Regional Medium-Term Hourly Electricity Demand Forecasting Based on LSTM

Preprint

Hongfei Sun,[1] Dongliang Duan,[2] Hongming Zhang,[1,3] Seong Choi,[1] Jie Rockey Luo,[4] and Liuqing Yang[5]

1 National Renewable Energy Laboratory
2 University of Wyoming
3 Lower Colorado River Authority
4 Colorado State University
5 Hong Kong University of Science & Technology

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National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
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Regional Medium-Term Hourly Electricity Demand Forecasting Based on LSTM

Hongfei Sun, Dongliang Duan, Hongming Zhang, Seong Choi, Jie Rockey Luo, and Liuqing Yang

***Abstract*—This paper aims to forecast high-resolution (hourly) aggregated load for a certain region in the medium term (a few days to over a year). One region is defined as some places with similar climate characteristics because the climate influences people's daily lifestyles and hence the electric usage. We decompose the electric usage records into two parts: base load and seasonal load. Considering both temperature and time factors, different deep learning methods are adopted to characterize them. The first goal of our approach is to predict the peak load which is critical for power system planning. Furthermore, our proposed forecast method can provide the depiction of the hourly load profile to provide customized load curves for high-level real-time applications. The proposed method is tested on real-world historical data collected by CAISO, BPA, and PACW. The experimental results show that trained by three years of data, our method could reduce the prediction error for one-year lead hourly load below 5% MAPE, and predict the occurrence of the peak load for next year in CAISO with an error within three days. Furthermore, as a byproduct, an interesting observation on the impact of COVID-19 on human life was made and discussed based on these case studies.**

***Index Terms*—Medium-term load forecasting, deep learning, Long Short-Term Memory (LSTM), time coding.**

I. Introduction

Load forecasting has attracted extensive attention since the 2000s because people gradually realize that it plays a significant role in system operations and control, such as generator allocation and price planning [1]. Load forecasting can be challenging due to the growing uncertainties in both the internal factors, such as the capacity of the existing power generation, etc. and the external factors including the time change, climate, etc [2].

Based on the time scale, the lead time of medium-term load forecasting (MTLF) is usually from few weeks to one year. From 2000 to 2015, MTLF received relatively less attention because the demand for perceiving summer or winter peak load months ahead was not so urgent for power utilities. At that time, research of MTLF mainly used traditional models: economic method [3] and time series models [4]. These approaches focused on capturing the monthly or yearly load trend, which cannot meet the latest needs in load forecasting. From 2016 to 2022, with the development of data acquisition, the penetration of renewable resources, and the increasing demand of predicting summer or winter peak load, MTLF received growing attention. During this time, artificial intelligence based methods became a trend [5]–[8]. The industry generally expected the error of short-term load forecasting to be less than 5% mean average percentage error (MAPE). Thus, researchers working on MTLF were making efforts towards this goal. Although some studies can meet the error of less than 5% MAPE, they either cannot guarantee hourly resolution or cannot achieve a year-long lead time. They all have limitations in terms of pre-conditions to be satisfied, input information requirements, the difficulty of model deployment, and the training time.

In recent years, a new motivation leads MTLF to have a higher requirement for the high-resolution (hourly) load forecasting. That is to serve power system real-time applications. For example, Real-Time Contingency Analysis (RTCA) and Automatic Generation Control (AGC) are primary Energy Management System (EMS) real-time applications widely used in control rooms. They highly depend on the quality of real-time measurements on loads and generations, so the upgraded study for these applications requests sufficient high-resolution and customizable load curve data for at least one year.

Although there are some existing works studied hourly resolution load forecasting, few of them can satisfy all the following conditions simultaneously: *1) Prediction error less than* 5% *MAPE. 2) Lead time longer than one year. 3) Hourly output resolution. 4) Easily customizable.* To our knowledge, the results of [9] can satisfy the above conditions with 7 types of input factors and 5-year training data set, but our method has satisfied above conditions with 2 types of input factors and as few as 3 years of training data, and hence our model is easier to implement.

This paper provides a hybrid method to predict hourly-resolution load for a region in the medium-term (a few days to over a year). We decompose the original load records into two parts: base load term and seasonal load term, and model them by different deep learning methods with two types of input factors, namely temperature and time. Generally, more input

Hongfei Sun is with the Center of Power Systems Engineering, National Renewable Energy Laboratory (NREL), Golden, CO 80401. Email: Hongfei.Sun@nrel.gov.
Dongliang Duan is with the Department of Electrical and Computer Engineering, University of Wyoming, Laramie, WY 82071. Email: dduan@uwyo.edu.
Hongming Zhang was Chief Modeling Engineer with NREL from 12/2019 and 10/2021. He is currently with Lower Colorado River Authority in Texas. Email: hongming.zhang@srp-ok.com
Seong Choi is with the Center of Power Systems Engineering, National Renewable Energy Laboratory (NREL), Golden, CO 80401. Email: seong.choi@nrel.gov.
Jie Rockey Luo is with the Department of Electrical and Computer Engineering, Colorado State University, Fort Collins, CO 80523. Email: rockey@colostate.edu.
Liuqing Yang is with the Internet of Things Thrust and Intelligent Transportation Thrust, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, China, and the Department of Electronic and Computer Engineering, The Hong Kong University of Science and Technology, Hong Kong SAR, China. Email: lqyang@ust.hk.

factors will increase the flexibility of the model, but the prices are a higher margin for mistakes and a larger implementation complexity. We believe that on the premise of meeting the accuracy requirement, it is preferred to involve fewer factors. That is also the reason why we reduce the “dimension” of various climate factors into temperature. The base load training data consists of the low-frequency components of original records to represent the medium/long-term load variation trend. The seasonal load training data consists of all higher frequency components and the measurement noise except the base load, to represent the seasonal or periodic variation trend for both the short and medium terms. The temperature information is collected for base load and seasonal load in terms of daily average and max-min air temperature. To introduce time information, we propose three kinds of time coding schemes: weekly coding, weekday coding, and hourly coding, in which the base load uses the first two and the seasonal load uses all three. The rational is that the base load is trained by down-sampled low-frequency components of the original records, while the short hourly period will introduce lots of similar values among the hours. This would unnecessarily increase the computational cost without improving the accuracy. All input factors are interpolated or up-sampled to the same length as the training data to match the model. The base load is trained by a multi-layer perceptron (MLP) network, and the seasonal load is trained by Long-Short Term Memory (LSTM) network [10]. The final load forecast is obtained by combining the seasonal and base loads.

To demonstrate the effectiveness of the proposed method, 2 case studies for California Independent System Operator (CAISO), Bonneville Power Administration (BPA), and PacifiCorp West (PACW) load demand forecasting are presented. CAISO and BPA are America’s South and North classic power Balancing Authorities (BAs) with different load profiles. BPA and PACW are two BAs located in almost the same geographic area but also with different load profiles. By using the 2016-2018 load data as the training data, the first case study predicts the time of summer peak load occurrence for CAISO 2019 with an error within three days. The second case study uses 2015-2017 data of all three BAs as the training data and successfully reduces the prediction error below 5% MAPE for 2018 and 2019 of three BAs. Introducing more training data will further decrease the prediction error. Based on our tests, the gain obtained by more training data would saturate when the historical training data are more than 8 years because of the timeliness of climate factors for MTLF. Eventually, by analyzing the load forecasting results for the 2020 year for all of them, we objectively discuss the impact of COVID-19 on people’s daily lifestyles. The results show that COVID-19 changed people’s daily lifestyles a lot, and it brings much more influence on load profiles in South America than in North America. We also investigate the possible reasons for the different impacts.

Section II describes the methodology of modeling the different parts of the load curve and their learning methods. Section III discusses the performance and results by case study. Section IV presents the conclusion remarks and comments on the future work.

II. Methodology

This section first introduces the decomposition of the aggregated regional hourly load records into two parts and model them in different ways, namely base load, and seasonal load.

A. Region Segmentation

Climate change has a crucial impact on people’s daily lives. The load demand reflects the consumer’s daily lifestyle, so climate change is one of the most critical factors influencing medium-term load forecasting. Therefore, it is necessary to divide a vast area into several sub-regions according to similar climate factors.

For each region, the aggregated regional hourly medium term load can be expressed as a decomposition model:

$$y(t) = B(t) + S(t) + R(t)\ , \tag{1}$$

where $B(t)$ is called the base load and indicates the medium/long-term load variation trend. The $S(t)$ is called the seasonal load, representing the seasonal or periodic variation trend for both short/medium term. The $R(t)$ denotes the residual between the prediction and the actual load $y(t)$.

In Eq. (1), we aim at developing models to predict $B(t)$ and $S(t)$. We extracted different components from $y(t)$ as training data. Then, we train different models for these two terms with different forms of temperature and time factors, with the following considerations. For MTLF, some factors, such as population growth and economic change, have little influence and could be ignored, but the climate factor is significant. According to [11], the climate or weather conditions include temperature, humidity, wind speed, and cloud cover, and we can ultimately reduce all of them to the temperature factor. Besides, the time factor always influences the load profiles because the time factor is directly related to people’s daily lifestyles.

B. Base Load Modeling

We choose multi-layer perceptron (MLP) neural network to model $B(t)$ because it keeps the nonlinear relationship between input factors (e.g., time coding) and the labeled base load, noted as $B_l(t)$. The multiple layers and the nonlinear activation make MLP different from a linear perception, and it can identify data that is not linearly separable [12]. Also, it has relatively low computation cost.

1) Labeled Data Extraction:

Based on the data set introduced above, we can extract $B_l(t)$ from the original records by keeping the low-frequency component to train the MLP model, because $B(t)$ captures the medium/long-term load curve variation trend.

Using Digital Fourier smoothing (DFS) [13], we can accurately control how much low-frequency component needs to be kept. The cutoff frequency of the DFS should be determined by the number of weeks in the entire length of records. The low-frequency component is maintained based on the weekly repetition because the periodic characteristics of the load curve occur in ranging from daily, weekly to monthly [11].

2) Input Factors:

The average temperature records of each day of main cities or populated areas are needed for temperature factors. Just average temperature is necessary because $B(t)$ as a trend-capturing part does not require the details of daily temperature change. However, we cannot use these average temperature data directly because the number of samples would not match the length of $B_l(t)$. The sampling rate of $B_l(t)$ will remain more extensive than one sample per day. Therefore, the original temperature sequence needs to be interpolated to have the same length as $B_l(t)$. To keep the smooth change and minimize the computation time cost, we use the Catmull-Rom splines interpolation for upsampling [14].

The time factor for $B(t)$ includes weekly coding and weekday coding. Time should be fair to each sample, and the value of a time variable should not be taken to have quantitative meaning. Thus, the input variable of the time factor should not be a rational number variable but a categorical variable.

To relate the time variation to $B_l(t)$, we introduce weekly coding to label 52 weeks of the year, because we consider keeping the low-frequency information in weekly repetition, as shown in Figure 1. We transformed the number of weeks into 6 parallel binary variables.

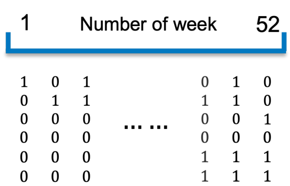

Fig. 1: The weekly time coding.

To facilitate the model in capturing short-term periodical properties, we introduce weekday coding to label weekdays from Monday to Sunday for each week. For example, the model should at least identify workdays and weekends. As shown in Figure 2, we transform weekdays into 3 parallel binary variables.

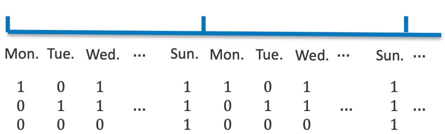

Fig. 2: The weekday time coding.

To make the input time factors have the same length as $B_l(t)$, we need to create the time coding portfolio for each sample from $B_l(t)$.

C. Seasonal Load Modeling

The $S(t)$ model is built on long-short term memory (LSTM) neural network. It is a kind of Recurrent Neural Network (RNN), which can relate the current output not only to the current input but also to the long- or short-term past inputs. LSTM can capture the periodicity exhibited in $S(t)$ for the daily, weekly, and monthly load.

1) Labeled Data Extraction:

Seasonal load includes all higher frequency components and measurement noise except $B(t)$, so we extract the labeled seasonal load, noted as $S_l(t)$ by subtracting $B_l(t)$ from the original records $y(t)$:

$$S_l(t) = y(t) - B_l(t) \tag{2}$$

After this subtraction, $S_l(t)$ should be centralized at 0, roughly fluctuating around 0 symmetrically.

2) Input Factors Organization:

Unlike $B(t)$, we introduce the temperature factors by the minimum and the maximum records of each day of main cities or populated areas in the sub-region. Because $S_l(t)$ changes in peaks and troughs every day, the temperature changes in minimum and maximum could highlight the feature of seasonal changes better to match $S_l(t)$. We also need to implement Catmall-Rom splines interpolation to up-sample the temperature sequence to have the same length as $S_l(t)$.

Unlike $B(t)$, the time factors for $S(t)$ are introduced by weekly, weekday, and hourly coding. The weekly coding labels the variations in the pattern of $S_l(t)$ among different seasons. The weekday coding cycle from Monday to Sunday will easily help the training process distinguish between working days and weekends. Also, as a rule of thumb, Thursdays tend to have the highest load peaks of one week, and this coding method could help the training process capture the periodic nature in $S(t)$ for both long-term and short-term. The hourly coding is to help the model match the loads' peaks and troughs more accurately.

For a similar reason from $B(t)$, we need to create the time coding portfolio for each sample from $S_l(t)$.

In LSTM, the current output (also called a hypothesis) is related to the current input and the past inputs. When using the LSTM, the input matrix has three dimensions: the number of input factors, training samples, and memory length. There are many ways to implement the LSTM model, and we use it with a fixed size of memory. The number of input factors should be the number of prominent cities that collected temperatures plus their time coding binary variables. The number of training samples is equal to the length of $S_l(t)$. Each sample in $S(t)$ corresponds to a complete set of input factors. Each set of input factors includes a piece of memory of the corresponding data. We denote the length of memory as m. In our proposed method, the size of memory m should at least satisfy $c \times 24 \times 2^2$, where c is the sampling rate of the $S_l(t)$ with unit samples per hour. The reason for this is to make the two adjacent weekdays to have three different binary time variables. As Figure 3 shows, the input matrix should be this, assuming that the temperature for the three main cities is collected. The index of input samples s should be $m < s < n$, and each sample includes $s - m$ historical samples as the memory.

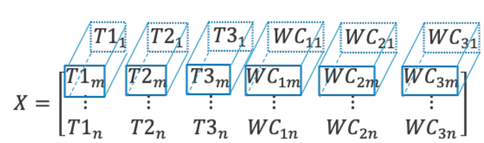

Fig. 3: The inputs matrix formation of LSTM.

III. Case Study

This section provided 2 case studies: the 2019 peak load prediction for CAISO, and year-ahead load prediction for CAISO, BPA, and PACW. Eventually, by analyzing the load forecasting results for the 2020 year for all of them, we discuss the impact of COVID-19 on people's daily lifestyles.

In our TensorFlow platform experiments, the configuration of the MLP model for $B(t)$ is: 2 hidden layers with 50 and 30 neurons separately, the rectified linear unit function is used as the activation function, and the model is solved by the stochastic gradient-based optimizer (ADAM). The LSTM model for $S(t)$ used 6 classical LSTM layer and one densely-connected layer before the output layer, and the loss is quantified by the mean squared error, which is solved by ADAM also.

A. CAISO 2019 Summer Peak

We chose CAISO as an example because its entire region is in the same climate zone and BA. That means the aggregated load data for the entire region is easy to obtain. The data on electricity demand for CAISO from 2009 to the present could be downloaded at [15].

For CAISO, due to the increase in air-conditioning usage by the hot climate, summer is the highest period of electricity consumption throughout the entire year. The peak electricity consumption week of the whole year also appears in summer. Thus, the resilience of the electricity system for CAISO is highly challenged in summer and usually has some active or passive blackouts occur in recent years' summer. We use the load records for CAISO from 2016 to 2018 to extract $B_l(t)$ and $S_l(t)$ to train the proposed models. In addition, we collect the input information of temperature from three major cities of California: San Francisco, Los Angeles, and San Diego.

The extraction of $B_l(t)$ is shown as Figure 4. The time domain yearly load was transformed to the frequency domain by the DFS, and we plotted the amplitude responses. In this amplitude response, there are some prominent peaks, and they intuitively explain the periodic characteristics of the load curve. These periodic characteristics of the load curves range from the daily load, the weekly, monthly, and seasonal to yearly load curves [11]. Because we computed the DFT-transferred load curve on each year, the minimal high-amplitude cycle is one, which means one year and maps to the highest peak in the middle of Figure 4. Moreover, we could discover that there will be a high amplitude for about every $\pm 52(year^{-1})$. Each year has 52 weeks, and people's daily lifestyle highly repeats every week. Hence, we consider keeping the low-frequency information in weekly repetition by keeping the truncated at least $\pm 52(year^{-1})$ in the frequency domain. In practice, people usually choose the absolute value of the truncated cycle a little larger than $52(year^{-1})$ to have more tolerance, and in our research, $60(year^{-1})$ is used (marked between two red lines).

The final aggregated load forecasting was obtained by combining $B(t)$ and $S(t)$. The forecasting results for CAISO August are plotted in Figure 5. In this figure, the orange curve is the recorded load curve, and the blue curve is the predicted load curve. As the figure shows, we successfully predicted the peak load week of 2019 for CAISO.

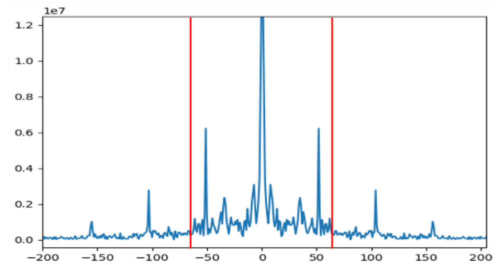

Fig. 4: Digital Fourier Transform of yearly load curve and low-frequency component extraction.

B. Year-Round Prediction for CAISO, BPA, and PACW

Based on our dataset, we predicted the load curve from 2015 to 2020, and each year was trained by all data from 2014 to the previous year. For example, the prediction of 2017 uses a training set from 2014 to 2016, and the prediction of 2020 uses a training set from 2014 to 2019. Figure 6 records the MAPE between the prediction curve and the label curve from 2015 to 2020. The MAPE are decreasing from 2015 to 2019, but when we compute the prediction for 2020 with six years of data training, the MAPE increased for CAISO and BPA. It is because COVID-19 changed people's daily lifestyles.

Due to the pandemic of COVID-19 in 2020, people are locked down in their homes for most of the time, which has changed people's daily lifestyles significantly. It directly impacted the load profile of the power system. We computed the forecasting MAPE for 2020 to see how much impact COVID-19 brings.

From Figure 6 we notice that the increased prediction error for 2020 of CAISO is much larger than the increased prediction error for 2020 of BPA. It demonstrates that COVID-19 brings much more impact on CAISO than on BPA. We believe that this is because of the different high load demand periods between CAISO and BPA. The high load demand period for BPA is winter around January, but the high load demand period for CAISO is summer around August. It is well known that COVID-19 broke out in North America after March and reached a severe situation in August. Therefore, COVID-19 brings much more influence on CAISO.

IV. Conclusions and Future Work

In this paper, an algorithm was proposed to forecast high-resolution (hourly) aggregated load for a region in the medium-term (a few days to more than one year). We first decomposed the hourly load records for the region into two parts, namely the base load and the seasonal load. We found the relationship between the extracted load data and input factors (temperature and time) by model the base and seasonal loads with different deep learning networks, namely MLP for the base load and LSTM for the seasonal load. We designed time coding for input factors to highlight the temporal relationship between samples. An effective hourly aggregated medium-term load prediction can be obtained by assembling two parts

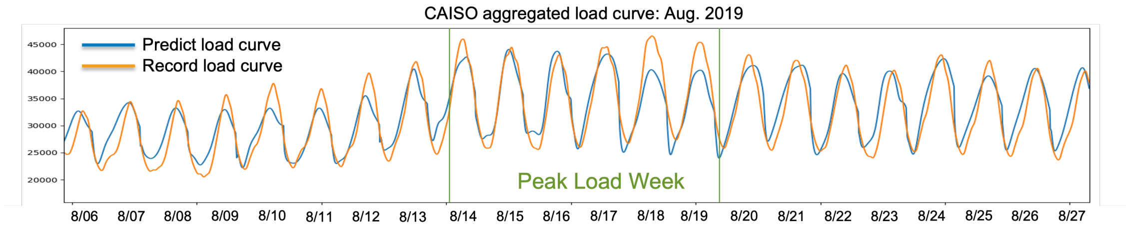

Fig. 5: The aggregated load for CAISO in August 2019.

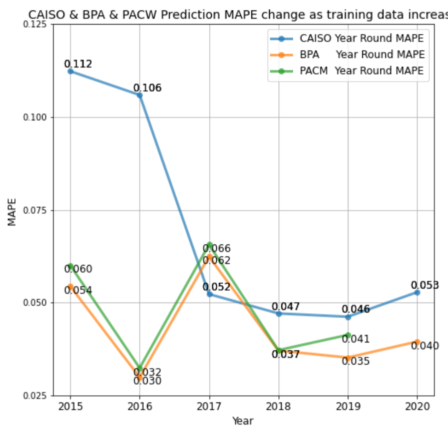

Fig. 6: The prediction error as the size of training data increases for 2017-2020, which shows the impact of COVID-19.

of forecasting. The proposed method can produce an accurate prediction of the peak load and depict hourly load profile. It can also provide a customizable load curve for higher-level real-time applications. Finally, two case studies for CAISO and BPA, and PACW load demand forecasting were presented. Eventually, by analyzing the load forecasting results for 2020, we objectively discussed the impact of COVID-19 on people's daily lifestyles.

In the future, in addition to climates and time, some factors would be increasingly important for demand modeling, such as distributed energy resources (DERs). Hence, we will incorporate these information to our model. Mathematically analyzing the impact of COVID-19 on the power society based on load modeling would be another interesting expansion. The proposed model has a limited capability to learn the higher frequency components in the seasonal load and the residual term, which causes the current mismatch between predicted and actual data (seen in Figure 5), and in the next step we will try to improve our model in this aspect.

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