IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 7 February 2024, accepted 22 February 2024, date of publication 26 February 2024, date of current version 4 March 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3370442

RESEARCH ARTICLE

Predicting Energy Demand Using Machine Learning: Exploring Temporal and Weather-Related Patterns, Variations, and Impacts

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This work was supported in part by the Eversource Energy Center, University of Connecticut, through the project titled "Optigrid: Planning and Optimizing the Power Grid During the Low Carbon Transition in Connecticut."

ABSTRACT This study aims to develop models for predicting hourly energy demand in the State of Connecticut, USA from 2011 to 2021 using machine learning algorithms inputted with airport weather stations' data from the Automated Surface Observing System (ASOS), demand data from ISO New England (ISO-NE). We built and evaluated nine different model experiments for each machine learning algorithm for each hour of the day addressing energy demand patterns, variations between workdays and weekends, and COVID-19 impacts. Error metrics analysis results highlighted that the GBR model demonstrated better performance compared to the MPR and RFR models. Incorporating both temporal and weather features in the models resulted in a noticeable improvement in error metrics. A consistent overestimation trend was observed for all models during the validation period (2018–2019) which may be attributed to energy efficiency measures and integration of behind-the-meter generation, with a further notable increase in overestimation following the onset of COVID-19 due to a change of habits during the pandemic in addition to decarbonization initiatives in the State. This study emphasizes the need for adapting models to dynamic consumption and weather patterns for improved grid management.

INDEX TERMS Energy demand, machine learning, weather stations, ISO New England, COVID-19, Bayesian optimization.

I. INTRODUCTION

Energy is critical for economic, social, and technological progress, but its consumption poses challenges for energy security and climate change [1]. The energy transition is eliminating the traditional distinctions between demand and supply, primarily due to the increasing involvement of prosumer resources [2]. Future renewable energy systems need technologies like storage, demand-side management, and sector integration, including industry electrification, to handle production fluctuations and decarbonize challenging sectors [3]. Climate change can make energy systems vulnerable, impacting supply, demand, transportation, infrastructure, and the broader economy [4]. It significantly affects energy demand by potentially altering the extent and intensity of daily and seasonal heating and cooling needs and posing considerable threats to infrastructure and communities [5]. This emphasized the need to accurately establish the correlation between load and temperature [6]. The phenomenon of urban heat island (UHI), and the increased frequency of

The associate editor coordinating the review of this manuscript and approving it for publication was Ines Domingues.

extreme weather events such as heat waves due to climate change have resulted in escalating demand for space cooling energy consumption [7], [8].

Electricity demand is influenced by several critical factors, including population, households, wealth, culture, climatic circumstances, economic variables [9], [10], system operators, and market participants [6]. Given the anticipated increase in demand in the forthcoming period, it is essential to establish a correlation between prospective demand changes and the required generation and network capacity from a system planning perspective [11]. The prediction of electricity demand holds significant importance in facilitating the planning and operation of power systems, and for the development of production, distribution, and transmission facilities [12]. Energy system reliability requires careful planning and forecasting, with accurate short-term forecasts essential for optimal unit commitment, and long-term forecasts necessary for facilitating capacity planning and promoting adequate provision of transmission and generation resources for future demand [13].

Electricity demand is subject to considerable influence from climatic conditions [11], [14], which account for a significant portion of its intra-annual fluctuations [14], leading to expected alterations in demand patterns [11]. Additionally, electricity consumption patterns vary geographically, with some areas in the southern U.S. experiencing winter peak demand due to electric heating usage, unlike the typical summer peak in the USA [15]. Given a potential rise in the occurrence of extreme events and alterations in weather variables per climate projections, it is worthwhile to conduct a detailed investigation into the impact of weather-related conditions on energy demand [16]. According to Mirasgedis et al. [17], the factors that affect electricity demand are ranked in descending order of significance as follows: temperature, humidity, wind, rainfall, and cloud cover [16]. Cassarino et al. [9] employed temperature, wind speed, and solar irradiance variables to examine the influence of both social and meteorological factors on historical energy demand in Europe. The Hotmaps Project [18] provides estimations of daily cooling and heating demand for 28 European countries, employing temperature as the sole meteorological input. Conversely, When2Heat [19] offers hourly heating profiles for 16 European countries by incorporating both temperature and a wind speed as input variables [20].

The primary driving force for load forecasting has been identified as temperature [6], [21], and a strong negative correlation is found to exist in winter, and a positive in summer between demand and temperature [10], [21], [22]. During the winter season, a noticeable demand for lighting and heating occurs simultaneously with decreasing temperatures. On the contrary, during the summer season, the usage of electrical heating systems is typically non-existent, but the warm climatic conditions can result in an increased demand for refrigeration, fans, and air conditioning (AC) services [21], [23], [24]. Wind speed affects electricity demand through electrical heating and cools the wet exterior walls of buildings [21]. The study by MacMackin et al. [13] highlighted the significant impact of weather as a vital determinant of both daily and seasonal fluctuations in electricity demand, and the absence of comprehensive data on end-use consumption for space cooling and heating poses an important challenge in accurately predicting the impact of weather on electricity demand. Various heating and cooling technologies are used across diverse geographic regions, and when a nation uses electricity for cooling and/or heating, even a slight fluctuation in temperature can result in significant variations in the electricity demand [6].

Diurnal load patterns are influenced by human activities, which take place in domestic and occupational settings and during leisure hours. Holidays tend to decrease activity levels in non-domestic sectors [9]. During weekends, the load demand experiences a substantial decline [22], [25] owing to the decrease in economic activities during this time [22]. Giannakopoulos & Psiloglou [22] analyzed energy demand in Athens, Greece, and its correlation with temperature. The midday peak in daily variability is caused by intense electricity use for household and business needs, and the second peak is caused by extra lighting and temperature control in the late afternoon and early evening. July has higher workdays, and January has higher weekends consumption. AC usage drops on weekends in July as people leave offices for cooler outdoor settings. In January, individuals stay indoors on weekends, leading to higher energy use. Another study by Psiloglou et al. [26] compared electricity demand and air temperature in Athens, Greece, and London, UK. Electricity demand peaks in winter for both cities, with a second peak in summer only in Athens. Cities have lower electricity demand on holidays and weekends, particularly on Sundays and during the summer. They observed that electricity demand in Athens peaks twice, at midday and in the evening, while in London, it stays high during office hours. Yukseltan et al. [27] examined electricity consumption in Turkey by developing a regression model using harmonics of daily, weekly, and seasonal patterns. The electricity demand on an hourly basis was projected for both a 1-week and 1-day period, achieving a 3% mean absolute percentage error (MAPE) [27]. Contu et al. [6] explored temperature-related changes in electricity demand in Italy with a proposed approach customizable by geography and time, and the results illustrate that sensitivity coefficients vary by Italian region, and the reasons are linked to domestic demand such as building climate and technology. Dahl. et al. [28] used meteorological data and untraditional data like school holidays to analyze heat load forecasting by using three different machine learning models, namely the ordinary least squares (OLS), multilayer perceptron (MLP), and support vector regression (SVR) models, in Aarhus, Denmark. Model results showed the value of incorporating local holiday data for better forecasting accuracy, and the best forecast performance is achieved with SVR on weather, calendar, and holiday data, resulting in a mean percentage error (MAPE) of 6.4%. Brubacher and Wilson [29] considered the impact of irregular holidays on electricity demand within their model for hourly electricity consumption. To address the absence of data for holidays, they employed an interpolation technique by estimating the demand during the periods immediately preceding and following the holiday.

A study analyzed the meteorological variations in monthly electricity demand of Italy using a multiple linear regression model considering temperature, wind speed, relative humidity, cloud cover, and calendar effect factors [16]. A regression model by MacMackin et al. [13] predicted the influence of weather on electricity demand across sectors within Ontario, Canada. The demand was segmented into base, heating, and cooling categories within the model. Residential and commercial sector models fit well but came across challenges in effectively capturing cooling demand. Allen et al. [5] demonstrated the importance of accurate predictions of electricity demand for adaptation planning in the U.S. in a changing climate. An analysis established that higher temperatures over the next 40 years will have the greatest impact on electricity demand in areas with small populations, causing stress during peak demand. Fonseca et al. [15] examined the impact of climate change on hourly electricity demand patterns, season variations, and power system operations by using a regression model, an economic dispatch model, and twenty different climate projections. Hekkenberg et al. [24] explored electricity demand in the Netherlands, focusing on changes with increased cooling applications, and results showed significant temperature dependence in May, June, September, and October during summer holidays from 1997-2007. This trend has led to a 0.5% increase in electricity demand per degree of temperature difference during the summer. Three models were created by Zhang et al. [25] using linear regression, random forest, and gradient boosting with the solar capacity to predict hourly demand in southern California 24 hours prior, and findings displayed that models were more accurate with lower loads (morning, night, and winter), and models had larger errors during midday and summer with higher loads.

Several studies have examined the energy demand patterns after the year 2019, with a particular emphasis on pre-and post-COVID-19. COVID-19 rapidly shifted billions of people worldwide to working and learning from home [30]. Overall, there has been a decline in energy demand, but variations in energy use still exist. Despite the decrease in economic activity, the power grid continues to maintain its reliability [31]. Energy intensity has shifted noticeably, with COVID-19 mitigation efforts playing a non-negligible role in stabilizing energy demand, while regional energy recovery exhibits substantial disparities. The COVID-19 pandemic-induced shutdowns have had a considerable impact on the electricity demand levels in Europe, at both daily and weekly time scales [32]. Agdas and Barooah [31] analyzed electricity data in California, Florida, and New York, and found pandemic effects on electricity demand and grid stress vary regionally. Some stress indicators showed increases, decreases, or no clear difference. Jiang et al. [33] analyzed COVID-19's impact on energy demand, emphasizing challenges and opportunities, and the study highlighted the need to identify post-pandemic energy opportunities for increased efficiency. A study on COVID-19's impact on Ontario's energy sectors demonstrated that electricity demand in the province decreased by 14% due to the pandemic [34]. Wu et al. [35] analyzed data to predict half-hourly electricity demand in Victoria, and their model distinguished lockdown and non-restrictive periods, and revealed influential demand patterns during the intermittent lockdown. Baker et al. [36] examined COVID-19's impact on power usage in two U.S. states using diverse machine-learning algorithms. The study underscores the need for additional research and the application of algorithmic groups to understand electric power demand trends during uncertain events.

Correctly predicting energy demand has important implications for energy costs and security. For system operators and electric utilities to deliver electricity to their customers at any time, enough power should be generated. The grid is constantly in a delicate balance between over-generation and wasting energy, and under-generation and the risk of blackouts. With the ongoing trend of electrification in various sectors, the aging infrastructure is poised for significant challenges. This transition is marked by a dual impact, with increasing demand driven by such as the adoption of electric vehicles and a simultaneous decrease in demand due to the incorporation of renewable resources, such as solar photovoltaics (PVs), into the energy framework. The study is motivated by the essential need for accurate hourly energy demand prediction in Connecticut to enhance grid management. This is necessary for effective grid management, ensuring a stable and reliable electricity supply. Also, we aim to capture dynamic consumption patterns, including demand variations during workdays, and weekends, and the impact of the COVID-19 pandemic. Our motivation is to provide robust machine learning models that can handle dynamic consumption and weather patterns for effective energy management. The goal of this study is to develop models for predicting hourly energy demand in Connecticut (CT), using eight airport weather stations' data from the Automated Surface Observing System (ASOS), and demand data from ISO New England (ISO-NE). To achieve this goal, three distinct machine learning algorithms, namely multivariate polynomial regression (MPR), random forest regression (RFR), and gradient boosting regression (GBR) models, were constructed and evaluated using the period from 2011 to 2021. In this study, we performed a comprehensive analysis, considering baseline (bl), weather influence (wx), and time-weather interactions (twx) across all days of the week (all), workdays (wd), and weekends (wknd) for each hour of the day using the three machine learning algorithms: MPR, RFR, and GBR. This study addresses three research questions: (1) How does energy demand vary on an hourly, daily, monthly, and yearly basis? (2) How do trends in energy demand change between workdays and weekends, and what is the best setting for

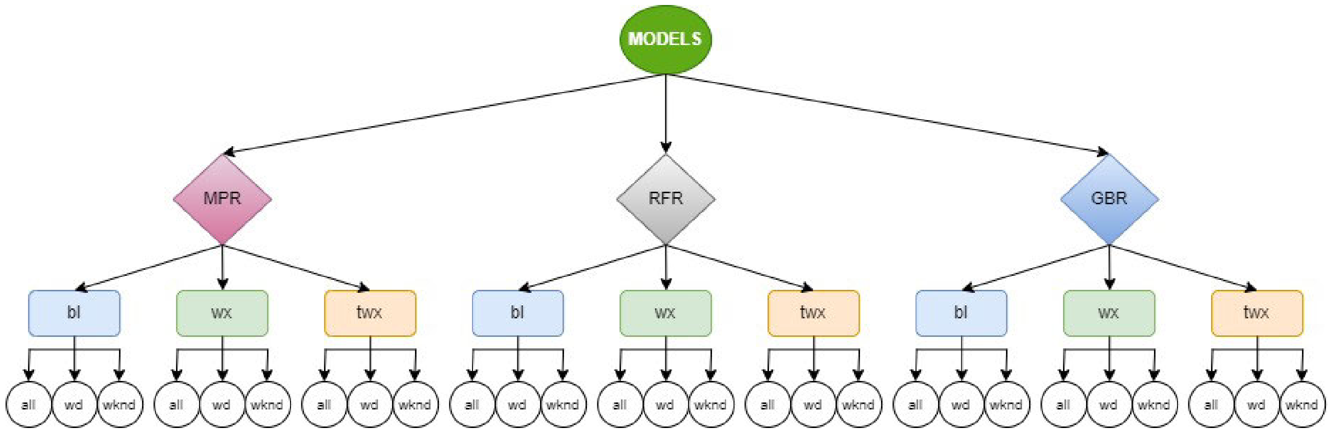

FIGURE 1. Illustration of the nine model experiments for each of the three machine learning algorithms (MPR, RFR, GBM) for each hour of the day in the study (resulting in 27 white dots on the bottom). Each of the three machine learning algorithms was fitted with varying time or weather configurations (bl, wx, twx) for different days of the week (all, wd, wknd) for each hour of the day. In general, the best-performing model experiments were the GBR for the 'twx' configuration segmented into workday ('wd') and weekend ('wknd') variations.

modeling these trends? (3) How does energy demand vary before and during the COVID-19 pandemic? The novelty of this work consists of the error analysis that was performed to assess the impact of COVID-19 on the performance of models trained with pre-pandemic data. We provide valuable insights from bias analysis, discovering variations in predictive accuracy across different months. Moreover, we studied temporal and weather-related demand patterns through a multi-model comparison for each hour of the day. Through the development of robust prediction models, this research contributes to the resilience and adaptability of the energy grid. Also, we recognize the need for accurate hourly energy demand prediction as a critical aspect of grid management, considering the outgoing trends of electrification and the incorporation of renewable resources.

II. STUDY AREA AND DATA

Connecticut (CT) has a population of approximately 3.62 million as of 2023 [37]. During the period spanning from 2010 to 2021, the state experienced a population growth rate of nearly 0.8%. In contrast, the population of the United States experienced a growth rate of 7.3% over the same period (during the 11 years) [38]. In 2022, the state's population growth rate was 0.08%, while the country experienced a growth rate of 0.38% [39]. Based on an examination of available data, it can be inferred that the growth rate in the state of CT is lower than that of other regions, leading to the exclusion of the population from consideration in the present study.

Generally, annual variations in wholesale electricity load are driven by temperature fluctuations [40], [41]. However, wholesale electricity demand in the New England region (comprising six states in the Northeastern United States: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont), also known as Net Energy Load (NEL) [42], has demonstrated a decline in recent years, primarily attributed to the influence of state policies encouraging the implementation of energy efficiency measures and the increase in behind-the-meter generation [40], [41], [42]. Nevertheless, load levels are anticipated to experience a notable increase in the upcoming decade due to the electrification of both the heating and transportation sectors [42]. CT has introduced policies for enhancing energy efficiency and renewable energy. Table 1 outlines the state's plan for decarbonization. Also, the state has two electricity demand forecasts: (i) Base case – Continuing existing consumption trends based on ISO-NE capacity, Energy, Loads, and Transmission (CELT) Forecast, and (ii) High Electrification Case – Anticipating rapid electric vehicle and building heating adoption [43].

TABLE 1. Milestones for connecticut decarbonization initiative [43].

Focus Area	Target
Energy Supply	40% renewable electricity by 2030, and 100% by 2040
Energy Efficiency	40% reduction in building energy use by 2030
Building Electrification	3 million air source heat pump (ASHP) installations
Transportation Electrification	500,000 Electric Vehicles (EVs) by 2030 and a 60% Light-duty EV (LDEV) in 2040
Storage	Install 580 MW by 2030, 1000 MW by 2040

Connecticut is on the east coast of North America, with cold winters and hot summers, its coastal areas have warmer and longer frost-free seasons than inland areas [44]. The study employed the use of hourly air temperature (C°) and wind speed (mph) as weather variables obtained from eight specific airport weather stations in CT through the Automated Surface Observing System (ASOS) network between the years 2011 and 2021. ASOS is the premier automated observing network, and ASOS stations at airports provide critical weather observations for the National Weather Services (NWS), the Department of Defense (DOD), and the Federal Aviation Administration (FAA) [45]. The hourly demand data used in this study was obtained from ISO New England

(ISO-NE) for the period spanning from 2011 to 2021, with units of measure expressed in megawatts (MW) [46]. The missing values in the weather and demand dataset were addressed using both forward and backward imputation methodologies.

III. METHODOLOGY

MPR, RFR, and GBR models were developed by using the period from 2011 to 2017 for training and testing purposes, 2018 to 2019 for pre-COVID-19 validation (val1), and 2020 to 2021 for post-COVID-19 validation (val2) for the data period of 2011 to 2021. To split the data for the analysis, a test size of 20% was selected and a fixed random state was used in all processing steps.

In the context of MPR, RFR, and GBR machine learning algorithms, a comprehensive analysis was performed considering three different model configurations for each machine learning algorithm: baseline (bl), weather influence (wx), and time-weather interactions (twx). The initial analysis was conducted for all days (all) of the week, and this involved the creation of one model variation for each hour of the day. Additionally, the dataset was partitioned into two subsets, namely workdays (wd) and weekends (wknd) variations to examine the changes in demand during these distinct periods. Therefore, three model variations (all, wd, wknd) for each hour of the day were generated for a configuration. There is a total of three different model configurations (bl, wx, twx) for a machine learning algorithm. Thus, nine different model experiments from different combinations of configurations (bl, wx, twx) and variations (all, wd, wknd) were created for a machine learning algorithm for each hour of the day. Consequently, nine different model experiments (such as experiments for MPR machine learning algorithm: MPR_bl_all, MPR_bl_wd, MPR_bl_wknd, MPR_wx_all, MPR_wx_wd, MPR_wx_wknd, MPR_twx_all, MPR_twx_wd, MPR_twx_wknd) were created for each machine learning algorithm for each hour of the day (Figure 1).

A. BAYESIAN OPTIMIZATION

Bayesian optimization constitutes a category of machine learning-based optimization techniques [47] and it stands as a powerful strategy for locating extreme values of objective functions [48]. Bayesian optimization efficiently identifies optimal values with minimal sampling, making it suitable for hyperparameter tuning of machine learning algorithms [49].

Hyperparameters play a vital role in machine learning algorithms as they directly control training algorithm behaviors and significantly impact the performance of machine learning models [49], [50], [51]. The efficacy of contemporary machine learning and data mining techniques is profoundly influenced by the appropriate configuration of their hyperparameters [51]. Optimizing hyperparameters is key for robust performance in non-parametric models, surpassing default settings' efficacy in machine learning [52].

B. MODELS

1) BASELINE MODEL (TEMPORAL FEATURES ONLY)

A baseline model can be defined as a simplistic approach that yields satisfactory outcomes in a given task and does not demand extensive expertise and time for its construction [53]. A baseline model is a basic reference in machine learning projects, and its main function is to provide context for trained model results [54]. The employment of a baseline model for machine learning has several advantages such as the ability to compare the performance of the actual model against a reasonable benchmark [55].

Within this study, simple baseline models were established for MPR, RFR, and GBR algorithms using solely the ''day of year'' and ''hour'' variables as input features, to include the intraday and seasonal variations of annual demand, without providing any weather information to the models. For example, the names of the baseline models for the MPR algorithm include 'MPR_bl_all'', ''MPR_bl_wd'' and MPR_bl_wknd'', and similar baseline models exist for RFR and GBR algorithms.

2) MULTIVARIATE POLYNOMIAL REGRESSION MODEL

Polynomial regression is an instance of linear regression that characterizes the association between the input variable x and the output variable y as a polynomial equation. Polynomial regression is employed specifically in cases where dependent variables show a non-linear relationship, signified by a scatter plot displaying a non-linear or curvilinear pattern [56], [57]. It fits the curve using a polynomial equation for maximum accuracy while avoiding over-fit or under-fit [58]. One of the primary advantages of the MPR model lies in its minimal computational time required for conducting forecasting while maintaining a considerable level of precision [59]. The main problems with MPR are multicollinearity and the limited contribution of higher degree terms to the equation [57]. A second order-multiple polynomial regression model which used two variables x_1 and x_2 can be mathematically represented by the following general equation (1):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 + \varepsilon \tag{1}$$

where,

β_1 and β_2 are denoted as linear effect parameters.

β_{11} and β_{22} are referred to as quadratic effect parameters.

β_{12} is stated as an interaction effect parameter.

ε is the error function.

In the study, MPR was conducted employing the LinearRegression module for regression analysis and the PolynomialFeatures module to generate polynomial features from the scikit-learn Python library. A polynomial order of three was chosen to generate polynomial features. To decrease the dataset dimensionality while retaining a significant amount of variability [60], principal component analysis (PCA) was performed with a component selection of two.

3) RANDOM FOREST REGRESSION MODEL

Random forest (RF) is a regression approach that integrates the capabilities of multiple decision trees (DT) algorithms to forecast or classify the value of the variable [61]. RF is a nonparametric data mining method that captures the non-linear structure of the dataset. This model typically shows a prominent level of predictive accuracy and exhibits sufficient resilience to outliers [25], [61], [62]. The RF method overcomes the well-known limitations of single DT, namely the absence of smoothness and the instability of splits [62], [63]. RF uses bagging to increase tree diversity and reduce model variance [64]. The RFR method demonstrates robustness and superior speed and prevents overfitting. The integration of randomized decision trees leads to a decrease in prediction variance and a decrease in generalization error [65].

A random forest exhibits randomness in two distinct manners: firstly, each tree is constructed using a random subset of the available observations, and secondly, every individual partition within each tree is generated using a random subset of candidate variables defined as "mtry" [66]. A technique is an ensemble method that merges the predictions of individual weak predictors, denoted as h_i. Two principal parameters in this context are the number of trees (represented as ntree) and the number of variables (mtry) utilized for partitioning at each node [67]. A regression predictor can be expressed as (2):

$$Y = h(X) = \frac{1}{ntree} \sum_{i=1}^{ntree} h_i(X) \tag{2}$$

In this study, RFR was employed, using the scikit-learn Python library with the RandomForestRegressor module. Hyperparameter tuning was conducted using the Bayesian optimization method with 100 iterations to identify the optimal combination of hyperparameters that enhances model performance. The parameters considered for optimization included min_samples_leaf: (1, 50), min_samples_split: (2, 50), max_depth: (1, 5), and n_estimators: (10, 1000).

4) GRADIENT BOOSTING REGRESSION MODEL

Gradient boosting (GB) represents a machine-learning methodology employed to resolve classification and regression problems. The principal concept underlying boosting is to aggregate a collection of decision trees through an iterative process to generate a robust learner [25], [63]. GB builds a model by adding stages of weak prediction algorithms and optimizing loss functions [65]. In every stage, a regression tree is fitted to the negative gradient of the provided loss function [68].

Within this study, boosting was conducted using the GradientBoostingRegressor (GBR) module from the scikit-learn Python library. Bayesian optimization was employed for hyperparameter turning with 100 iterations, involving the following parameters: min_samples_leaf: (1, 50), min_samples_split: (2, 50), max_depth: (1, 5), n_estimators: (10, 1000) and learning rate: (0.001, 1).

C. REGRESSION EVALUATION METRICS

MAE (Mean Absolute Error), equation (3), is a frequently employed and valuable measure in model evaluation [69]. An analysis [70] reveals that MAE stands out as the most suitable metric for capturing the average magnitude of errors. MAE employs a comparable metric for receiving input data, enabling the comparison of series composed of disparate scales [71].

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - \hat{y}_i \right| \tag{3}$$

where a given sample consisting of n observations denoted as y (y_i= *1, 2, …, n)* and n relating model predictions $\hat{y}$ [72], [73].

Mean absolute percentage error (MAPE), equation (4), is widely regarded as one of the most utilized metrics for assessing the precision of forecasts [74] due to its intuitive interpretation regarding relative error [75], and its simplicity [76]. It measures the degree of discrepancy between predicted and actual values [77]. MAPE is scalable and easy to interpret. However, it is problematic when actual values are zero or close to zero [74].

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{\left| y_i - \hat{y}_i \right|}{y_i} \times 100\% \tag{4}$$

Root mean square error (RMSE), equation 5, has been extensively used as a customary statistical measure to evaluate the performance of models in the fields of air quality, meteorology, and climate research [69]. RMSE is the square root of the MSE. The application of taking the root does not alter the rankings of models but produces a metric with the same unit y, representing the standard or typical error for errors that follow a normal distribution [72]. RMSE exhibits sensitivity to outliers and a high dependency on the fraction of the data utilized, thereby indicating a limited level of reliability [71].

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2} \tag{5}$$

The R^2 index holds significant importance in assessing the precision of the predicted outcome of a regression algorithm, with values ranging between 0 and 1 [78]. The definition of R^2 is formulated as follows (6):

$$R^2 = 1 - \frac{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2}{\frac{1}{n} \sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \tag{6}$$

where $\bar{y}_i$ represent the mean value of the actual value y_i.

Bias measures the average difference between two datasets. Negative values signify underestimation, positive values indicate overestimation and values approaching

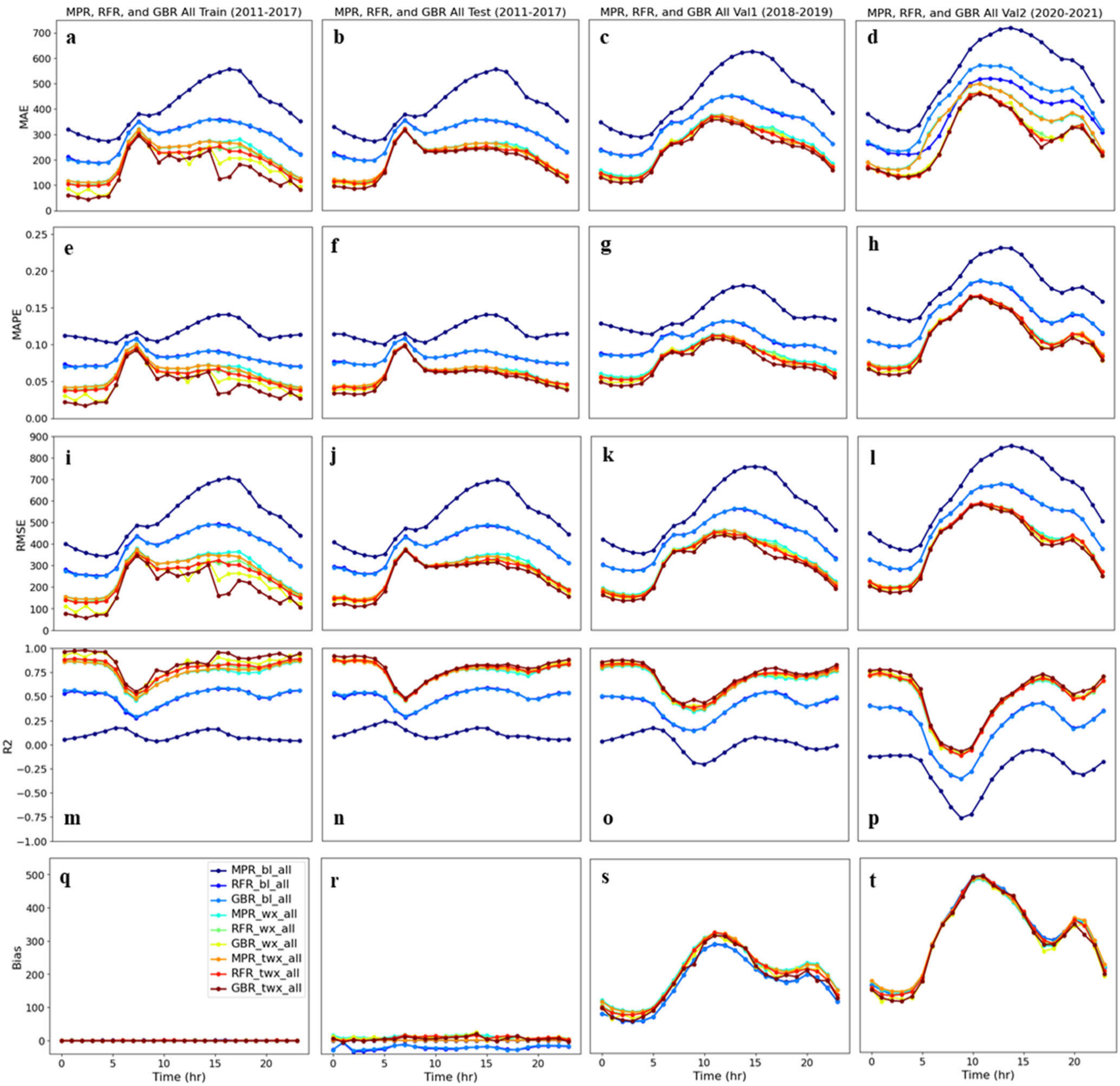

FIGURE 2. Error metric results of MPR, RFR, and GBR models across all days (all) with three different configurations (bl, wx, twx). In general, the GBR model (maroon and lime green lines) outperforms the MPR and the RFR models. As a result, we focus on the GBR model with different input configurations (bl, wx, twx) and sampling variation (all, wd, wknd) for the rest of the study.

zero indicate optimal performance [70]. Bias is defined as follows (7):

$$Bias = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{7}$$

IV. RESULTS AND DISCUSSION

A. ERROR ANALYSIS AND PATTERNS

In a broader context, Figure 2 illustrates a notable error increase during the COVID-19 pandemic (Figures 2d, 2h, 2l, 2p, 2t), (Val2: 2020-2021), compared to the preceding period (Figures 2c, 2g, 2k, 2o, 2s), (Val1: 2018-2019). For instance, considering the MPR baseline model across all days during a week (all) dataset, the MAE results indicated a minimum value of approximately 290 MWh at 4:00 and a maximum value of about 625 MWh at 15:00 before COVID-19 (Figure 2c) versus a minimum value of nearly 315 MWh and a maximum value of almost 720 MWh for the same periods (Figure 2d). Additionally, the findings from the error metric analyses highlight the efficacy of the GBR

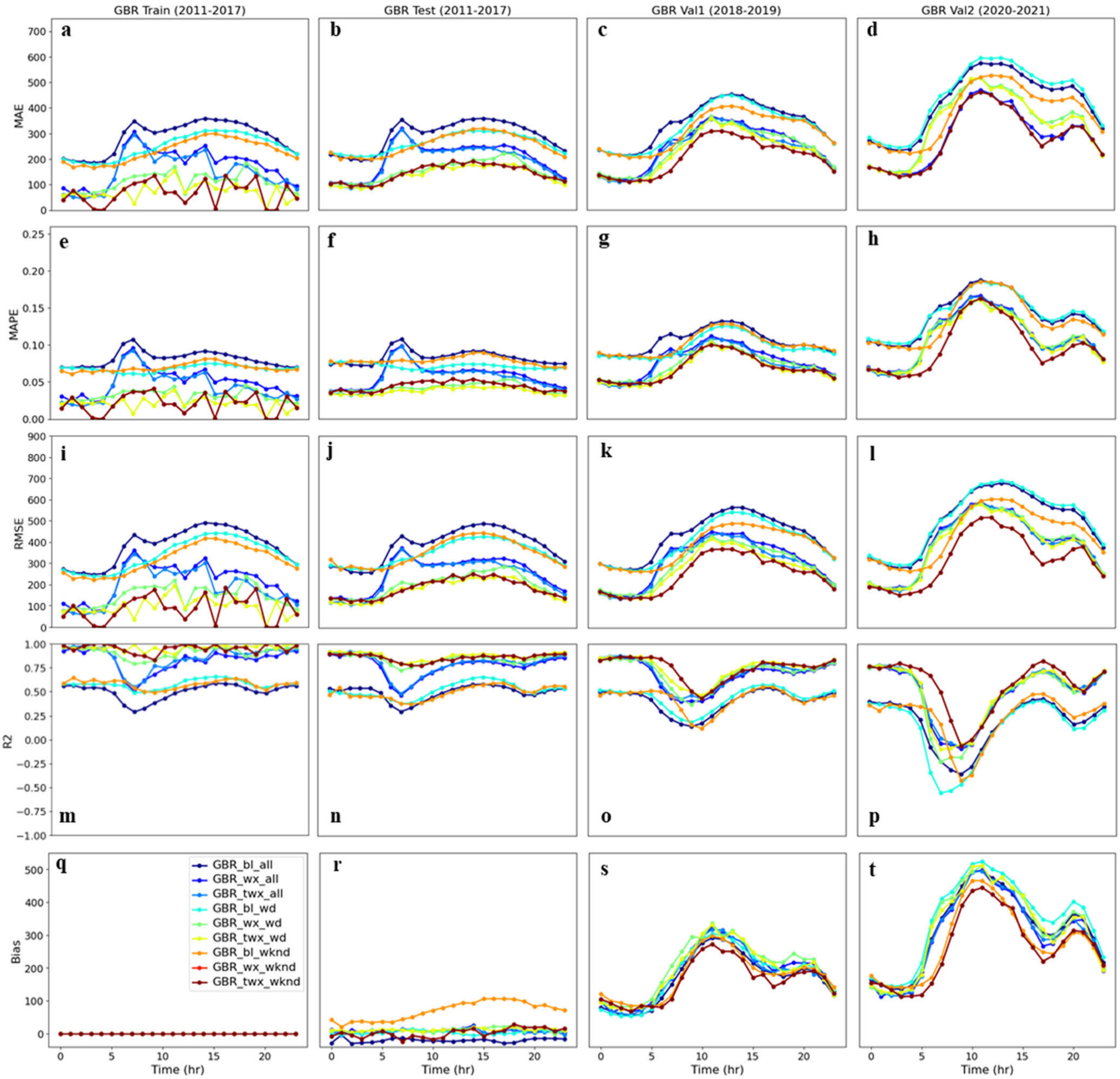

FIGURE 3. Error metric results of the GBR models across all days (all), workdays (wd), and weekends (wknd) dataset categories for three different input configurations (bl, wx, twx). The maroon ('GBR_twx_wknd') and lime green ('GBR_twx_wd') lines are generally the best models. Each subpanel shows the nine model experiments for each hour of the day.

and RFR models when compared to the MPR model throughout the periods before and during the COVID-19 pandemic. For example, when examining the results of the MPR baseline model, the minimum MAPE value was approximately 0.11 and the maximum value reached about 0.18 before the COVID-19 period (Figure 2g). Conversely, for the RFR and GBR baseline models, the results demonstrated a minimum MAPE value of 0.09 and a maximum value of 0.13 for the same time intervals after the COVID-19 period (Figure 2h). These results provide evidence supporting the effectiveness of tree-based models (RFR, GBR) in accurately predicting energy demand with heightened precision. Furthermore, the most promising outcomes were evident in the context of time-weather integrated analysis for MPR, RFR, and GBR models. Both weather and time-weather models displayed an approximate twofold improvement in error metric performance when compared to the baseline model in the analysis. As an illustration, considering the RMSE results for the GBR baseline model, the values exhibited a minimum of approximately 275 MWh at 3:00 whereas the GBR time-weather model demonstrated a minimum value of nearly 135 MWh for the same time (Figure 2k).

Broadly, overestimation is evident in the models during the validation periods (2018-2021). We believe the overestimation can be linked to the increase in the adoption of energy efficiency and solar photovoltaics in the state in recent years. Connecticut has implemented policies aimed at increasing both energy efficiency and the utilization of renewable energy sources [43]. Generally, the models exhibited their highest correlation within the period spanning from 00:00 to 4:00 and their lowest between 7:00 and 11:00 (Figures 2o, 2p). The diurnal pattern of error metrics revealed that the lowest levels were consistently observed between 2:00 and 4:00, a phenomenon attributed to the low energy consumption associated with sleeping hours during that period, resulting in less error on model predictions (Figures 2s, 2t). Conversely, the highest error levels were consistently recorded between 10:00 and 13:00, likely corresponding to active periods such as office work or household tasks, where energy consumption is high, thereby resulting in increased prediction error. Before the initiation of the COVID-19 pandemic, the initial peak in error metrics (Figures 2c, 2g, 2k), occurring between 06:00 and 08:00, can be attributed to the awakening hours. During this time, activities such as turning on lights, taking showers, and preparing breakfast, if at home, or upon arriving at the office, turning on lightning and computers, are commonplace. However, during the pandemic, this peak shifted to the period of 08:00 to 10:00 (Figures 2d, 2h, 2l). The second peak in error metrics, observed at approximately the same time frame range, persisted both before and after the COVID-19 period, specifically between 13:00 and 16:00. The third peak occurring between 17:00-19:00 can be attributed to the phenomenon of individuals returning home after work and initiating domestic responsibilities. This encompasses actions such as activating lighting, engaging air conditioning systems during the warmer months, or activating electric heaters in colder seasons. Conversely, in the periods coinciding with the occurrence of the pandemic and its outcome, a distinct secondary peak between 19:00 and 21:00 emerged, a consequence of the lockdown measures imposed during the pandemic. This new peak can be attributed to activities including the initiation of lighting systems or cooking, among other domestic activities.

The findings presented in Figure 2 demonstrated that the GBR model exhibited better performance compared to the MPR and RFR models. Since the GBR model performed better than the other models, we focused our results on the performance of the GBR model across all days, workdays, and weekends variations for the rest of the study. In general, the error metric results from the GBR model worsened during the COVID-19 pandemic (Figures 3d, 3h, 3l, 3p, 3t), Val2 (2020-2021), when compared to the preceding period (Figures 3c, 3g, 3k, 3o, 3s), Val1 (2018-2019). For example, when examining the GBR baseline model across all datasets, the MAE outcomes showed an approximate value of 450 MWh at 13:00 before the advent of the COVID-19 pandemic (Figure 3c). However, following the pandemic, this value underwent a notable shift, reaching nearly 570 MWh at the same time (Figure 3d). Additionally, weather and time-weather GBR models performed better when training was performed separately on the workdays and weekends than on all days, and better error performance was observed for the weekends than the workdays for both before and after COVID-19, highlighting the benefits of homogenous data training (Figure 3). However, a discernible shift in this trend was observed for the baseline-based model after the onset of the COVID-19 pandemic, and better error performance was seen for all datasets than the workdays while the weekends maintained the best error performance consistent with the pre-pandemic period. For instance, examining the RMSE outcomes of the baseline-based model at 20:00, the error measures were approximately 455 MWh for all datasets and nearly 435 MWh for the workday datasets before the COVID-19 pandemic (Figure 3k). Nevertheless, the RMSE results demonstrated nearly 555 MWh for all datasets, and approximately 575 MWh for the workdays for the same time after COVID-19 (Figure 3l). Also, our MAPE results demonstrate an average testing error between 3% and 5% for the best-performing and recommended models. These values are in line with the ones obtained by Alhendi et al. [79].

B. ACTUAL AND PREDICTED DEMAND

Scatter plots between actual and predicted demand for GBR models at six-hour intervals during the pre-(Val1: 2018-2019) and post-(Val2: 2020-2021) COVID-19 periods demonstrated an improvement in predictive capability, specifically in the transition from baseline models to time-weather-based models (Figure 4). Figure 4 contains error metrics in the bottom right corner of each subplot. The inclusion of time-weather parameters substantially enhanced the predictive capability of the model compared to other modeling approaches. For example, when analyzing Figure 4 by column, we notice MAPE (R^2) generally decreased (increased) as more features were included in the model. Bias has a less obvious pattern in this analysis but will be discussed in more detail in Section IV-C ("Time Series Analysis").

Overall, the shift from baseline models to time-weather models demonstrated a consistent reduction in MAPE, and an improvement in R^2 while bias conversely displayed overestimation after the COVID-19 pandemic. This indicates that a model trained only on time-dependent has a substantial increase in bias following the onset of COVID-19, and the model is overestimating because of individuals changing daily habits during the pandemic.

Furthermore, the model results demonstrate an ability to predict distinct patterns of energy utilization throughout the day. In general, the early morning and late evening hours (5:00 and 23:00) were predicted to be better than peak activity periods (11:00 and 17:00). The reason is likely because energy usage is minimal during early morning (5:00) and late evening (23:00) owing to limited activity in both work and household tasks. Conversely, the hours of 11:00 and 17:00, representative of peak activity periods, exhibited higher values of MAPE and bias and lower R^2 due to higher energy

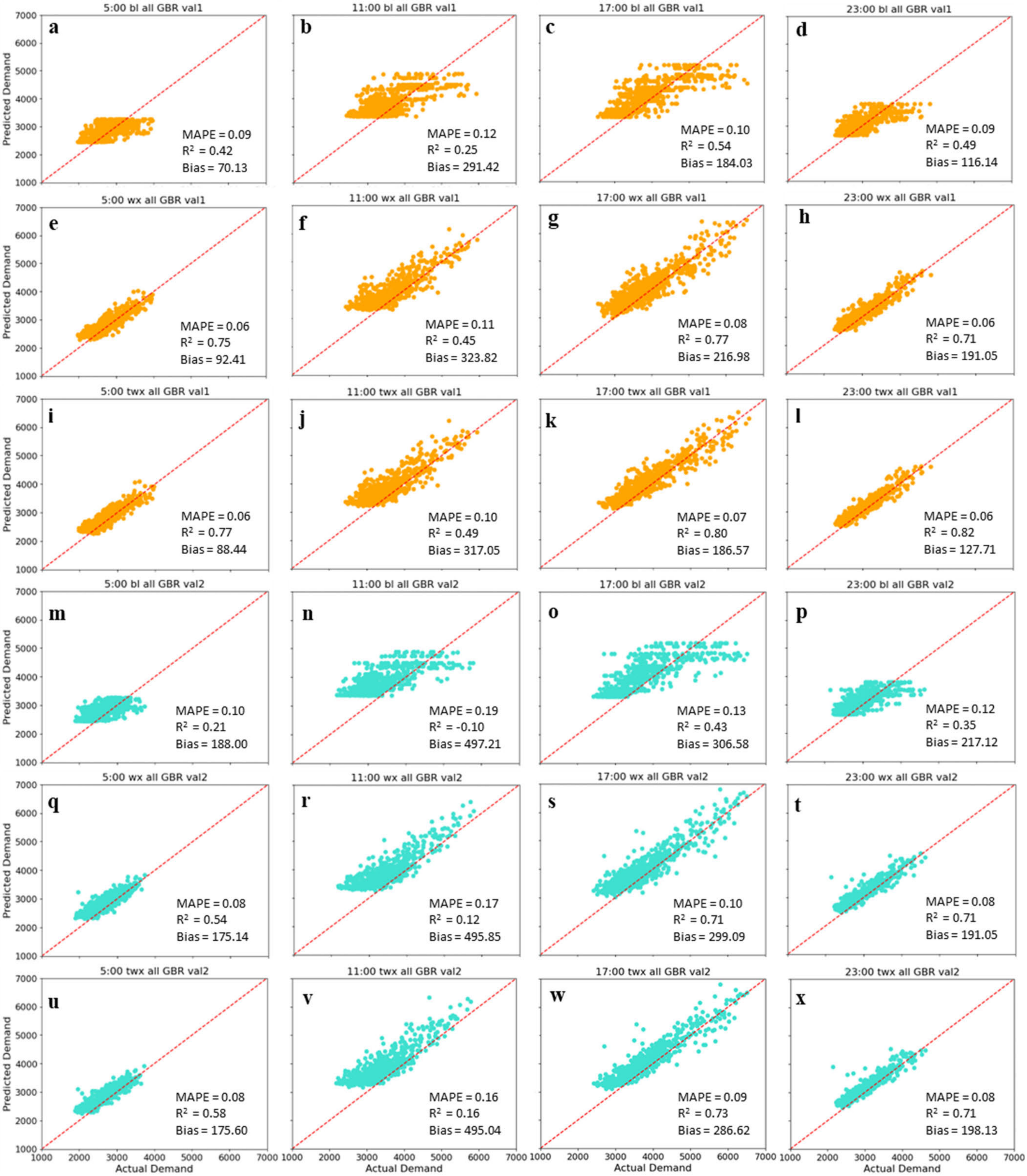

FIGURE 4. Pre (2018-2019) and Post (2020-2021) COVID-19 actual and predicted demand for the GBR model experiments across all days (all) for three different configurations (bl, wx, twx) in 6-hour intervals.

utilization. Specifically, at 11:00 (Figure 4j), the MAPE was recorded as 0.10, R^2 as 0.49, and bias as 317.05 which was poor performance compared to other hours of the day for the same configuration (Figures 4i and 4l.)

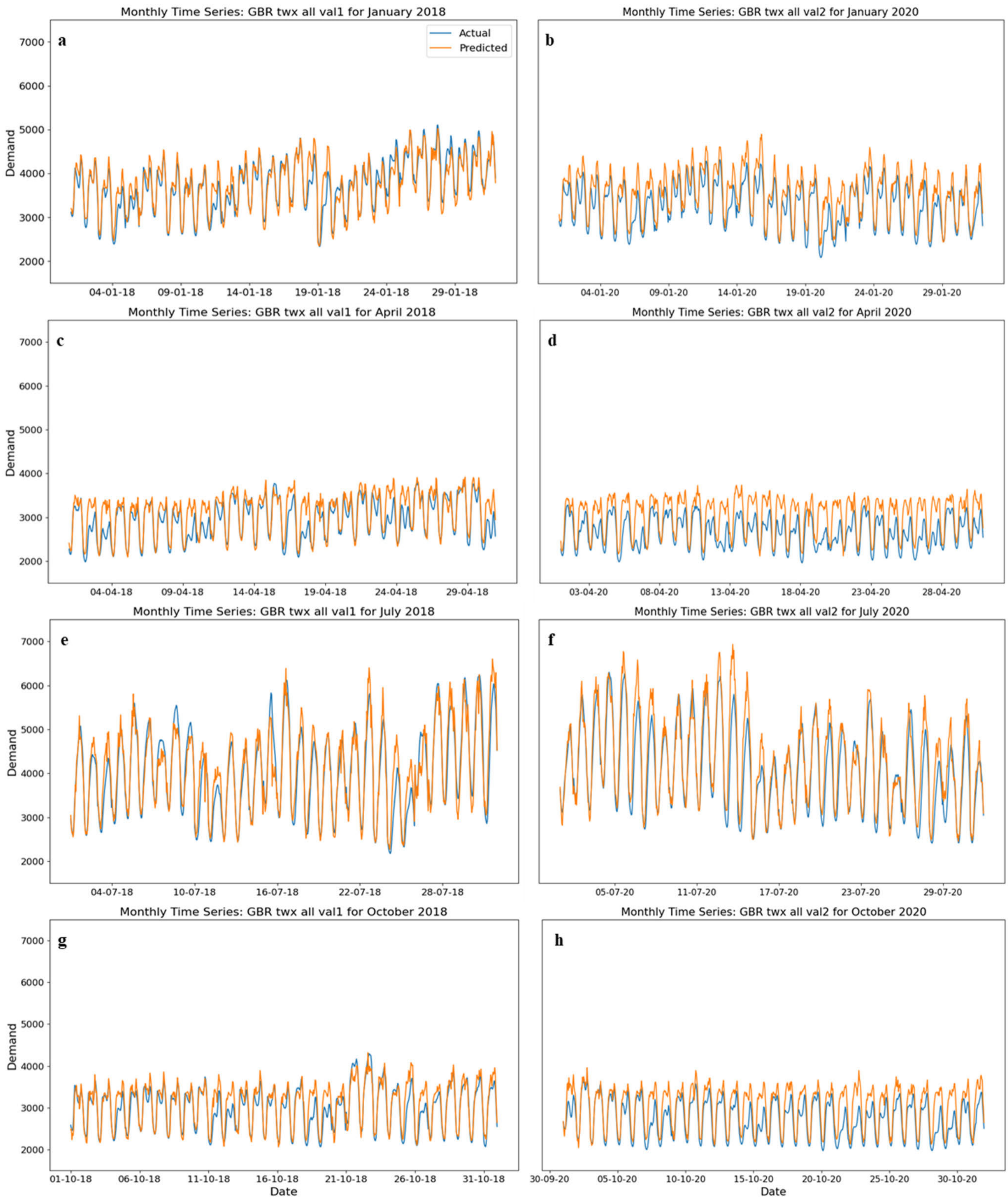

FIGURE 5. Time series analysis of actual (blue) versus predicted (orange) hourly demand for the GBR_twx_all model experiment for January, April, July, and October before (2018) and after (2020) the onset of COVID-19.

C. TIME SERIES ANALYSIS

The results obtained from the time series analysis presented in Figure 5 provide details of the time-weather GBR model experiment for all days (GBR_twx_all) in predicting hourly energy demand across various seasons, both before (2018) and after (2020) the advent of the COVID-19 pandemic.

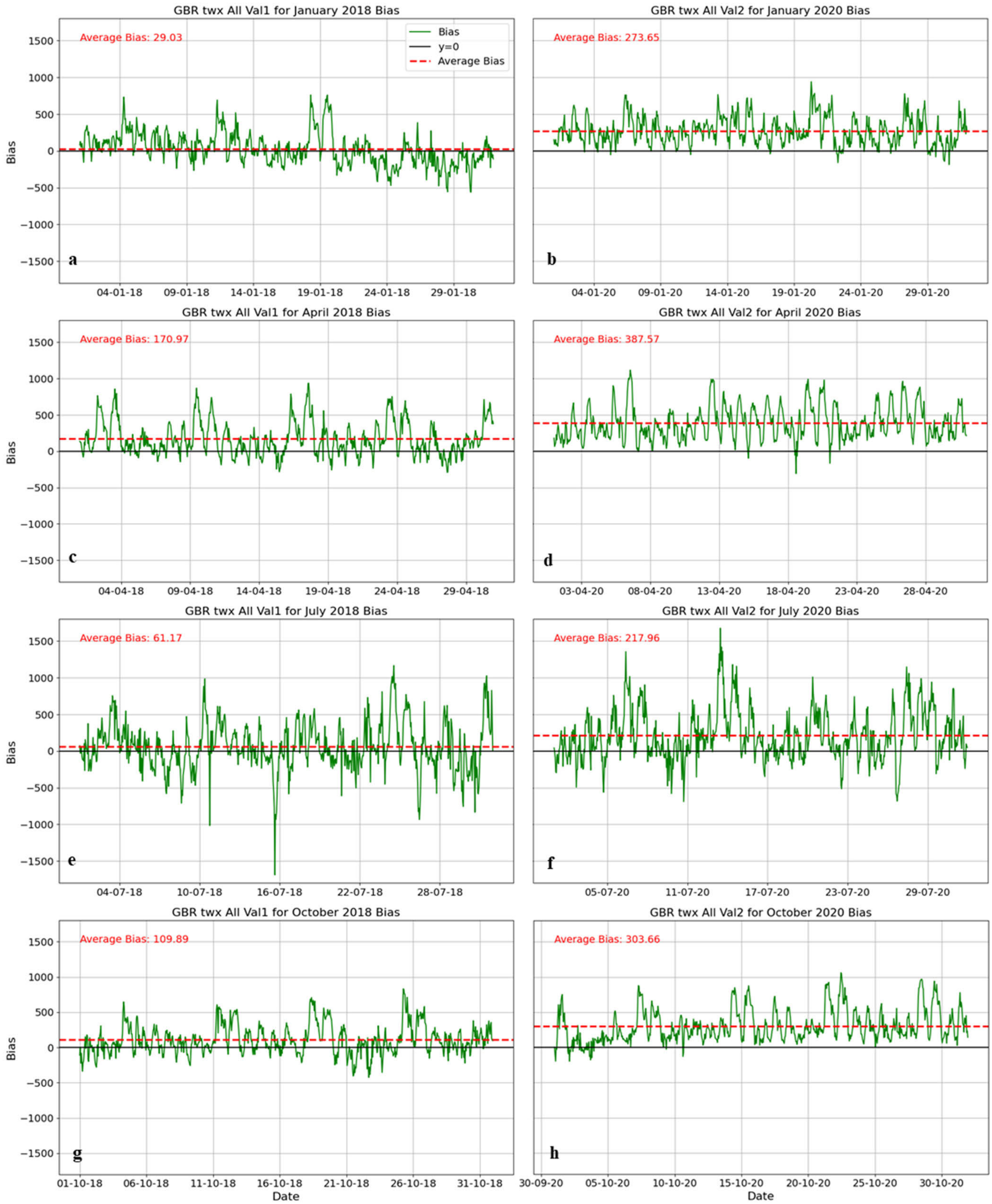

FIGURE 6. Bias results of time series analysis of actual versus predicted hourly demand for the GBR_twx_all model experiment for January, April, July, and October before (2018) and after (2020) the onset of COVID-19.

In 2018, the New England region experienced its initial annual escalation in the average wholesale electricity load since 2013 which showed growth of 1.7% compared to the average of 2017. Nevertheless, when adjusting for the weather variations, the load demonstrated relative stability and even exhibited a marginal decline of 0.1% [41]. In 2020, New England saw a record-low wholesale electricity load dropping by 2.3%. When normalized for weather, the reduction was 2.4% compared to 2019. The decline is attributed to energy efficiency, solar generation, and the impact of COVID-19 [42].

January was selected to represent the coldest month during winter in Connecticut, while July was chosen to signify the warmest month of the summer season. Additionally, April and October were selected to exemplify the transitional climate conditions representing the Spring and Fall seasons, respectively. The findings revealed that July (Figures 5e, 5f) exhibited elevated energy consumption compared to other months, a trend mostly attributed to raised temperatures during the summer season necessitating increased usage of air conditioning (AC) systems and cooling equipment. These findings are in line with a study carried out in the New England region [80] which shows the summertime demonstrated a slightly elevated level of overall energy consumption compared to other seasons throughout the year. Air conditioning is a significant contributor to energy consumption during the warmer months as it is used to maintain comfortable indoor temperatures. Conversely, January, the coldest month in Connecticut, demonstrated lower energy utilization compared to July. This discrepancy can be attributed to the fact that AC systems operate on electricity, whereas heating systems during the winter months to maintain indoor warmth depend on multiple energy sources, including coal, natural gas, and electricity. Consequently, forecasting energy usage during the winter season presents greater complexity due to the complex nature of heating mechanisms. On the other hand, the transitional climate conditions which can be found in April (Figures 5c, 5d) and October (Figures 5g, 5h) resulted in lower energy demand. These months mark the transition between winter and summer, creating a comfortable environment that necessitates less energy for temperature control, ultimately leading to a decrease in overall energy consumption.

Bias results of time series analysis of actual versus predicted hourly demand for the GBR_twx_all model experiment in Figure 6 showed distinctive predictive performance across various months both in pre- (Figures 6a, 6c, 6e, 6g) and post (Figures 6b, 6d, 6f, 6h) COVID-19 periods. The model exhibited a superior predictive capacity during January and achieved its best performance (Figure 6a) while the second-best bias result was observed in July (Figure 6e). According to the 2018 ISO-NE Annual Markets Report [40], quarters Q1 (January, February, March) and Q3 (July, August, September) experienced a measurable load increase in 2018 compared to 2017. Q1 saw a 0.9% rise due to a colder January (26°F vs. 33°F in January 2017). Q3 showed an 8% load increase linked to a 3°F rise in average temperature in the hot and humid July of 2018 where the daily high-temperature humidity index (THI) averaged 75°F, the highest level observed from 2014 to 2018. The hot and humid Q3 significantly impacted peak load, with nearly all top 5% peak load hours occurring then due to heightened air conditioning demand [40]. Conversely, a discernible and systematic trend of overestimation in predicting actual values was observed for all months (Figure 6b, 6d, 6f, 6h) in the post-COVID-19 era. This can be related to the increased use of energy efficiency technologies and behind-the-meter solar generation in Connecticut in recent years. This observed overestimation signifies the model's challenge in accurately estimating energy consumption after the pandemic.

Energy efficiency and behind-the-meter solar generation exhibit distinct seasonal effects on wholesale load. Specifically, energy efficiency exerts a more substantial influence during Q1 and Q4 (October, November, December), while behind-the-meter solar generation demonstrates a greater impact during Q2 (April, May, June) and Q3 [40], [41], [42]. After the pandemic period (2020), a better performance was observed for July in comparison to the other months. The improved predictions in July underscored the model's adeptness in capturing the energy demand dynamics specific to this period. In 2020, the average quarterly load decreased in all quarters, except for Q3 when compared to the previous year. During Q3, the average temperature was 71.2°F, representing a slight decrease from the 2018 average of 72°F. Specifically, in Q1, a year-over-year decline of 6% in the average load was observed, attributed to warmer temperatures [41].

In response to the COVID-19 pandemic in the US, a sequence of lockdown measures aimed at mitigating the pandemic's spread was introduced in March and sustained until July 2020 [81] and, Connecticut concluded its COVID-19 restrictions in May [82]. According to the ISO-NE 2018 Annual Report, average loads declined in Q2 and Q4 of 2018 on a year-over-year basis [40]. As per the ISO-NE 2020 Annual Report, statewide closures implemented in March 2020 to combat the spread of COVID-19 led to a general reduction in electricity demand persisting into Q2 with a 1.5% decrease in quarterly average load due to warmer weather and increased air-conditioning demand resulting from the pandemic, prompting a greater reliance on less efficient residential systems as many people stayed at home. Lastly, the average load in Q4 decreased by 2.6% year-over-year, primarily due to milder weather conditions [41]. Within our analysis, April exclusively signified the duration of the lockdown implemented during the COVID-19 pandemic. The average bias in April showed a remarkable disparity between the pre-COVID-19 period in 2018, where it was recorded at 170.97 (Figure 6c), and the subsequent era during the COVID-19 pandemic in 2020, particularly during the lockdown period when the average bias escalated significantly to 387.57 (Figure 6d). This observed overestimation highlights the model's challenge in accurately estimating energy consumption during this month after the pandemic. This disparity can be attributed to alterations in a range of factors including consumption patterns, shifts in energy usage patterns, altered economic conditions, and variations in societal activities. These underscore the necessity for recalibrating the modeling or sampling approach to account for the evolving dynamics of energy demand after impactful events, such as the COVID-19 pandemic. Conversely, in the context of monthly time series bias analysis for October in 2018 (Figure 6g), the bias outcome was indicated as 109.89, whereas in 2020 (Figure 6h), it escalated to 303.66. These results show that October exhibited a pattern closely resembling that of April both before and after the onset of the COVID-19 pandemic. April and October represent substantial seasonal transitions, moving from winter to spring (April) or from summer to fall (October). These transitions bring about considerable variations in weather conditions leading to increased unpredictability and bias in the model. Furthermore, these results emphasize the importance of considering seasonality, external influences, and other potential anomalies when constructing and refining prediction models for distinct time frames and months throughout the year.

V. CONCLUSION AND FUTURE WORKS

This study aimed to develop energy demand prediction models and compare three different machine learning algorithms (MPR, RFR, GBR) to assess their accuracy in predicting energy demand in Connecticut. The findings from this study shed light on several important aspects of energy demand prediction, particularly in the context of the pre (2018-2019) and post (2020-2021) COVID-19 periods.

In a broader context, error metrics for the MPR, RFR, and GBR models showed a significant decrease in performance during the COVID-19 pandemic compared to the pre-pandemic period. Error metrics analysis for all models highlighted that the GBR model exhibited better performance than the MPR and RFR models. These findings align with the research conducted by Zhang et al. [25], which demonstrated the overall superiority of the gradient boosting (GB) model in comparison to the multiple linear regression (MLR) and random forest (RF) models. Moreover, superior results were observed in the time-weather integrated analysis for all models, displaying approximately a twofold improvement in error metric performance and emphasizing the importance of considering weather conditions and time factors in energy demand prediction compared to the baseline model. The models demonstrated an accurate representation of consumption patterns during the day, with peak demand observed during active periods and lower energy demand during the early morning and late evening. Additionally, the GBR model results showed that the model performed better on weekends compared to workdays before and after COVID-19.

The time series analysis for pre- and post-COVID-19 provided insights into the seasonal variations in energy demand, with July exhibiting the highest energy consumption due to elevated temperatures and increased use of air conditioning systems. Conversely, January's lower energy use was influenced by diverse heating sources. Transitional months, like April and October, saw reduced demand due to mild weather. Furthermore, energy efficiency measures and the integration of behind-the-meter generation significantly influenced the distinctive pattern of energy demand observed across different months [40], [41], [42]. The time series analysis bias results indicated that January had the highest predictive accuracy, followed by July before the pandemic, and post-pandemic, July showed the best performance among other months. Overall, overestimation was noticeable in the models in the validation periods (2018-2021). Specifically, a systematic trend of overestimation was observed for all models after COVID-19 (2020-2021). These findings underscore the need for model recalibration to account for evolving demand dynamics after significant events such as the pandemic and highlight the importance of considering seasonality and external influences such as decarbonization initiatives [43] in forecasting models.

Our main contributions:

- We introduced a novel integration of machine learning algorithms (MPR, RFR, and GBR) to predict hourly energy demand. This combination is aimed at capturing diverse patterns of consumption, especially during dynamic events like the COVID-19 pandemic.
- We conducted and evaluated nine different model experiments for each hour of the day for each machine learning algorithm, considering variations between workdays and weekends. This comprehensive approach aims to provide a detailed understanding of energy demand patterns.
- Our study examines the impact of external factors, such as the COVID-19 pandemic, on model performance. This analysis contributes to understanding how unforeseen events can shape energy prediction models.
- Emphasizing the significance of incorporating both time and weather features, our study demonstrated a significant improvement in error metrics. This contribution highlights the importance of considering external variables for improved accuracy in energy demand predictions.
- We provided valuable insights from bias analysis, discovering variations in predictive accuracy across different months. This contributes to understanding the patterns that change with the seasons and how they affect energy demand.

As a result, this study contributes to energy demand prediction by underscoring the effectiveness of time-weather models, particularly the GBR model, in improving predictive accuracy. In general, the GBR model exhibited superior performance under the time and weather configuration when segmented into workdays and weekends rather than all days. Therefore, we suggest employing the GBR model, incorporating both temporal and weather features, and segmenting the analysis based on day types. On weekends, the models should be trained with weekend data alone, and the same is valid for workdays. The study emphasized significant shifts in error metrics during the COVID-19 pandemic, displaying the impact of this global event on energy demand prediction models and the increase in adoption of decarbonization technologies in the state in the last few years that significantly affected predictive accuracy. This work highlights the need for adapting models to dynamic consumption and weather patterns for improved grid management.

Future research directions and improvements can be summarized as follows:

- Investigating diverse machine learning algorithms for improving modeling precision.
- Evaluating variable importance by incorporating additional meteorological parameters into the model.
- Enhancing model robustness and predictive accuracy through exploring variable data sampling methodologies, data scaling techniques, and strategic arrangement of hyperparameter values.
- Exploring variable sampling methodologies to improve predictive accuracy and robustness.
- Assessing model generalizability for post-COVID-19 energy demand dynamics.
- Conducting in-depth sectoral analysis to discern sector-specific energy consumption patterns.
- Investigating technology adoption trends such as solar PVs, and EVs, and their impact on energy demand for future modeling enhancements.

ACKNOWLEDGMENT

The authors would like to thank the Federal Aviation Administration and ISO-New England for making publicly available the ASOS weather observations, and hourly demand data, respectively.

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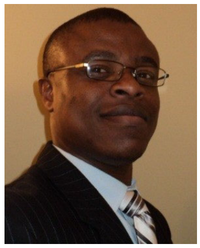

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