricity systems.

Keywords

Energy Forecasting, Electricity, Renewable Energy, Energy Planning, Demand Smoothing

1. Introduction

For the last two decades, the share of renewable sources in the energy mix has been increasing globally. The share of primary energy from renewable sources increased from 7.82% in 2002 to 14.21% in 2022 [1]. As of 2022, hydropower, solar and wind constitute about 90% of the renewable sources of electricity generation, with solar growing at the fastest rate [1]. Among the non-renewable sources of electricity, coal continues to be a significant contributor to global warming. Although to adhere to the Paris Agreement, all coal-based power plants need to be phased out by 2040 [2], only a few countries have committed to phase out coal-power [3]. Moreover, even though many countries have ended financing of overseas coal-based power plants, coal continues to play a significant role in their own total electricity production [4]. In fact, globally coal constituted more than one-third of the electricity mix in 2024 [5].

These data show that despite global efforts to decarbonize electricity generation, coal still holds a significant share and is likely to remain so in the near future. Moreover, while the share of renewable energy based power plants (RE) in the installed capacity has increased, their share in the actual electricity production has not increased proportionately for two major reasons. First, the supply from RE sources such as solar and wind is variable and highly intermittent. For example, solar power is available only during sunshine hours and is often not aligned with demand. Second, even when the RE supply is plentily available, often it cannot be used completely due to the existence of coal-based power plants. As coal-based power plants cannot readily shutdown or be brought online, they need to run at or above a threshold level at all time. The electricity so produced is often supplied at a very low wholesale price. As a result, due to merit-order effect, this supply is used first to meet the demand even when RE supply is available and the RE supply is used to meet the excess demand. This often leads to underutilization of RE supply. We illustrate this problem using a typified example.

Consider a coal-based power plant with two units, each with generation capacity of 50 units, and an RE power plant with 55 unit capacity. Let the marginal cost of generation for the coal-based power plant be $25 per unit. As the marginal cost of generation of an RE plant is typically negligible, for ease of illustration, we consider it to be $0. Intuitively, as the marginal cost of generation of a coal-based power plant is higher than that of the RE plant, it should cater only to the demand in excess of the RE supply. However, due to its inflexibility to ramp up or down the generation at short notice or economically, the coal-based plant needs to operate at or above a threshold level. Let that threshold be 30% of its capacity, *i.e.*, 30 units. Due to this forced generation, irrespective of demand, it would offer this electricity at a wholesale price lower than or equal to that of the RE plant. Therefore, due to merit-order, the RE plant's supply is used to cater to the demand in excess of this threshold supply. In **Table 1**, we provide the data for a time horizon comprising five time periods.

Table 1 illustrates that due to the inflexibility and the resulting minimum threshold generation of coal-based power plant, utilization of available RE is lower even when the demand exceeds the available RE. Note that, the total demand, available RE supply and RE supply used are 267, 180, and 67 units, respectively. This translates to about 25% share of RE in the total demand met, the remaining 75% is met through supply from the coal-based power plant. The coal-based power plant suffers a total loss of $2250 in periods 1 through 3 as it supplies those 30 units each at $0. Intuitively, one may think these losses would drive the coal-based power plant out of business and thus would be better for the environment. However, that is far from truth. First, due to the indispatchability and intermittency of solar and wind based RE sources, one needs a dispatchable source of electricity. Second, the brunt of these losses is borne by the investors, which in case of many developing countries are state institutions. As a result the brunt is eventually borne by the public.

Table 1. Illustration of available RE capacity utilization without granular forecasting.

Time period	Demand	Available RE supply	Supply from coal-based plant	Actual RE supply used	Wholesale price	Utilization of available RE supply
1	35	50	30	5	0	10%
2	42	55	30	12	0	22%
3	50	45	30	20	0	44%
4	65	25	40	25	25	100%
5	75	5	70	5	25	100%

One obvious solution to this problem is to use battery-energy storage systems (BESS) to store the RE power generated during the excess supply period (periods 1, 2 and 3 in our illustration) to use it during excess demand period (*i.e.*, period 5). However, BESS is still not economically viable, and often requires government subsidies [6]. A more viable solution is to be able to forecast demand and available RE supply at an hourly granularity well in advance. Having reliable forecasts can allow coal-based power plants to plan their operations better. With a reliable hourly forecast for demand and RE availability, coal-based power plants can use planned shutdown of a few of their many units leading to the reduction of the threshold. This will not only increase the share of RE in the electricity used but will also reduce the coal-based power plant's losses. We describe the impact of in advance availability of such granular forecast using the data presented in **Table 1**. Assume that based on the periodwise granular forecast made available in advance, the coal-based power plant decides to operate only one of its two units, *i.e.*, its available capacity reduces to 50 units. As a result the threshold also reduces to 15 units. We describe its impact in **Table 2**.

As can be seen from the table, with granular forecasting the utilization of available RE significantly increases in each of the first three periods. As a result, the share of RE in the total demand met increases from 25% to more than 42%. Additionally, it reduces the losses suffered by the coal-based power plant from $2250 to $1125.

Table 2. Illustration of available RE capacity utilization with granular forecasting.

Period	Demand	Available RE supply	Supply from coal-based plant	Actual RE supply used	Wholesale price	Utilization of available RE supply
1	35	50	15	20	0	40%
2	42	55	15	27	0	49%
3	50	45	15	35	0	78%
4	60	25	35	25	25	100%
5	75	5	70	5	25	100%

While these illustrations showcase the value of hourly forecast made available a year or so in advance, this topic has not been studied in the electricity load forecasting literature. Researchers have studied the problem of hourly load forecasting and that of forecasting load a year in advance (also, referred to mid-term load foreasting or MTLF) separately. Most of the models for forecasting hourly load are short-term forecasting models, *i.e.*, they forecast the load a few hours to a week in advance. On the other hand, models that forecast load a year in advance do so for either monthly demand or at an aggregate level. To the best of our knowledge, this is the first work to present a model for forecasting hourly demand a year in advance. We clarify that our contribution is not the introduction of a new generic multiple-seasonality model. While established approaches such as TBATS/BATS (trigonometric seasonality, Box-Cox transformation, ARMA, Trend, Seasonal), dynamic harmonic regression (DHL), and Prophet-style models can accommodate multiple seasonal cycles, these methods typically rely on parametric representations such as Fourier terms, exponential smoothing recursions and numerical optimization, and are primarily applied in short-term or general multi-horizon contexts. In contrast, we propose a centered moving average (CMA) based parsimonious, univariate MTLF model for forecasting hourly load. CMA based forecasting is commonly used by industrial engineers and production managers due to its simplicity, ease of understanding and no requirement for any parameter initialization [7]. We extend it to the context of load forecasting where the hourly load time series exhibits three levels of seasonality—intra-day, intra-week and intra-year. We test the performance of our proposed model using real-life load data from six European countries with diverse demographic and economic characteristics. We use their data to test the robustness of our model. Furthermore, we extend two of the most popular STLF models, Holt-Winters (HW) and Holt-WInters-Taylor (HWT) exponential smoothing methods [8] to MTLF, and use them as a benchmark to compare the performance of our proposed model.

This paper contributes to both literature and practice. First, as illustrated through the examples earlier, there is a need for forecasting hourly demand a year in advance, *i.e.*, MTLF models that forecast demand at hourly granularity, particularly in light of increasing solar and wind based RE supply. Such models can increase the share of RE in the electricity consumed, thus lead to greener electricity. They can also reduce the losses suffered by coal-based power plants, which eventually affect investors and public. Second, we present a simple, intuitive, easy to implement MTLF forecasting model that accounts for the three levels of seasonality often exhibited by hourly electricity data over a year. Unlike STLF models in the literature that require initializing parameters, where the number of parameters increases with the levels of seasonality, our model does not require initialization of any parameter. Third, most of the models presented in the literature are developed for a particular country or a region within a country and they are tested on data from that region or country only. We, on the other hand, test our model on data from six countries with varying characteristics. We find that our proposed model provides very accurate forecast for each of the six countries with the MAPE (mean absolute percentage error) for the six countries ranging from 3.27% to 5.52%, with an average of 4.52%, and standard deviation of 0.009. This low standard deviation emphasizes the robustness of our model. Fourth, we extend two of the most popular STLF models, HW and HWT, and use them as benchmark to compare the performance of our proposed model. While the average MAPE for our model is 4.52%, that for HW is 13.51% and for HWT is 9.33%. Similarly, while the standard deviation of MAPE for our model is 0.009, that for HW is 0.064 and for HWT is 0.031. These results establish that our model significantly outperforms these models in terms of both accuracy and robustness.

The paper is organized as follows. In Section 2, we review the relevant literature. We present our proposed CMA based MTLF model for forecasting hourly demand in Section 3. In Section 4, we present the Holt-Winters exponential smoothing, and Holt-Winters exponential smoothing models for multiple seasonality, and provide the details of the data used for comparing the performance of our proposed model with these benchmark models. We present the result of the performance comparison in Section 5. We conclude the paper in Section 6 and provide directions for future research.

2. Literature Review

In this section, we review literature from three streams relevant to our work. First, we present a categorization of literature based on the lead time and granularity of the forecast. We use this categorization to emphasize the research gap that this paper aims to address. Second, we review the techniques used for load forecasting and justify our choice of a univariate model for mid-term load forecasting for hourly demand. Third, we review the load forecasting literature on the basis of the test data used. We observe that most papers use data from a single country or a state/city within a country. We, on the other hand, test our forecasting model on data from six different countries.

The literature on load forecasting can be broadly classified along two dimensions—the lead time for forecasting and the granularity of the forecast. The lead time for forecasting is defined as the duration between the time of forecasting and the time of realization of demand. For instance, if a forecast is made at time t

for the demand to be realized at time $t+l$, then the lead time for the forecast is l. Based on the lead time, load forecasting is classified into short-term load forecasting (STLF) where the lead time is up to a week, mid-term load forecasting (MTLF) where the lead time ranges from a week to a year, and long-term load forecasting (LTLF) where the lead time is typically greater than a year [9]. The granularity of a forecasting model is defined as the time window for which demand is forecasted such as a minute, an hour, or a month. Most of the models reported in the literature forecast demand for time windows ranging from a quarter of an hour to a year. We refer readers to [10] and [11] for a comprehensive review of the literature on load forecasting. We summarize some salient literature along these dimensions in **Table 3**. The blank cells in the table indicate a lack of literature on certain load forecasting models, some of which may not be practical. For instance, forecasting annual demand a day in advance may not have much practical applications. The table also highlights the gap in the literature that this work aims to address.

Table 3. Categorization of literature on load forecasting.

Lead time		Granularity				
		Half an hour	Hour	Hour of a week	Month	Year
STLF	Half an hour	Taylor (2003)				
	Hour		Douglas *et al.* (2002)			
	Day	Taylor (2010) Wang *et al.* (2011)	Hagan and Behr (2007)			
MTLF	Month				Zhu *et al.* (2011); Azadeh *et al.* (2007, 2008)	
	Year		Proposed Model	Al-Hamadi and Soliman (2005)		Akay and Atak (2007), Kucukali and Baris (2010)
LTLF	>1 Year				Hong *et al.* (2013)	

Our work focuses on forecasting hourly demand a year ahead so as to help power plants better manage their supply, specially in presence of intermittent and variable renewable energy supply. As can be seen from the table, most of the models for forecasting hourly demand do so a day or a week ahead, *i.e.*, they are STLF models. This is understandable as hourly load forecasts are primarily used for wholesale price bidding in the day-ahead or spot market.

Projections of demand also affect the capacity investment and divestment decisions for power plants [12] as they enable the management to make informed investment decisions based on changing market demand [9]. Although a few articles forecast hourly demand, they forecast either the aggregate or the average hourly demand for a week or a year [13]. Using the average hourly demand forecast for capacity decision might result in overestimation of the capacity of power plants based on renewable sources of energy due to their inherent intermittency. This, in turn, can lead to underestimating the required capacity of conventional power plants [14]. Moreover, as the average forecasts also discount the impact of seasonality on load, it may result in overestimating the demand in leaner periods and underestimating it in peak periods, both of which are undesirable situations for power plants. Therefore, in this paper, we propose an MTLF model for forecasting hourly demand a year in advance while accounting for the multiple levels of seasonality typically exhibited by electricity demand. To the best of our knowledge, this paper is the first attempt to predict hourly demand a year in advance. The proposed model will help power plants and regulators plan their operations efficiently. This model will also assist regulators in estimating tariffs based on the time of use (ToU) pricing a year in advance; thus, allowing commercial and retail consumers plan and manage their consumption accordingly.

Table 4. Summary of literature on load forecasting.

Author	Region	Granularity	Prediction lead time	Method	Variables	MAPE
Kucukali and Baris (2010)	Türkiye	Yearly	Year	Fuzzy logic	GDP	0.041
Akay and Atak (2007)	Türkiye	Yearly	Year	Grey prediction with rolling mechanism	Time	0.037
Wang *et al.* 2011	New South Wales (Australia)	Half Hourly	Day	Weighted Lyapunov exponent forecasting method + PSO	Time	0.025
Zhu *et al.* 2011	China	Monthly	Month	Hybrid (MA + combined + PSO)	Time	0.088
Azadeh *et al.* 2008	Iran	Monthly	Month	ANN/time series simulation/DOE	Time	0.018
Azadeh *et al.* 2007	Iran	Monthly	Month	GA + ANN	Price, time, number of customers	0.037
Taylor (2010)	Britain and France	Half Hourly	Day	ARMA, HW, HW for triple seasonality	Time	0.017
Taylor (2003)	England and Wales	Half Hourly	Day	HW with multi-plicative seasonal ARIMA model	Time	0.012
Hagan and Behr (2007)	Oklahoma (USA)	Hourly	Day	A non-linear variant of Box-Jenkins transfer function	Time, temperature	0.0373 (average)
Douglas *et al.* (2002)	Oklahoma (USA)	Hourly	1 - 5 Days	Bayesian estimation with a dynamic linear model	Time, temperature	0.03 to 0.05

A variety of forecasting techniques, both univariate and multivariate, have been proposed in the literature. While univariate models are typically used for STLF, most MTLF and LTLF models are multivariate. These multivariate MTLF models use economic factors, population, and weather forecasts as independent variables to predict demand. As mentioned earlier, most MTLF and LTLF models forecast demand at a granularity of a week or more. While these independent variables, *i.e.*, economic factors, weather etc. can be reasonably forecasted at weekly or monthly granularity, forecasting them for finer granularity, a year in advance is fraught with error [15]. Therefore, we propose a univariate model.

Different researchers have used different forecasting techniques. For instance, exponential smoothing, Holt-Winter exponential smoothing, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and Bayesian models have been used for STLF [8] [16]-[18]; genetic algorithm (GA), artificial neural network (ANN), and particle swarm optimization (PSO) based methods have been used for MTLF [19]-[21]; and grey prediction and fuzzy logic based methods have been used for LTLF [22] [23]. We summarize the literature on load forecasting in terms of their lead time, granularity, independent variables used in prediction, forecasting technique used, region for which the model is developed and the forecasting accuracy in terms of the mean absolute percentage error (MAPE) in **Table 4**.

As can be seen from the table, most load forecasting models proposed in the literature have been tested on data obtained from only one region. Thus, the robustness of these models remains uninvestigated. We check the robustness of our proposed model by testing it on data from six countries. These countries vary significantly in terms of their population density, median age of their population, demand for electricity, contribution of the manufacturing sector to their gross domestic product (GDP), per capita GDP, and geographic spread.

3. The Proposed Forecasting Method

In this section, we propose a univariate MTLF model to forecast hourly demand a year in advance. Our centered moving average (CMA) based multiplicative model accounts for three levels of seasonality and trend in demand. We use a univariate model as most predictor variables such as economic indicators are difficult to predict accurately at an hourly granularity a year in advance. CMA based forecasting methods are commonly used both in practice and research for forecasting product demand in manufacturing and operations domain due to their parsimony and ease of use [24]. In this paper, we extend these models (i) to the context of electricity demand forecasting, and (ii) to account for triple seasonality which is commonly observed in hourly electricity demand. We do not use Holt-Winters (HW) and the Holt-Winters-Taylor (HWT) exponential smoothing methods which are often used for load forecasting at hourly granularity in STLF as both these methods have high dimensionality wherein smoothing of cycles corresponding to respective seasonalities requires initialization and updation of a large number of parameters [15]. However, in Section 4 we extend these models to MTLF to compare their performance with that of our proposed model.

Electricity demand typically consists of multiple seasonal cycles and a trend [25]. Hourly electricity demand is typically affected by the hour of the day—demand is typically higher during morning and evening hours, and relatively low during afternoon and night time, day of the week—demand is typically higher in weekends than weekdays, and time of the year—initial days of the year have higher demand than those in the middle of the year [8] [25]. **Figure 1** exhibits these effects using real life data for Germany. Therefore, in our model we capture these three seasonalities, *i.e.*, intra-day seasonality, *i.e.*, hour of the day effect (HoD), intra-week seasonality, *i.e.*, day of the week effect (DoW), and intra-year seasonality, *i.e.*, week of the year effect (WoY).

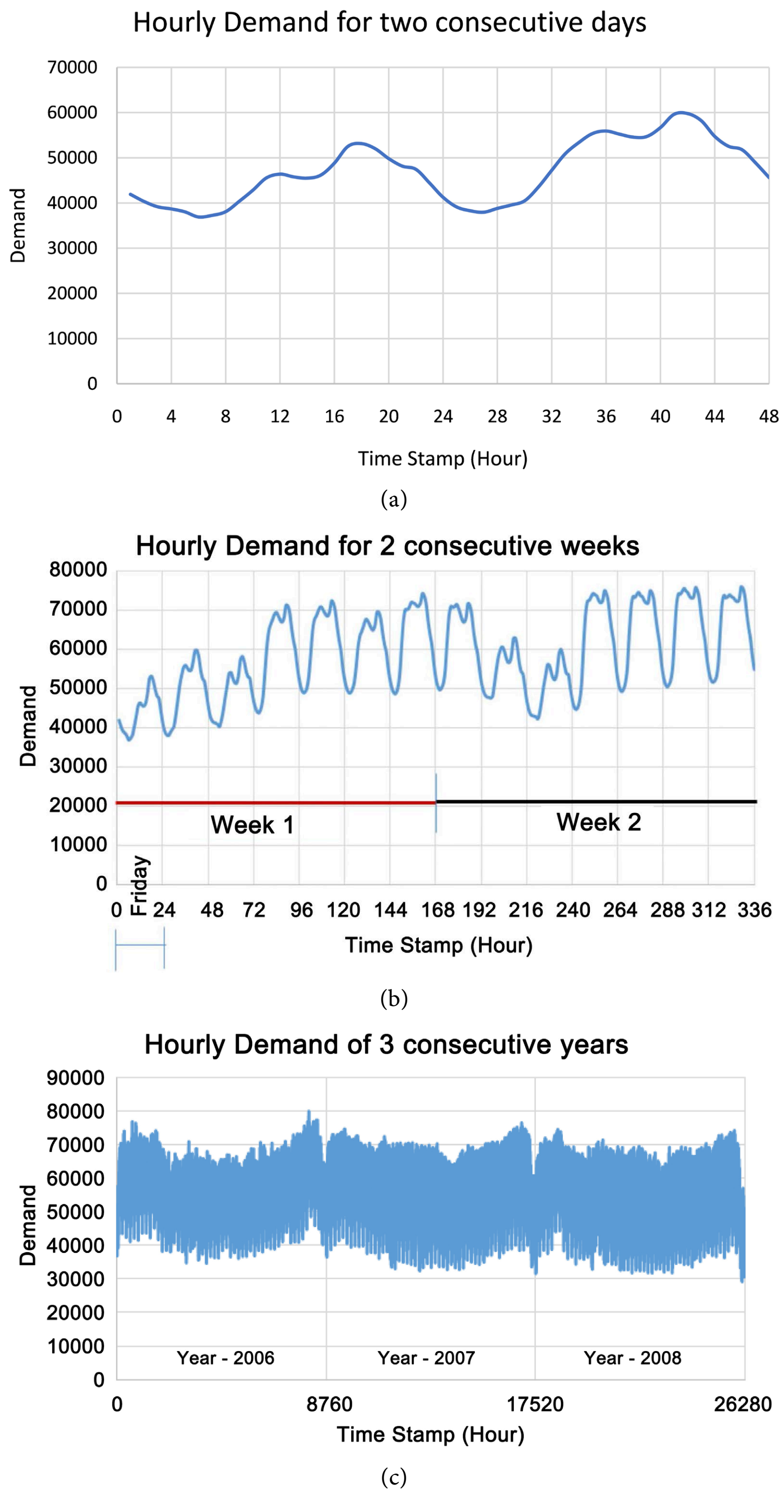


Figure 1. Intra-day, intra-week, and intra-year seasonality in hourly demand data for Germany.

While at a macro level, there appear to be 24 seasonality indices due to hour of the day effect, 7 indices due to day of the week effect, and 52 for the week of the year effect, the effect of the day of week on all 24 hours of the day need not be the same. Similarly, the effect of the week of the year on all the hours in the week need not be the same. Therefore, due to the granularity of our analysis, we need to consider the hour of the week (HoW), *i.e.*, 24 × 7 = 168 indices to capture the intra-week effect, and hour of the year (HoY), *i.e.*, 24 × 365 = 8760 indices to capture the intra-year effect. These indices are then used to derive seasonality indices pertaining to DoW and WoY effect. Although intra-year effect, in terms of HoY, captures the impact that time of the year has on demand, it does not subsume the HoD and HoW effect, since not each day of the year falls on the same day of the week for every year. As the method proposed in this paper is intended to serve strategic decision making in conventional power plants or regulatory bodies with respect to investments (or divestments) in additional capacity, special days, such as holidays, do not warrant separate treatment as would be the case for short term load forecasting [25]. Moreover, our preliminary experiments' results suggest that considering special days separately does not have a significant impact on the forecast accuracy.

Our CMA based multiplicative forecasting model is an extension of the conventional multiplicative model (Y = Trend × Seasonality) wherein seasonalities are evaluated by smoothing the data using moving average [24]. The reason we chose this model is its intuitive methodology, relative ease of usage, and its widespread acceptability among practioners, operations managers, and industrial engineers, who are typically involved in making capacity decisions for power plants. While our model is an extension of the multiplicative model, it involves several improvements and modifications over the conventional multiplicative model. We deviate from the model proposed in [8] in our consideration of intra-year seasonality. We not only consider each hour of a typical year separately, we use these hourly seasonality indices to arrive at the seasonality indices for the week of the year effect.

Our preliminary experiments suggest that an extra day on leap years and a different day of the week on every 1st of January has an impact on the demand. Therefore, to maintain uniformity we divide the horizon under consideration into batches of 52 weeks such that each consecutive batch starts on the same day of the week. We refer to a batch as a year. This helps us avoid the bias due to different number of different days of the week in a year, thus improving the forecast accuracy. This also eases the evaluation of the model. In particular, each "year" in our analysis is defined as a contiguous block of 52 weeks (364 days) beginning on the same weekday across all batches. We anchor the batching scheme to the evaluation year to ensure that the final training batch ends immediately before the forecast horizon begins. Since January 1, 2016 (*i.e.*, first day of our test year) fell on a Friday, we define the 52-week batches backward such that the last day of the last training batch falls on December 31, 2015 (a Thursday). This results in Year 7 being defined as January 2, 2015 to December 31, 2015. Continuing similarly backward in time yields Year 6 as January 3, 2014 to January 1, 2015, and so on. This construction ensures that every batch begins on the same weekday and therefore preserves consistent hour-of-week alignment across all batches used for estimating seasonal indices. The forecast horizon is then defined as the subsequent calendar period (Year 8), starting on January 1, 2016, and the resulting hourly forecasts are evaluated against the corresponding calendar timestamps in 2016. Figure 2 describes our definition of a year using data from the years 2010 to 2015.

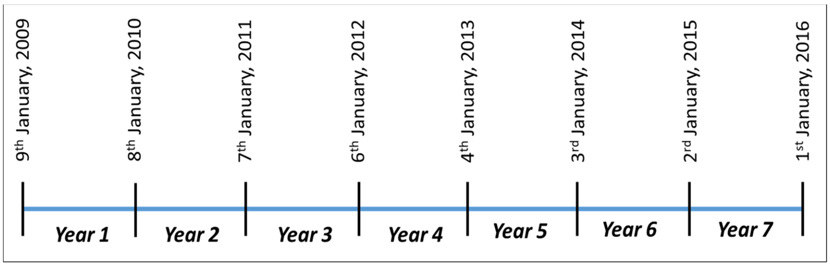


Figure 2. Definition of a "year" (consisting 52 weeks).

Table 5. Schematic representation of our forecasting model.

Stage	Step
Stage 1: Evaluating seasonality indices and de-seasonalising demand	**Step 1:** Finding hourly seasonality Indices, S_h, for each hour of the day effect and deseasonalizing demand for HoD effect **Step 2:** Finding hourly seasonality indices ($S_{h,d}$) for the hour of the week effect and deseasonalizing demand for HoW effect **Step 3:** Finding hourly seasonality indices ($S_{h,d,m}$) for the hour of the year effect and deseasonalizing demand for HoY effect
Stage 2: Determining trend component	**Step 4:** Estimating the trend line based on deseasonlized data obtained after Step 3
Stage 3: Forecasting demand	**Step 5:** Reseasonalizing the trend forecasted demand (Step 4) for the three seasonalities

We now present our proposed MTLF model to forecast hourly demand a year in advance. Let the hourly electricity demand time series consist of T observations indexed $1,2,\cdots,T$, and let Y_t denote the hourly demand for time slot (or hour) t. Our forecasting model consists of three stages, namely, Stage 1: Evaluating Seasonality Indices and De-seasonalising Demand, Stage 2: Determining the Trend Component, and Stage 3: Forecasting. Table 5 provides a schematic representation of the model. Stage 1 of model comprises three steps, the first of which uses the demand data to compute seasonality indices for hour of the day (HoD) effect, and uses these indices to deseasonalize the data for HoD effect. The second step uses the output of Step 1 to compute the seasonality indices for hour of the week (HoW) effect, and uses these indices to deseasonalize the data for HoW effect. The last step in this stage uses the output of Step 2 to compute the seasonality indices for hour of the year (HoY) effect, and uses these indices to deseasonalize the data for HoY effect. So, at the end of Stage 1, we obtain data deseasonalized for all the three levels of seasonality and with only trend component remaining. This data is used to estimate a trend line and to forecast the effect of trend. In Stage 3, this forecast is reseaonalized using the seasonality indices computed in Stage 1 to arrive at the final forecast.

We now describe our model in detail.

Stage 1: Evaluating Seasonality Indices and De-Seasonalising Demand

In this stage, we compute each of the HoD, HoW and HoY effects and deseasonalize the data for these in that order. This entails the following three steps.

Step 1: *Finding hourly seasonality Indices* S_h *for each hour of the day effect*

1) Compute the hourly moving average MA_t^H for the hour of the day effect: Given Y_t, the actual demand for time slot t, compute the hourly moving average $\text{MA}_{t'}^H$, where $t' = t - 0.5$, as

$$\text{MA}_{t'}^H = \sum_{t-12}^{t+11} Y_t / 24 \quad \forall\, t = 13, \cdots, T - 11$$

2) Compute the centered moving average CMA_t^H for the hour of the day effect: Since technically, moving averages evaluated earlier fall between two data points, we center them by computing the hourly centered MA, CMA_t^H for hour t as:

$$\text{CMA}_t^H = \frac{\text{MA}_{t'}^H + \text{MA}_{t'+1}^H}{2} \quad \forall\, t = 13, \cdots, T - 12 \text{ and } t' = t - 0.5.$$

3) Compute the rudimentary indices RS_h for the hour of the day effect: Given the demand Y_t and the centered MA CMA_t^H, compute the rudimentary index RS_h for hour $h \in \{1, 2, \cdots, 24\}$ as $\text{RS}_h = \text{Average}\left(\frac{Y_t}{\text{CMA}_t^H}\right) \quad \forall\, h = 1, 2, \cdots, 24$

where t is h^{th} hour of any day

4) Compute the seasonality indices S_h for the hour of the day effect: Using the rudimentary indices RS_h, compute the seasonality index S_h pertaining to hour h as

$$S_h = \text{RS}_h \times \frac{24}{\sum_{j=1}^{24} \text{RS}_j} \quad \forall\, h = 1, 2, \cdots, 24$$

5) Compute the demand DY_t^H deseasonalized for the hour of the day effect: Given the seasonality indices for each hour, compute the demand DY_t^H de-seasonalised for the hour of the day effect as,

$$\text{DY}_t^H = \frac{Y_t}{S_h} \quad \forall\, t = 1, 2, \cdots, T \quad \text{where } t \text{ is } h^{th} \text{ hour of any day.}$$

Step 2: *Finding hourly seasonality indices* $S_{h,d}$ *for the hour of the week effect*

Every hour of a given day of a week has its own pattern of demand. Thus, in total there are 24 × 7 = 168 patterns. Therefore, using the demand data de-seasonalised for hour of the day effect, we compute 168 hourly seasonality indices pertaining to the hour of the week effect. We follow a similar procedure as in Step 1 to arrive at these seasonality indices.

1) Compute the hourly moving average $\text{MA}_{t'}^{H,D}$ for the hour of the week effect: The window for moving average in Step 2 is 7 days, *i.e.*, 168 hours.

$$\text{MA}_{t'}^{H,D} = \sum_{t-84}^{t+83} \frac{\text{DY}_t^H}{168} \quad \forall\, t = 85, \cdots, T-83 \text{ and } t' = t-0.5.$$

2) Compute the hourly centered moving average $\text{CMA}_t^{H,D}$ for the hour of the week effect:

$$\text{CMA}_t^{H,D} = \frac{\text{MA}_{t'}^{H,D} + \text{MA}_{t'+1}^{H,D}}{2} \quad \forall\, t = 85, \cdots, T-84 \text{ and } t' = t-0.5.$$

3) Compute the hourly rudimentary indices $\text{RS}_{h,d}$ for the hour of the week effect: $\text{RS}_{h,d} = \text{Average}\left(\frac{\text{DY}_t^H}{\text{CMA}_t^{H,D}}\right) \quad \forall\, h = 1, 2, \cdots, 24$ and $d = 1, 2, \cdots, 7$ where t is the h^{th} hour of the d^{th} day of a week.

4) Compute the hourly seasonality indices $S_{h,d}$ for the hour of the week effect:

$$S_{h,d} = \frac{\text{RS}_{h,d} \times 168}{\sum_{j=1}^{24} \sum_{k=1}^{7} \text{RS}_{j,k}} \quad \forall\, h = 1, 2, \cdots, 24 \text{ and } d = 1, 2, \cdots, 7$$

5) Compute the hourly demand $\text{DY}_t^{H,D}$ deseasonalized for the hour of the week effect: Given the hourly seasonality indices, we now evaluate the demand deseasonalized for the hour of the week effects as, $\text{DY}_t^{H,D} = \frac{\text{DY}_t^H}{S_{h,d}} \quad \forall\, t = 1, 2, \cdots, T$ where t is the h^{th} hour of the d^{th} day of a week

Step 3: *Finding hourly seasonality indices* $S_{h,y}$ *for the hour of the year effect*

Every hour of a given day of a year has its own pattern of demand. Thus, in total there are $24 \times 52 \times 7 = 24 \times 364 = 8736$ patterns. Therefore, using the demand data de-seasonalised for intra-day and intra-week effect, we compute 8736 hourly seasonality indices pertaining the hour of the year effect. We follow a similar procedure as in Step 1 to arrive at these seasonality indices.

1) Compute the hourly moving average $\text{MA}_{t'}^{H,Y}$ for the hour of the year effect:

$$\text{MA}_{t'}^{H,Y} = \sum_{t-4368}^{t+4369} \frac{\text{DY}_t^{H,D}}{8736} \quad \forall\, t = 4369, \cdots, T-4369 \text{ and } t' = t-0.5.$$

2) Compute the hourly centered moving average $\text{CMA}_t^{H,Y}$ for the hour of the year effect: $\text{CMA}_t^{H,Y} = \frac{\text{MA}_{t'}^{H,Y} + \text{MA}_{t'+1}^{H,Y}}{2} \quad \forall\, t = 4369, \cdots, T-4370$, and $t' = t-0.5$.

3) Compute the hourly rudimentary indices $\text{RS}_{h,y}$ for the hour of the year effect: $\text{RS}_{h,y} = \text{Average}\left(\frac{\text{DY}_t^{H,D}}{\text{CMA}_t^{H,Y}}\right) \quad \forall\, h = 1, 2, \cdots, 24$; $y = 1, 2, \cdots, 365$ and t is h^{th} hour of y^{th} day of a year.

4) Compute the hourly seasonality indices $S_{h,y}$ for the hour of the year effect:

$$S_{h,y} = \frac{\text{RS}_{h,y} \times 8736}{\sum_{j=1}^{24} \sum_{k=1}^{364} \text{RS}_{j,k}} \quad \forall\ h = 1, 2, \cdots, 24;\ y = 1, 2, \cdots, 364$$

5) Compute the hourly demand $\text{DY}_t^{H,Y}$ deseasonalized for the hour of the year effect: Given the hourly seasonality indices, we now evaluate the demand deseasonalized for all the three effects as, $\text{DY}_t^{H,D,Y} = \frac{\text{DY}_t^{H,D}}{S_{h,y}}$ $\forall\ h = 1, 2, \cdots, 24$; $y = 1, 2, \cdots, 364$ and t is h^{th} hour of y^{th} day of a year.

Stage 2: Determining the Trend Component

In Stage 2, we use the demand deseaonalized for hour of the day effect, hour of the week effect, and hour of the year effect (obtained after Stage 1) to estimate the trend line.

Step 4: *Estimating the trend line based on the deseasonalized data obtained at the end of Step* 3

1) Using the deseasonalized hourly demand data obtained at the end of Step 3 of Stage 1, we estimate the intercept α and slope β of the trend line using the least square method. So, the forecast $\hat{Y}_t'$ for hour t based only on trend is given as

$$\hat{Y}_t' = \alpha + \beta \times t$$

Stage 3: Forecasting Demand

In this stage we use the trend forecasted hourly demand $\hat{Y}_t'$ and re-seasonalize it to take into account hour of the year effect, hour of the week effect, and hour of the day effect.

Step 5: *Forecasting the Demand*

1) Given the trend forecasted hourly demand $\hat{Y}_t'$ for the next year (as obtained at the end of Stage 2), we determine the seasonality adjusted hourly demand $\hat{Y}_t$ for each hour by multiplying it with the seasonality indices for the corresponding hour of the year, corresponding hour of the week, and the corresponding hour of the day. Thus, the hourly forecast $\hat{Y}_t$ for hour h of day y of the year which fall on day d is given by

$$\hat{Y}_t = \hat{Y}_t' \times S_{h,y} \times S_{h,d} \times S_h.$$

4. Performance Evaluation: Data and Benchmark Models

In this section, we present the benchmark models and the real life data that we use to compare the performance of our forecasting model. As mentioned earlier, in the literature we could not find any model that forecasts hourly load a year or more in advance. Since we could not find such models, we extend two of the most well-known univariate STLF models from the literature, namely, the Holt-Winters (HW) method [18] [26] and Holt-Winters-Taylor (HWT) method [8] to MTLF load forecasting with triple seasonality. We use these as benchmark models to compare the performance of our model. For sake of completeness, we describe the HW and HWT models as applied for forecasting hourly demand a year in advance in Section 4.1. To compare the performance of our model with these benchmark models, we use real life electricity demand data from six European countries which vary in terms of their geographical, demographic and ecomonic characteristics as described in Section 4.2.

4.1. Benchmark Models

Holt-Winters (HW) and Holt-Winters-Taylor (HWT) exponential smoothing methods have received a lot of attention for short term load forecasting (STLF) post the study by Taylor [18]. Both these methods can account for multiple levels of seasonality. However, their application for mid-term forecasting (MTLF) is rather non-existent. This could be attributed to the fact that, as most MTLF models endeavor to forecast demand at an aggregate level, like monthly or yearly demand, they could ignore the impact of seasonality on the demand at a granular level. As this paper focuses on MTLF at an hourly granularity which exhibits mutliple levels of seasonalities, we extend HW and HWT to account for these seasonalities.

Both these models have additive and multiplicative variants. Our preliminary results found the multiplicative models to be more accurate, therefore, we use them as benchmark models. Details on additive models can be found in [8] [18] [26]. Using estimated smoothed level l_t and local slope b_t of demand at time t, at time t the models forecast the demand $\hat{y}_{t+h}^{t}$ at time $t+h$. The local seasonality index pertaining to a given seasonal cycle is then estimated by smoothing ratio of observed value to local level and product of indices pertaining to other seasonal cycles. In both models S_j represents the length of the seasonal cycle j.

4.1.1. Multiple Seasonal Holt-Winters Method (HW)

Taylor [18] extended the Holt-Winters exponential smoothing method [26] to incorporate multiple levels of seasonality. A multiplicative model for triple seasonal Holt-Winters (HW) method can be presented through the following equations:

Forecast: $\hat{y}_{t+h}^{t} = \left(l_t + h \times b_t\right) \times s_{t+h-S_1}^{1} \times s_{t+h-S_2}^{2} \times s_{t+h-S_3}^{3}$

Level: $l_t = \alpha \times \dfrac{y_t}{s_{t-S_1}^{1} \times s_{t-S_2}^{2} \times s_{t-S_3}^{3}} + (1-\alpha)\left(l_{t-1} + b_{t-1}\right)$

Trend: $b_t = \beta\left(l_t - l_{t-1}\right) + (1-\beta) b_{t-1}$

Seasonality 1: $s_t^1 = \gamma_1 * \dfrac{y_t}{\left(l_{t-1} + b_{t-1}\right) \times s_{t-S_2}^{2} \times s_{t-S_3}^{3}} + (1-\gamma_1) \times s_{t-S_1}^{1}$

Seasonality 2: $s_t^2 = \gamma_2 * \dfrac{y_t}{\left(l_{t-1} + b_{t-1}\right) \times s_{t-S_1}^{1} \times s_{t-S_3}^{3}} + (1-\gamma_2) \times s_{t-S_2}^{2}$

Seasonality 3: $s_t^3 = \gamma_3 * \dfrac{y_t}{\left(l_{t-1} + b_{t-1}\right) \times s_{t-S_2}^{2} \times s_{t-S_1}^{1}} + (1-\gamma_3) \times s_{t-S_3}^{3}$

Here, y_t is the observed demand at time stamp t and $\alpha, \beta, \gamma_1, \gamma_2, \gamma_3$ are the non-negative smoothing parameters to be determined by minimizing the sum squared errors for the data. All the smoothing parameters are constrained to be positive and less than 1.

4.1.2. Multiple Seasonal Holt-Winters-Taylor Method (HWT)

Taylor [18] also extended the previous model by adding a parameter ϕ as an adjustment for first order residual autocorrelation [8]. We assume the following multiplicative model for triple seasonal Holt-Winters-Taylor (HWT) method:

Forecast: $\hat{y}^t_{t+h} = (l_t + h \times b_t) \times s^1_{t+h-S_1} \cdot s^2_{t+h-S_2} \cdot s^3_{t+h-S_3} \cdot \phi_h \cdot e^t$

Error: $e^t = \dfrac{y_t}{(l_{t-1} + b_{t-1}) s^1_{t-S_1} \cdot s^2_{t-S_2} \cdot s^3_{t-S_3}}$

Level: $l_t = \alpha \cdot \dfrac{y_t}{s^1_{t-S_1} \cdot s^2_{t-S_2} \cdot s^3_{t-S_3}} + (1-\alpha)(l_{t-1} + b_{t-1})$

Trend: $b_t = \beta(l_t - l_{t-1}) + (1-\beta) b_{t-1}$

Seasonality 1: $s^1_t = \gamma_1 * \dfrac{y_t}{(l_{t-1} + b_{t-1}) \cdot s^2_{t-S_2} \cdot s^3_{t-S_3}} + (1-\gamma_1) \cdot s^1_{t-S_1}$

Seasonality 2: $s^2_t = \gamma_2 * \dfrac{y_t}{(l_{t-1} + b_{t-1}) \cdot s^1_{t-S_1} \cdot s^3_{t-S_3}} + (1-\gamma_2) \cdot s^2_{t-S_2}$

Seasonality 3: $s^3_t = \gamma_3 * \dfrac{y_t}{(l_{t-1} + b_{t-1}) \cdot s^2_{t-S_2} \cdot s^1_{t-S_1}} + (1-\gamma_3) \cdot s^3_{t-S_3}$

4.2. Test Data

To test the performance of our forecasting model, we consider time series of load for the period 2009 to 2015 for six European countries, Spain, France, Belgium, Bosnia and Herezegovina, Czech Republic, and Germany (**Figure 3**). The data for all the countries were obtained from the European Network of Transmission System Operators for Electricity (ENTSO-E) database [27].

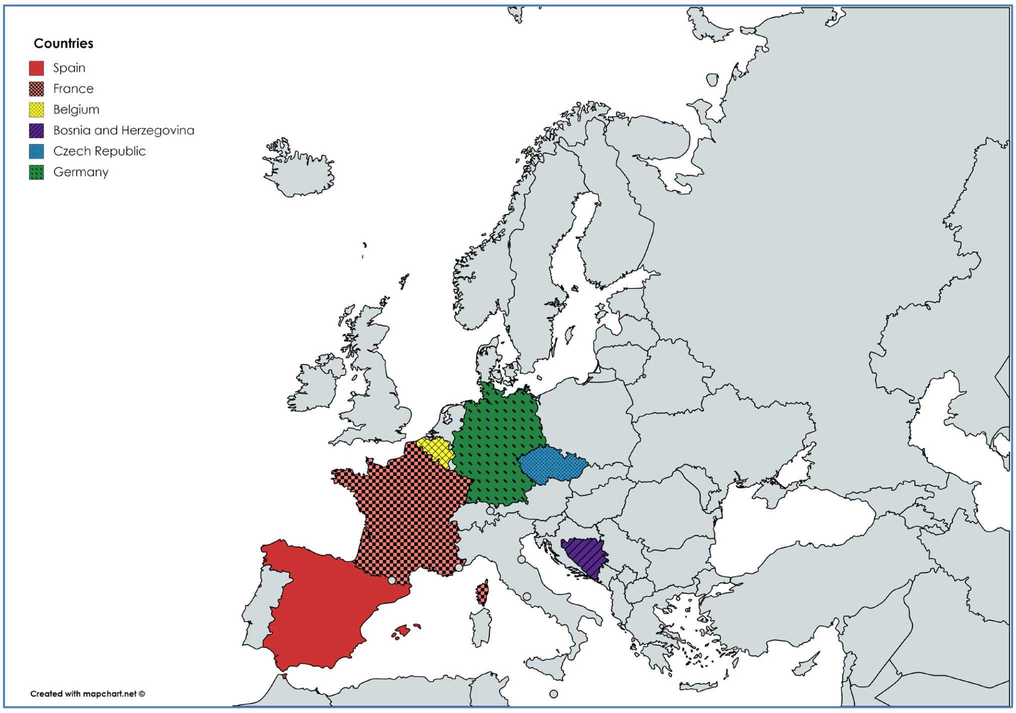


Figure 3. Countries considered for testing model performance.

These countries vary significantly on demand, population, density, area coverage, and economy, thus help us test the accuracy and robustness of our forecasts. Table 6 captures demographic, geographic, and economic details of these countries. As can be seen from the table, Germany has the highest population and the highest median age. It also has a high population density although Belgium leads on population density. While a high population could translate into higher demand, a higher median age could mean a lower per capita electricity consumption [28]. While the economies of the countries considered in this paper are dominated by the service sector, Czech Republic and Germany have a significant manufacturing sector. France has the highest peak load and a very high average load, Germany has the highest average load and comparatively a low variance in demand. A study of the load profiles of all six countries supports the presence of three levels of seasonality.

Table 6. Demographic, geographic and economic characteristics of the countries considered for load forecasting.

Country	Population		Size (km)		Median	Load			GDP Per capita (US $)	Share of manufacturing (%)
	Total	Density	Length	Width	Age	Max (MW)	Avg. (MW)	CV of load		
Belgium	11,237,274	368	228.3	111.32	41.4	14,274	9915	0.15	40361.2	13
B & H	3,825,334	75	216.6	335.38	42.1	2237	1382.4	0.19	4584.2	13
CR	10,538,275	134	406.7	222.51	42.1	11,142	7284.1	0.17	17715.6	24
France	66,458,153	103	922.0	959.00	41.4	102,098	55,338	0.22	36613.4	10
Germany	81,197,537	227	642.0	833.00	47.1	79,884	55,898	0.18	41323.9	21
Spain	46,449,565	92	1017	805.00	42.7	44,880	28,915	0.17	25789.5	13

5. Results and Discussion

In this section, we compare the performance of our forecasting model with the benchmark models (HW and HWT) using real life data from six European countries (see Section 4.1). We use the fixed-origin approach in which hourly demand for the entire year 2016 is forecast using data from 2009 to 2015 as it reflects the intended practical use of the model for full-year-ahead planning. As the proposed method is non-parametric and does not involve parameter tuning or model selection, the risk of overfitting to a particular holdout year is limited. In addition, robustness is assessed across six countries with diverse structural characteristics, thereby reducing dependence on a single dataset. For each of the six countries, we forecast the demand for each hour of the year 2016 using the benchmark models and our proposed CMA method for MTLF based on the hourly demand data from 2009 to 2015. We compare these forecasts with the actual realized demand for year 2016 using the mean absolute percentage error (MAPE)

$$\text{MAPE} = \sum_t \frac{\left|Y_t - \hat{Y}_t\right|}{Y_t}$$

where, Y_t is the actual realized demand and $\hat{Y}_t$ is the demand predicted for time period t.

Both the HW method and the HWT method entail initializing the seasonality indices for a cycle prior to the data point of interest. [18] and [8] describe the method for initializing these indices. We use the seasonality indices derived from our proposed CMA method as the initial values for the indices as it improves the performance of the HWT method. We present the countrywise forecast accuracy in terms of MAPE for each of the three models in Table 7.

Table 7. Countrywise forecast accuracy (MAPE) for different models and their summary statistics.

Country	CMA (%)	HWT (%)	HW (%)	Gap1 $= \frac{\lvert CMA - HWT \rvert}{CMA}$	Gap2 $= \frac{\lvert CMA - HW \rvert}{CMA}$
Belgium	3.42	6.06	9.52	77.2	178.36
Bosnia & herezegovina	4.85	5.63	10.99	16.1	126.60
Czech republic	4.98	13.94	13.87	179.9	178.51
France	5.52	6.80	26.24	23.2	375.36
Germany	3.27	6.77	9.44	107.0	188.69
Spain	5.10	9.33	11.01	82.9	115.88
Average MAPE	4.52%	8.09%	13.51%		
Std. Dev. of MAPE	0.009	0.031	0.064		

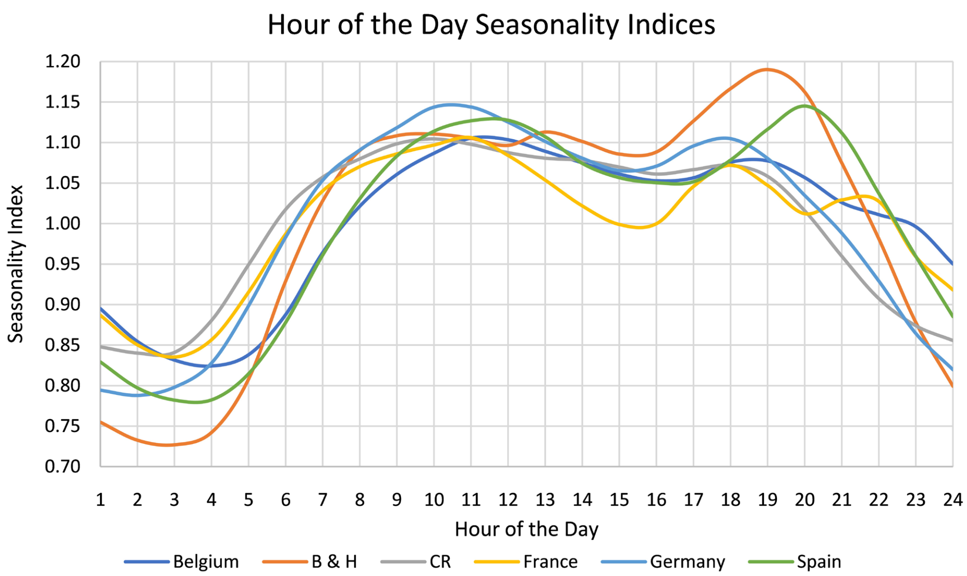
Table 8. Forecast accuracy (MAPE) for different models based on manufacturing intensity.

Comparative manufacturing intensity	Countries	Average MAPE		
		CMA	HWT	HW
High	Czech Republic, Germany	4.13%	10.36%	11.66%
Moderate	Belgium, Spain	4.46%	7.01%	10.51%
Low	Bosnia and Herzegovina, France	5.52%	6.80%	26.24%

The first six rows of the table present the countrywise forecast accuracy (in terms of MAPE) of the proposed model (CMA) and the benchmark models, HWT and HW (Columns 2, 3 and 4, respectively). The last two columns present the performance gaps of HWT and HW vis-a-vis CMA. The last two rows of the table present the average and standard deviation of MAPE across the six countries. As can be seen from the table, MAPE for our proposed CMA model ranges from 3.27% to 5.52% for the six countries. Moreover, our CMA model significantly outperforms both the benchmark models for each of the six countries. Also, the significantly lower standard deviation of MAPE across countries for CMA emphasizes the robustness of our model. Gap1 which compares the performance of CMA and HWT, highlights that MAPE for HWT can be 179.9% higher than that for CMA. Gap2 presents a similar metric comparing CMA and HW. The value of Gap2 ranges from 115.88 to 375.36 implying that in the best case MAPE for HW is 115.88% higher than that for CMA. These results clearly establish CMA as a better MTLF forecasting model for hourly load. Our results also corroborate the findings of [8] that the HWT model performs better than the HW model. In **Table 8**, we present the performance of the models with respect to the manufacturing intensity in individual countries.

Comparison of Seasonality Indices across Countries

Our proposed CMA model evaluates seasonality indices for the effects of the hour of the day (24), the hour of the week (24 × 7) and the hour of the year (24 × 7 × 52) on demand. Evaluation of indices at this level of granularity leads to a more accurate forecast than that based on seasonality indices at an aggregate level, *i.e.*, hour of the day, day of the week and week of the year. This difference can potentially be attributed to the fact that the latter method averages the impact of each specific hour type pertaining to the corresponding seasonality. However, for practical purposes, a decision-maker is likely to obtain more insights from seasonality indices evaluated at the aggregate level. Therefore, we present the aggregate seasonality indices pertaining to each level of seasonality for each of the countries in **Figures 4-6**.



B & H: Bosnia and Herzegovina CR: Czech Republic

Figure 4. Aggregate hour of the day seasonality indices.

Note that the seasonality indices presented here are discrete and pertain to the corresponding time points. We have presented these indices as continuous graphs for the sake of illustration. The figures capture the various seasonal cycles in terms of the demand for electricity in different countries. For instance, demand typically peaks in the evening (17th to 20th hours of the day) due to the lighting of homes and commercial enterprises (the subsequent decrease is due to the reduced energy consumption at night). As can be seen from Figure 5, in a particular week, demand decreases on the weekend (Saturday and Sunday) due to a reduction in commercial activities and in the operation of factories. Figure 6 shows a higher demand during winter than in summer (Week 1 represents early January in the figure). In cold countries, the demand for energy is higher in winter due to the need for heating. Although we have not considered holidays or special events in the analysis, the sudden decrease in demand at the end of the year indicates the effects of year-end holidays on the demand in all countries except Bosnia and Herzegovina.

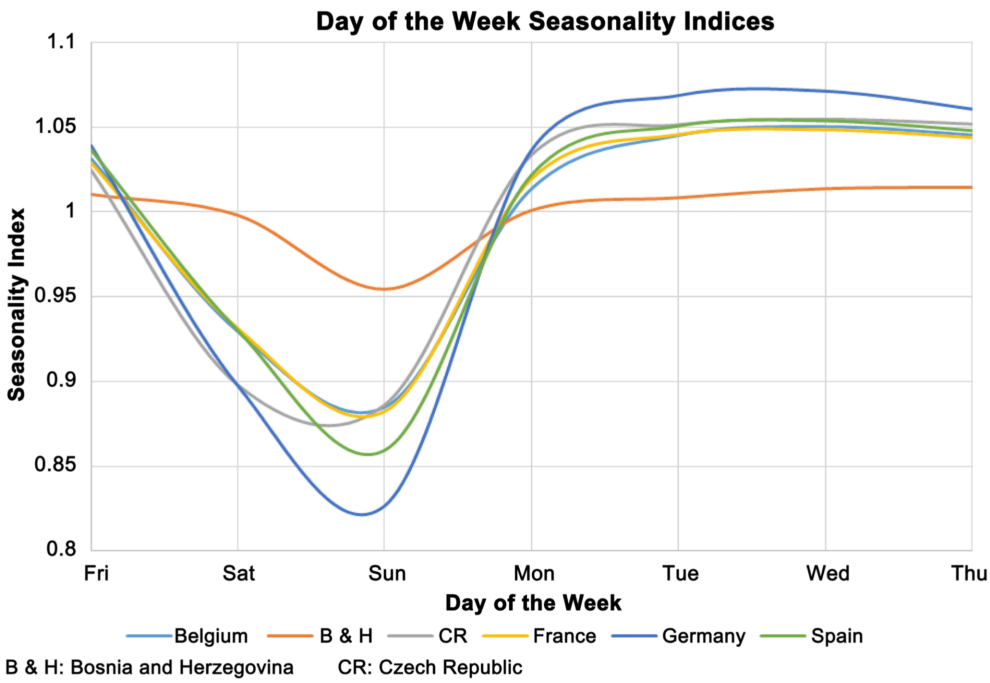


Figure 5. Aggregate day of the week seasonality indices.

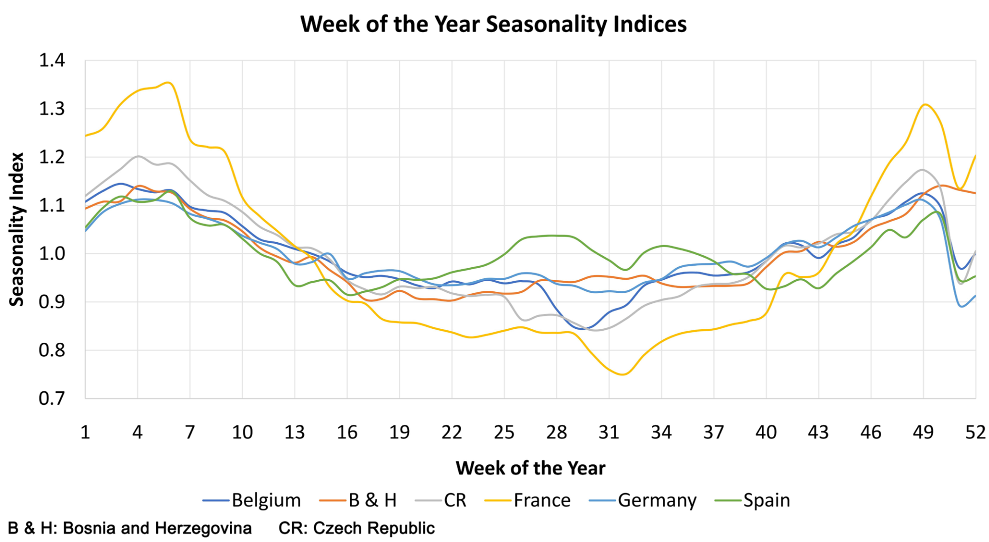


Figure 6. Aggregate week of the year seasonality indices.

The seasonality indices at each level appear to follow the same pattern in all countries. However, as is evident from **Figure 6**, France and the Czech Republic have the highest variance in the seasonality indices pertaining to the effect of the week of the year (WoY). Bosnia and Herzegovina, followed by Spain, show the highest variance in their seasonality indices pertaining to the effect of the hour of the day (HoD). As shown in **Table 7**, France has the highest MAPE when demand is forecasted using the CMA and HW methods, this is perhaps due to the high variance in its seasonality indices.

In addition to forecasting the total demand for electricity, our model can be used to predict the supply of energy available from intermittent energy sources such as solar and wind energy. If the total demand and the supply from intermittent energy sources are predicted on an hourly basis, the demand to be met by conventional power plants can be estimated with reasonably high accuracy. This forecast can help conventional power plants to plan their capacity in a much better manner and avoid the operational challenges they currently face.

6. Conclusions

This paper addresses an important and largely unexplored problem in the electricity forecasting literature, *i.e.*, forecasting hourly electricity demand a year in advance. While prior research has focused either on short-term forecasting at finer granularity or on mid- to long-term forecasting at coarse aggregation levels, the increasing penetration of intermittent renewable energy sources necessitates forecasts that are both granular and well in advance. Reliable hourly demand forecasts available well in advance can enable conventional power plants, particularly coal-based plants with operational inflexibilities, to better plan outages and capacity utilization, thereby improving renewable energy utilization while reducing economic losses.

Therefore, in this paper, we propose a centered moving average (CMA) based multiplicative forecasting model that explicitly captures three distinct seasonal cycles commonly observed in hourly electricity demand: intra-day, intra-week, and intra-year seasonality. The model is univariate, parsimonious, and easy to implement, requiring no parameter initialization or optimization. By sequentially deseasonalizing demand across multiple seasonal cycles and then re-seasonalizing trend-based forecasts, the proposed approach provides a transparent and practitioner-friendly alternative to more complex exponential smoothing and machine-learning-based methods.

Using real-life hourly demand data from six European countries with diverse demographic, geographic, and economic characteristics, we demonstrate that the proposed CMA model consistently outperforms extended versions of two widely used benchmark methods, namely, Holt-Winters (HW) and Holt-Winters-Taylor (HWT) methods, when applied to mid-term forecasting at an hourly level. The proposed model not only achieves substantially lower mean absolute percentage errors (MAPE), but also exhibits significantly lower variability in forecasting accuracy across countries, underscoring its robustness. These results highlight the advantages of explicitly modeling multiple seasonalities at a fine temporal resolution while maintaining model simplicity.

Beyond forecasting accuracy, the proposed framework offers meaningful managerial and policy insights. Hourly mid-term demand forecasts can support more informed capacity planning decisions for conventional generators, facilitate higher penetration of renewable energy by reducing forced minimum generation from inflexible plants, and aid regulators in designing time-of-use tariffs well in advance. The interpretability of the seasonality indices further enables decision-makers to understand consumption patterns across hours, days, and seasons, making the model particularly suitable as a "white-box" decision-support tool.

This study also opens several avenues for future research. First, while the model assumes a specific sequence of de-seasonalization, further work could formally examine alternative sequencing strategies and interactions among seasonal cycles. Second, extensions that integrate probabilistic forecasting or uncertainty quantification could enhance its usefulness for risk-aware planning. Third, combining the proposed CMA framework with forecasts of renewable energy availability could enable integrated demand-supply planning models for power systems with high renewable penetration. Fourth, while we evaluate the accuracy of our model using a single forecast year (2016), future research could implement a rolling-origin (walk-forward) backtesting framework in which multiple forecast years are generated using expanding training windows. Such an analysis could provide additional evidence of temporal stability and further strengthen validation of the proposed approach. Finally, it will also be interesting to study the distribution of forecast accuracy across hours of different models and identify the root causes for higher percentage errors. Future research may also incorporate additional simple baseline models for comparison, such as seasonal-naive forecasts based on 8736-hour lags or same-hour-of-week repetition from the previous year, to further quantify practical improvement over minimal-structure models.

Overall, this paper demonstrates that a simple, transparent, and carefully structured time-series method can deliver substantial practical value. As electricity systems continue to evolve toward greater reliance on intermittent renewable sources, granular mid-term forecasting tools such as the one proposed here are likely to play a critical role in enabling greener, more efficient, and economically sustainable power systems.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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