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Actionable Peak Electric Load Day Forecasting Method for Facilities with Renewable Electricity Cogeneration

Final Report by the Recipients of the
2019-2020 IIF-SAS Grant to Promote Research on Forecasting
in the Category of Business Applications

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Executive Summary

This final report documents the research completed by the recipients of the 2019-2020 IIF-SAS Grant to Support Research on Forecasting in the category of Business Applications, Omar Aponte, M.E. and Katie T. McConky, Ph.D. This research was motivated by observing how the constant evolution of the electric grid with the integration of generation from renewable sources and "smart" components makes peak electric load management an essential aspect to ensure the grid's reliability and safety. In order to pass the financial burden of managing these loads on to the consumers, utilities around the world have established peak load charges that can amount to up to 70% of electricity costs in the case of the United States of America. These pricing schemes have created a need for efficient electric load management strategies that consumers can implement in order to reduce the financial and environmental impact of peak electric loads.

The research titled "Actionable Peak Electric Load Day Forecasting Method for Facilities with Renewable Electricity Cogeneration" provides important insights and contributions to the forecasting practice in the field of electric load forecasting. Thanks to the support provided by the 2019-2020 IIF-SAS Grant to Support Research on Forecasting, this research has contributed: (1) a peak electric load day (PELD) forecasting methodology applicable to consumers with behind the meter renewable electricity generation (BTMREG) that demonstrated the potential to achieve 93% of the potential savings in kW, equivalent to approximately US$ 142,129.01 in peak load charges; (2) the first side-by-side performance comparisons of electric load and PELD forecasting models for scenarios with and without BTMREG; and (3) the first PELD forecasting model savings comparison for scenarios with and without BTMREG. One of the insights suggests that counterintuitively, BTMREG adoption can translate into higher peak load savings.

1. Research Motivation

Utilities in the United States have been increasingly taking advantage of smart grid technologies that enable them to set dynamic pricing schemes, such as Time of Use (TOU) and Real Time Pricing (RTP) rate structures [1,2]. Under these pricing schemes, a consumer's electricity costs are determined based on the consumer's unique time dependent electricity demand pattern, and can vary significantly from month to month. The majority of TOU and RTP rates also contain a consumer demand charge [2,3]. The demand charge is based on the highest rate of electricity consumption observed during a billing period, typically per month, and is charged in $/kW. This demand charge can amount to up to 70% of an electric bill [2,3], however, the number of days in a month contributing to demand charges is typically very small. Figure 1 illustrates the month of April 2019 for a circuit at the Rochester Institute of Technology (RIT). In Figure 1 it can clearly be seen that April 9th, 19th and 26th have higher peak demands than most of the other days of the month, while April 8th, 12th and 18th have significantly higher peak demands. If these days are predicted ahead of time, demand response actions could take place to lower demand during these specific days. While significant emphasis has been placed on generating accurate electricity demand forecasts [5,6], little attention has been paid to transforming these forecasts into actionable intelligence to enable facilities to prevent avoidable demand charges such as the ones described.

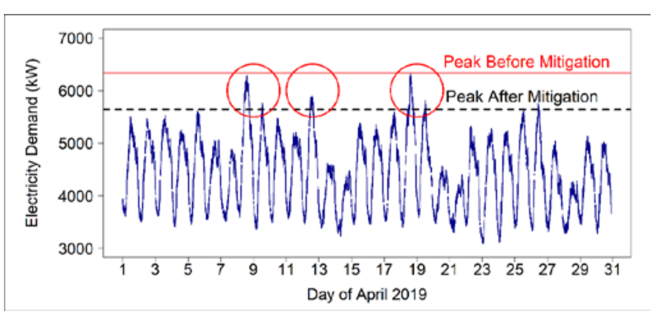

Fig. 1. Energy demand for one circuit at RIT for the month of April 2019.

Recently, research was conducted for RIT that provided evidence that if peak demand days are predicted, significant savings can be made [7]. Specifically, the authors were able to accurately predict 70% of a year's peak electric load days (PELDs) using machine-learning techniques, and estimated potential savings related to these predictions to be approximately USD$ 80,000 per year. However, none of the published research found so far evaluates the performance of these PELDs forecasting methodologies when renewable electricity generation (REG) is present. Shortly after the study [7] was completed, RIT reconfigured their electricity infrastructure into two circuits, each of which contain a 2 MW solar field. The presence of REG increases the hour to hour demand variability substantially, and thus makes the forecasting of PELDs significantly more challenging than for a facility with no REG. Figure 2 illustrates the difference between the electric load to be forecasted when REG is present (Net Demand) and the electric load to be forecasted in its absence (Demand) for May 9th, 10th, and 11th, 2019. Figure 3(a) provides a closer view of May 9th 2019 as a sample case and includes smoothed demand curves using a 12 data-points (One-Hour), each at 5 minutes intervals, Moving Average along with the corresponding Mean Absolute Percentage Deviation (MAPD) from the smoothed curves. The higher MAPD value along with the noticeable worse graphical fit shows how the Net Demand exhibits a higher variability than the Demand. Figure 3(b) further supports this claim by showing how the hourly variance tends to be higher for the Net Demand during the hours of active REC (6-19).

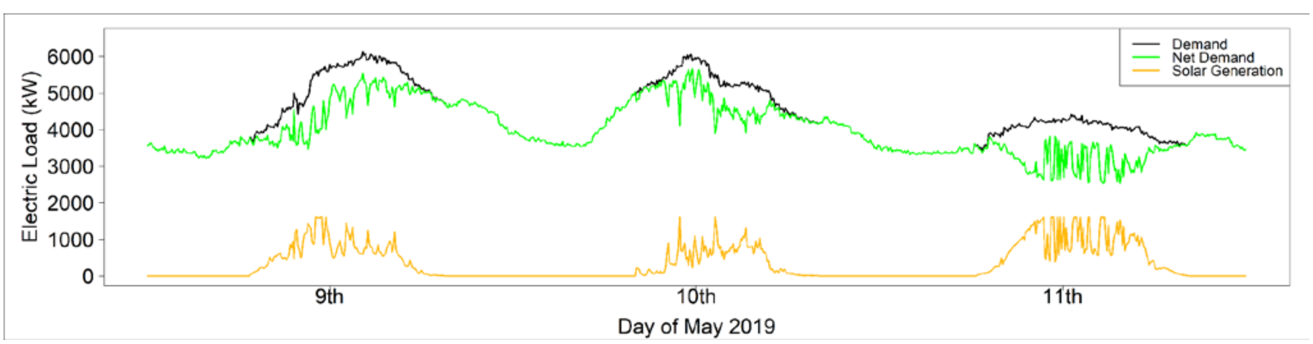

Fig. 2. Electric Demand, Net Demand, and Solar Generation at RIT during May 9th-11th, 2019.

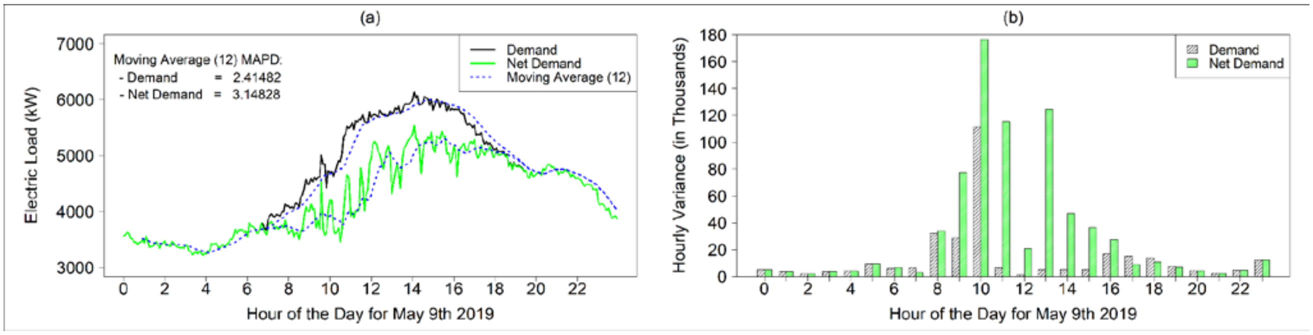

Fig. 3. Electric Demand, Net Demand, Moving Averages and Hourly Variance for May 9th, 2019.

There are currently no published works describing a methodology for forecasting peak electric load days when REG is present. The adoption of REG is on the rise worldwide, but the output of this type of generation is dependent on weather conditions, which makes it as variable as weather itself [8-10]. Figure 3 illustrates the intermittency (variability) of solar-based REG at RIT for 3 non-consecutive days, each day with different predominant weather from 6:00 AM to 6:00 PM. The fluctuations in output from renewable sources such as the sun and the wind are known to range from minutes to hours to multiple days [10].

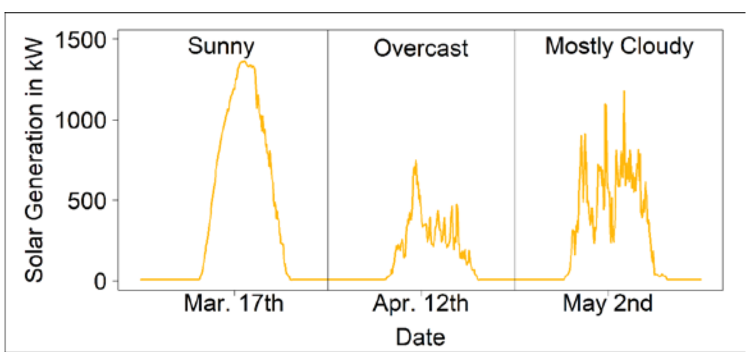

Fig. 4. Solar Generation at RIT during 3 days with different weather from 6:00 AM to 6:00 PM in 2017.

The completed research sought to evaluate how the output fluctuations from renewable sources impact current forecasting techniques used to trigger demand response actions and to document a novel methodology for forecasting PELDs that takes into account the presence of REG. The outcome of this research included the development and dissemination of a forecasting methodology that could be used by facilities management personnel in order to identify when to execute demand response actions, such that avoidable and significant demand charges could be prevented.

2. Specific Aims

The completed research specifically aimed to:

1. Expand the published scientific research related to peak electric load days forecasting in order to provide actionable intelligence to facility operators on when to run demand response actions.

2. Compare the performance of current methodologies for forecasting peak electric load days (which don't specifically target impacts from renewable energy generation) to new algorithms that do take into consideration renewable energy generation and related data.

3. Demonstrate the performance of a novel methodology for forecasting peak electric load days with renewable electricity generation present that out-performs current forecasting methodologies which fail to account for the presence of renewable electricity generation.

3. Summarized Methodology Outline

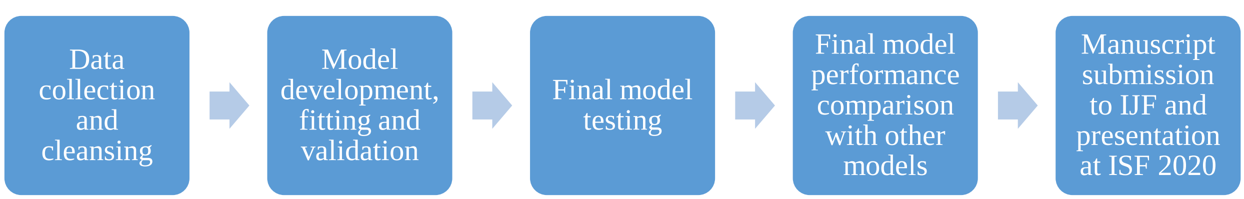

Fig. 5. Summarized methodology outline.

a. Phase 1: Data collection and cleansing

The completed research was conducted using real data collected at the Rochester Institute of Technology (RIT) in Rochester, NY, USA. The research group had access to more than 480,000 records of electricity demand data and solar generation data from two, 2 MW solar fields on campus dating back to June 2016. This data had been collected from the university's electric meters at a 5-minute frequency and stored for research initiatives such as the one completed. Operational data such as the academic calendar and special events data was available to the research group through RIT's official calendars. Weather data for RIT's location was obtained from an outside historical weather data bank. Traditional data cleansing operations such as outlier detection and removal, and data imputation took place as the final data set was assembled before the model development and fitting phase.

b. Phase 2: Model development, fitting and validation

After completing Phase 1, several machine-learning techniques such as Auto-Regressive Integrated Moving Average (ARIMA), Classification and Regression Trees (CART), and Artificial Neural Networks (ANN), were developed using the cleansed data set. Variable selection techniques were used to create parsimonious models. The training data set was split such that 80% of the data was used for model fitting. The remaining 20% of the training data was used for validation according to the procedures found in Makridakis, S., Wheelwright, S. C. and Hyndman, R. J. (1998), *Forecasting: methods and applications*, 3rd edition, John Wiley and Sons. The Synthetic Minority Oversampling Technique (SMOTE) was used to overcome class imbalance in the data set for the classification-based models. Standard goodness of fit performance measures such as the MAPE, were assessed during this phase in order to determine the best performing model.

c. Phase 3: Final model testing

The best models obtained from Phase 2 were re-trained using all of the training data and tested against unseen data according to the procedures found in Makridakis, S., Wheelwright, S. C. and Hyndman, R. J. (1998), *Forecasting: methods and applications*, 3rd edition, John Wiley and Sons. Forecast performance was measured by calculating the confusion matrix related to the accuracy of peak day predictions.

d. Phase 4: Final model performance comparison with other models

Three forecasting techniques (ARIMA, Random Forest, and ANN) obtained from published peer-reviewed works that fail to account for the presence of renewable electricity generation were selected for this phase. The same procedures used in Phases 2 and 3 to generate forecasts in scenarios with REG present was repeated using each of the selected techniques in scenarios without REG present. These results allowed a side-by-side performance comparison that provided insights into how the output fluctuations from renewable sources impact current forecasting techniques used to trigger demand response actions.

e. Phase 5: Manuscript submission to IJF and presentation at ISF 2020

The project was completed with the presentation of the research findings at the International Symposium on Forecasting (ISF) 2020 and the submission of a manuscript reporting the research results to the International Journal of Forecasting (IJF) that is currently awaiting peer review.

4. Research Findings and Contributions

The completed research has generated the following findings and contributions aligned with each of the three specific aims outlined in Section 2 of this report:

Specific Aim 1:

1.1 A manuscript titled "Actionable Peak Electric Load Day Forecasting Methodology Applicable to Facilities with Behind the Meter Renewable Electricity Generation" reporting the results obtained during this research was submitted on Nov. 8th, 2020 to the International Journal of Forecasting (IJF) and is currently awaiting peer review. This manuscript seeks to expand the published scientific research related to peak electric load days forecasting in order to provide actionable intelligence to facility operators on when to run demand response actions.

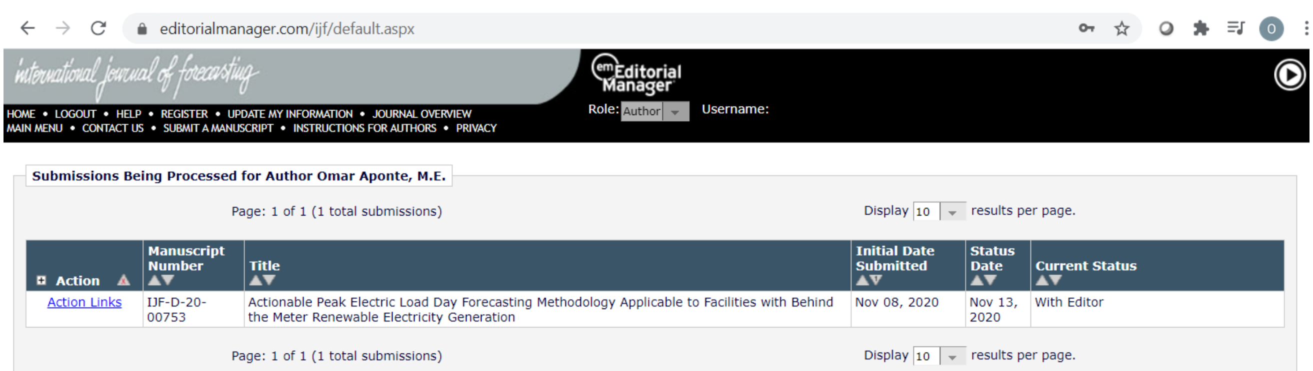

Fig. 6. Screen capture of the status of the submitted manuscript to the IJF.

1.2 A presentation titled "Actionable Peak Electric Load Day Forecasting Methodology for Facilities with Behind the Meter Renewable Electricity Generation" reporting the results obtained during this research was delivered on Oct. 28th, 2020 at the 40th International Symposium on Forecasting (ISF) 2020. This presentation provided insights into the potential of implementing peak electric load days forecasting as a tool to generate actionable intelligence to facility operators on when to run DRAs. More information about this presentation can be found at: https://whova.com/portal/webapp/iiofe_202006/Agenda/1323734

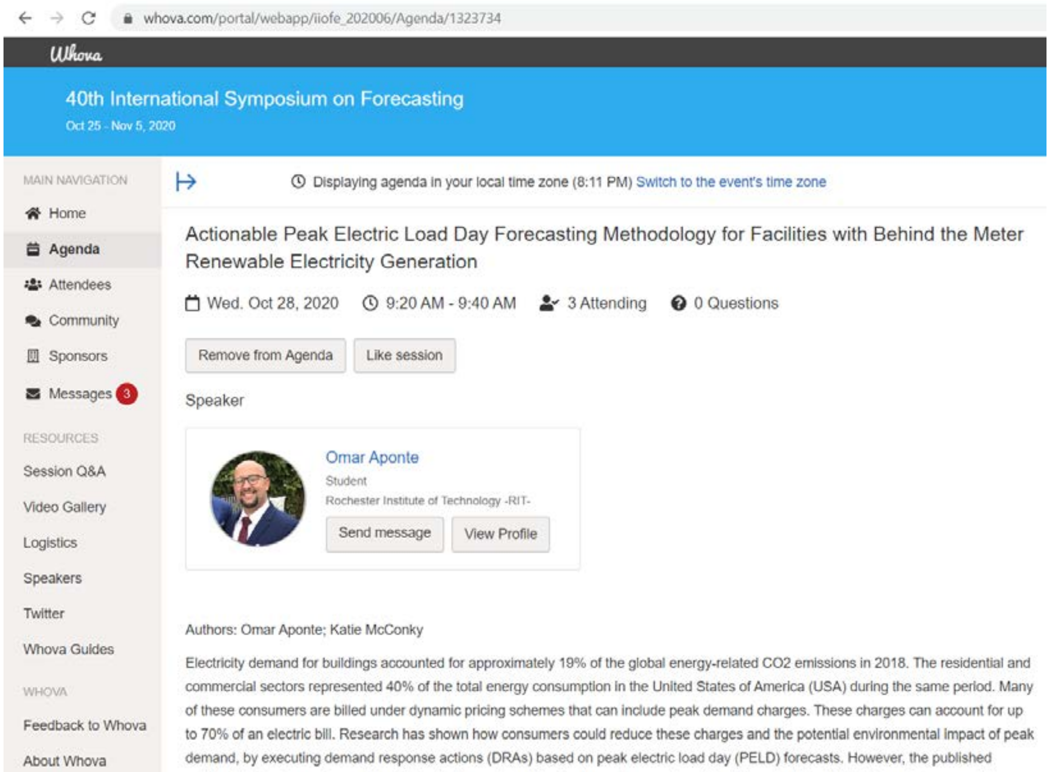

Fig. 7. Screen capture of the details about the presentation delivered during the 40th ISF 2020.

Specific Aim 2:

The completed research produced the first of their kind side-by-side empirical comparisons between the performance of ARIMA, CART, random regression and classification forest, ANN, and ensemble (also known as hybrid) based models at forecasting electric load and PELDs for scenarios with and without behind the meter renewable energy generation (BTMREG). The results of these comparisons between current methodologies for forecasting PELDs (which don't specifically target impacts from REG) to new algorithms that do take into consideration REG and related data, provided six important insights in regards to past, present, and potential future research.

2.1 Counterintuitively, there can be more potential and model savings (both in kW and in peak load charges) to be achieved by facilities using PELD forecasting methodologies after adopting BTMREG. The results show how implementing these methodologies after BTMREG adoption becomes even more important than before the adoption in order to achieve financial savings. At first, many researchers and practitioners might not consider this outcome because by definition, a customer's load profile is reduced when BTMREG is adopted (net demand scenario) which can translate into less opportunities for load reduction.

2.2 The months with the highest outside temperatures and consequently the highest energy usage for cooling purposes were also the months with the greatest savings to be achieved at the university selected for this study.

2.3 Both a random regression forest model and an ANN based regression model outperformed ARIMA and CART regression-based models at predicting future electric load levels for both the net demand (with BTMREG) and the demand (without BTMREG) scenarios.

2.4 Empirical evidence suggesting that the presence of BTMREG affects the performance of the models was only observed for the regression-based models evaluated. The results obtained from the classification-based models as well as the ensemble models evaluated did not show evidence of an effect on the performance of these models due to the presence of BTMREG.

2.5 Class imbalance issues in the data set need to be addressed in order to achieve the best performances when implementing the classification-based PELD forecasting approach regardless of the presence or absence of BTMREG.

2.6 A proposed single vote ensemble approach outperformed the current majority vote approach proposed by [7] but produced a significantly greater number of false positive predictions when compared to the other models evaluated. The use of ensemble forecasting for PELD forecasting can be further explored by evaluating additional ensemble forecasting methodologies.

Specific Aim 3:

3.1 A novel methodology for forecasting peak electric load days with BTMREG present based on CART and ANN models demonstrated the capacity to have achieved 93% of the potential savings in kW and US$ 142,129.01 savings in electricity costs during a yearlong testing period. These results were above those obtained by a previously published hybrid forecasting methodology that did not to account for the presence of REG.

5. COVID-19 Impact on Original Research Proposal

The original research proposal included budget lines to present the results of the research at the 40th International Symposium on Forecasting originally planned to be held in Rio de Janeiro, Brazil on July 5-8, 2020. However, the event was rescheduled as a virtual event due to the COVID-19 worldwide pandemic which affected travel and in-person gatherings around the world. This was the only impact of the COVID-19 pandemic on the original proposal. The scope of work originally proposed was not affected by the COVID-19 pandemic. We plan to use the remaining travel funds to attend the 2021 or 2022 International Symposium on Forecasting, whenever in-person conferences resume.

6. Future Plans and Research Efforts

The researchers' first priority during the months following the submission of this report will be to follow up with the review process of the manuscript "Actionable Peak Electric Load Day Forecasting Methodology Applicable to Facilities with Behind the Meter Renewable Electricity Generation" submitted on Nov. 8th, 2020 to the International Journal of Forecasting (IJF). The researchers are committed to respond to all comments received from the editor and the reviewers, and to perform all necessary improvements to the manuscript until it is accepted and published.

Additional research questions have been identified throughout this effort which could serve as basis for future research efforts related to PELDs forecasting methodologies and their potential business applications:

- How do the models perform in different settings, such as manufacturing or residential premises?
- What are the effects of training the models with just the hours when peak electric loads occur?
- For threshold based models, what is the best method to predict the monthly threshold?
- How effective is the methodology for other types of REG sources such as wind and hydro?

7. Budget Update

Our budget included only expenses related to travelling to Rio De Janeiro, Brazil for the 40th International Symposium on Forecasting in July, 2020. These travel expenses include support for both Dr. Katie McConky and Ph.D. Candidate Omar Aponte to travel to and attend the conference, arriving July 4th and departing July 9th. Estimated expenses are shown in the table below and include indirect costs of $3,148. The total budget request comes to $9,918.

Expense	**Initial Budget ($)**		**2020 Expenditures ($)**	
	McConky	Aponte	McConky	Aponte
Flights	1,800	1,800		
Hotel	750	750		
Taxis/Transportation	200	200		
Food	250	250		
Registration	500	190	175	175
Travel Visa	NA	80		
Total	3,500	3,270	Total Used	350
Total Expenses	6,770			
Indirect Costs (46.5%)	3,148			162
Total Request	9,918		Total Remaining	9405

A detailed budget of 2020's expenditures is as follows:

Katie McConky
- $125 International Institute of Forecasters Membership
- $50 ISF 2020 Workshop 3: Deep Learning for Forecasting

Omar Aponte
- $25 Student Online Membership to International Institute of Forecasters
- $50 ISF 2020 Workshop 3: Deep Learning for Forecasting
- $50 ISF 2020 Workshop 2: MIDAS Touch and Regime Switching Models
- $50 ISF 2020 Workshop 5: Forecasting to Meet Demand

We currently have approximately $9400 remaining for travel to ISF 2021 or 2022.

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Actionable Peak Electric Load Day Forecasting Methodology Applicable to Facilities with Behind the Meter Renewable Electricity Generation

--Manuscript Draft--

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Abstract:	Many electricity consumers in the USA are billed load based charges that can amount to up to 70% of electricity costs. Research has shown that the financial impact of peak load charges can be reduced by acting on the intelligence provided by peak electric load day (PELD) forecasts. Unfortunately, published methodologies have not been thoroughly tested for the increasing number of facilities adopting behind the meter renewable electricity generation (BTMREG). This paper contributes: (1) a PELD forecasting methodology applicable to consumers with BTMREG that achieved 93% of the potential savings in kW, approximately US$ 142,129.01 in peak load charges; (2) the first side-by-side performance comparisons of electric load and PELD forecasting models for scenarios with and without BTMREG; and (3) the first PELD forecasting model savings comparison for scenarios with and without BTMREG. One of the insights provided suggests that counterintuitively, BTMREG adoption can translate into higher peak load savings.
Suggested Reviewers:	Iain Staffell, Ph.D. in Chemical Engineering Imperial College London i.staffell@imperial.ac.uk Dr. Staffell has published related work and the topic of this paper aligns with his research activities.
	Baran Yildiz, Ph.D. in Engineering University of New South Wales baran.yildiz@unsw.edu.au Dr. Yildiz has published related work and the topic of this paper aligns with his research activities.
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	Dr. Pfenninger has published related work and the topic of this paper aligns with his research activities.
	Muhammad Waseem Ahmad, Ph.D. in Building Energy Cardiff University ahmadm3@cardiff.ac.uk Dr. Ahmad has published related work and the topic of this paper aligns with his research activities.
	Mosaddek Hossain Kamal Tushar, Ph.D. in Electrical and Computer Engineering University of Dhaka Faculty of Engineering and Technology tushar@cse.univdhaka.edu Dr. Tushar has published related work and the topic of this paper aligns with his research activities.
Opposed Reviewers:	
Additional Information:	
Question	**Response**

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November 8th, 2020

Editors of the International Journal of Forecasting

Dear Editors,

We thank you for dedicating your time to review our submission "Actionable Peak Electric Load Day Forecasting Methodology Applicable to Facilities with Behind the Meter Renewable Electricity Generation". This paper seeks to address the research gap created by the limited amount of published research detailing peak electric load day (PELD) forecasting methodologies applicable to the increasing number of facilities adopting behind the meter renewable electricity generation (BTMREG) worldwide. In addition, the published research lacks studies comparing the performance of PELDs forecasting methodologies with and without BTMREG. Three main contributions provided by the article can be highlighted. First, the development and testing of a PELD forecasting methodology applicable to both consumers with and without BTMREG. The experimental results showed that 93% of potential savings in kW (approximately US$ 142,129.01) could be achieved at a university in the United States of America (USA) with BTMREG by implementing an artificial neural network (ANN) based model.

The second contribution is the documentation of the first of their kind side-by-side comparisons between the performance of autoregressive integrated moving average (ARIMA), regression and classification trees (RCT), random regression and classification forest, ANN, and ensemble based models at forecasting electric load and PELDs for scenarios with and without BTMREG. These comparisons provided four important insights in regards to past, present, and potential future research. The third and final contribution is the first of its kind PELD forecasting model savings comparison for scenarios with and without BTMREG. This comparison provided insight suggesting that counterintuitively, BTMREG adoption can translate into higher peak load savings. The data set developed will be submitted as an appendix following the peer review process.

This work is distinct from previous works in the electric load forecasting field because most of the work in this particular field focuses on the accuracy of electric load forecasts while our work focuses on the accurate classification of an upcoming day as either a PELD or a Non-PELD in order to take advantage of significant cost savings opportunities. This work is also distinct in the field of PELD forecasting because it provides first of their kind results and a methodology applicable to facilities regardless of the presence of BTMREG. Virtually any building and/or facility in the world can apply the proposed methodology in order to reduce the financial and environmental impact of peak demand.

We look forward to receiving your and the reviewers' comments.

Thank you,
Omar Aponte, M.E.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Actionable Peak Electric Load Day Forecasting Methodology Applicable to Facilities with Behind the Meter Renewable Electricity Generation

Abstract

Many electricity consumers in the USA are billed load based charges that can amount to up to 70% of electricity costs. Research has shown that the financial impact of peak load charges can be reduced by acting on the intelligence provided by peak electric load day (PELD) forecasts. Unfortunately, published methodologies have not been thoroughly tested for the increasing number of facilities adopting behind the meter renewable electricity generation (BTMREG). This paper contributes: (1) a PELD forecasting methodology applicable to consumers with BTMREG that achieved 93% of the potential savings in kW, approximately US$ 142,129.01 in peak load charges; (2) the first side-by-side performance comparisons of electric load and PELD forecasting models for scenarios with and without BTMREG; and (3) the first PELD forecasting model savings comparison for scenarios with and without BTMREG. One of the insights provided suggests that counterintuitively, BTMREG adoption can translate into higher peak load savings.

1. Introduction

Commercial and residential facilities require a significant amount of energy and contribute a considerable amount of greenhouse gas (GHG) emissions worldwide. International and domestic agencies that focus on energy related statistics include a distinct category to report the energy consumed by commercial and residential buildings. This practice is a testament to the significant impact of these consumers' energy usage. The International Energy Agency (IEA) reported that buildings were responsible for 28% of global energy-related CO2 emissions in 2018 (IEA, 2019a). The United States' Energy Information Administration reported that the residential and commercial sectors represented 39% of the total energy consumption in the United States of America (USA) during 2019 including losses (USEIA, 2020). During 2018, sustained ongoing efforts to decarbonize energy generation worldwide increased the share of renewable energy in global power capacity to 33% (REN21, 2019). However, the increase in building electricity consumption was five-times faster than the improvements in the carbon intensity of the power sector during the 2000-2018 period (IEA, 2019a). Given buildings' significant energy requirements and contributions to GHG emissions, it is imperative that research efforts continue to focus on ways to increase buildings' energy efficiency in order to reduce their energy related costs and environmental impact.

Many commercial and residential buildings are billed under dynamic pricing schemes that can include peak load charges (also referred to as a consumer demand charges or peak demand charges) (Dutta and Mitra, 2017; McLaren et al., 2017; Hledik, 2014). Peak load charges are typically based on the highest electric load (in kW) observed during a billing period, typically a month, and are charged in $/kW (McLaren et al., 2017; Hledik, 2014). These peak load charges can amount to up to 70% of an electric bill in the USA (McLaren et al., 2017). However, the number of days in a month contributing to peak load charges is typically very small. Figure 1 illustrates real electric load data for a circuit at the university campus in the USA selected to perform the current study during the month of April 2019. Figure 1 clearly shows that April 8th, 12th and 18th have significantly higher load levels than the other days of the month. If these peak load days are forecasted ahead of time, demand response actions could be executed to mitigate the electric load during these specific days and reduce the peak load charges described earlier. The lead-time provided by these peak electric load day (PELD) forecasts is very important because some demand response actions require several hours either to be executed, to show results, or both.

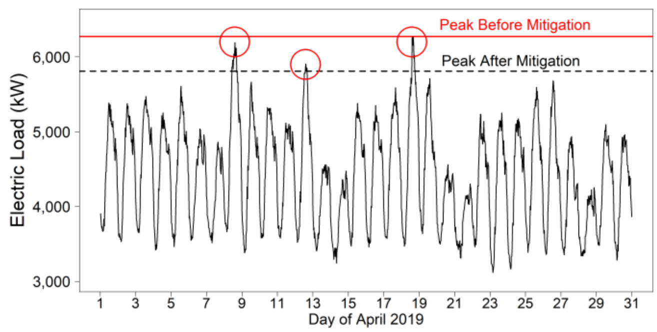

Fig. 1. Electric load for a circuit during April 2019.

Most of the published research on electric load forecasting focuses on generating accurate electric load forecasts for both utilities and consumers, but there is limited research on the application of these forecasts to avoid the peak load charges described earlier. Saxena et al. (2019) noted that studies focusing on forecasting a billing period's peak electric load days (PELDs) in order to trigger demand response actions to reduce peak load charges are scarce. These authors reviewed how autoregressive integrated moving average (ARIMA), support vector regression machine (SVRM), classification and regression trees (CART), artificial neural network (ANN), and multivariate adaptive regression splines (MARS) based models, among others, have been used to develop forecasting models for next-day building electric load and peak load. However, being able to predict the next day's electric load does not provide actionable intelligence to determine if the next day will contribute to peak load charges for the billing period. Saxena et al. (2019) developed an ensemble (also referred to as hybrid) machine-learning model focused specifically on predicting if the next day will be a PELD for a billing period. Saxena et al. (2019) tested their model using data from a university in the USA; the ensemble model predicted 70% of actual PELDs and revealed potential savings in the neighborhood of US $80,000 after a yearlong testing period. This work provided evidence of how consumers could potentially reduce peak load charges by executing demand response actions based on the results of PELDs forecasting efforts. As the Saxena et al. (2019)'s methodology was being prepared for implementation at a university in the USA, the university's electricity infrastructure underwent a reconfiguration. The university's electricity infrastructure was divided into two main circuits. Each of these main circuits now included a solar field designed to provide up to 2 Megawatts (MW) of behind the meter renewable electricity generation (BTMREG). While the Saxena et al. (2019) methodology had been validated for a university campus with no BTMREG, the methodology had not been tested for circuits with BTMREG able to make up for as much at 25% of the electric load.

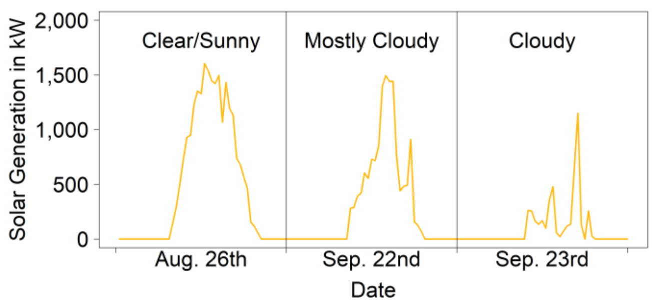

Fig. 2. Solar Generation during 3 days with different weather from 6:00 AM to 6:00 PM in 2019.

Researchers have already noted that renewable electricity generation (REG) output is as variable (intermittent) as weather itself (Staffell and Pfenninger, 2018; Chaiamarit and Nuchprayoon, 2014). Aponte and McConky (2019) documented how REG output could represent a challenge for the accuracy of current PELDs forecasting methodologies. REG output can fluctuate for periods ranging from minutes to hours to multiple days (Staffell and Pfenninger, 2018). Figure 2 illustrates the intermittency (variability) of solar-based REG at the university campus in the USA selected to perform the current study for three non-consecutive days, each day with different predominant weather (clear/sunny, cloudy, and mostly cloudy) from 6:00 AM to 6:00 PM. This characteristic of REG challenges the accuracy of both electric load forecasts (Tushar et al., 2018) and PELDs forecasts (Aponte and McConky, 2019). Chaiamarit and Nuchprayoon (2014) demonstrated that REG affects electric load characteristics and net demand (also referred to as net load). Net demand is defined as the result of subtracting the electric load generated behind the meter (on the consumer's side) from the total load required by the consumer (also referred to as building demand or just demand). From this point on, whenever the term net demand is used, it will be referring to a scenario with BTMREG; and whenever the term demand is used, it will be referring to a scenario without BTMREG. Aponte and McConky (2019) performed a data-driven analysis of a yearlong electric load and solar generation data for a university in the USA that highlighted five main findings. First, as expected the load values for the net demand scenario (with BTMREG) were lower than the load values for the demand scenario (without BTMREG) when the BTMREG was active. Second, the peak loads observed when BTMREG was present, happened during the hours when the BTMREG was either low or inactive and normal operations were still ongoing at the facilities. Third, as a direct consequence of the previous finding, demand response strategies need to be reevaluated to ensure that demand response actions can be performed during the new times with high concentration of peak loads. Fourth, the number of PELDs during a month changed with the adoption of BTMREG. Consequently, the number of days during which demand response actions needed to be executed also changed with the adoption of BTMREG. Fifth, the adoption of BTMREG also changed the potential savings after executing demand response actions. The study concluded that new demand response strategies have to be developed as soon as facilities adopt BTMREG in order to ensure maximum reduction of peak demand charges.

1.1 Novelty, contributions, and paper organization.

As far as our review of the published literature (see Section 2) was able to assess, even though there is an abundance of published work related to future load forecasts, published research detailing PELDs forecasting methodologies applicable to the increasing number of facilities adopting BTMREG is very limited. Furthermore, published studies comparing the performance of PELDs forecasting methodologies with and without BTMREG are not available. The research described in this paper seeks to address this research gap by providing three main contributions. First, a PELD forecasting methodology applicable to both consumers with and without BTMREG. This methodology was tested using ARIMA, CART, random regression and classification forest, ANN, and ensemble (also known as hybrid) based forecasting models. Second, the first of their kind side-by-side performance comparisons of electric load and PELD forecasting models for scenarios with and without BTMREG. Third, the first of its kind PELD forecasting model savings comparison for scenarios with and without BTMREG.

The remainder of this paper is organized as follows. Section 2 summarizes the findings obtained through a preliminary data analysis and a review of the published literature. Section 3 provides an overview of the methodology developed for the current study. Section 4 describes the experimental setup and procedure followed during the current study. This section includes details about the data set construction, data pre-processing, and the implementation of the forecasting models. Section 5 presents the results obtained after implementing and comparing each of the models along with a discussion about the best model selection process and the potential and model savings. The concluding remarks for this paper as well as potential future research questions are provided in Section 6.

2. Preliminary data analysis and review of the published literature

A preliminary analysis of the electric load and solar generation data of the university campus in the USA selected to perform the current study revealed that the presence of BTMREG increases the hour-to-hour net demand variability substantially. This net demand profile is the most important component of a consumer's electricity cost. Figure 3 illustrates the difference between the electric load to be forecasted when BTMREG is present (net demand) and the electric load to be forecasted in its absence (demand) for May 9th, 10th, and 11th, 2019. Figure 4(a) provides a closer view of May 9th 2019 as a sample case. This figure includes a smoothed load curve using a 2 data-points (One-Hour) moving average along with the corresponding Mean Absolute Percentage Deviation (MAPD) calculated according to Equation 1.

$$MAPD = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{|Actual_i - Smoothed\ Value_i|}{|Actual_i|}\right) \times 100 \quad (1)$$

The higher MAPD value (2.2519 vs 1.3518) along with the noticeably worse fit illustrates how net demand exhibits a higher variability than demand. Figure 4(b) further supports this claim by illustrating how the hourly standard deviation tends to be higher for net demand during most of the hours with active BTMREG (6-19). In the absence of BTMREG, the load profile can be predicted using the consumer's past electric load data, weather and operations data, along with some minor influence from other factors. With the introduction of BTMREG, the influence of highly variable and difficult to predict weather conditions (such as cloud coverage) in the load profile is anticipated to make the forecasting process significantly more challenging. These initial findings, along with those documented by Aponte and McConky (2019), motivated a search for published research detailing accurate PELDs forecasting methodologies for facilities with BTMREG.

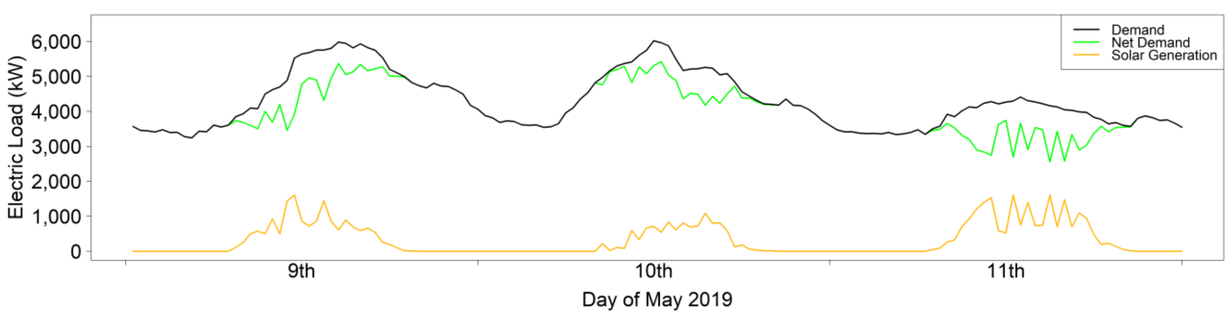

Fig. 3. Demand, net demand, and solar generation during May 9th-11th, 2019.

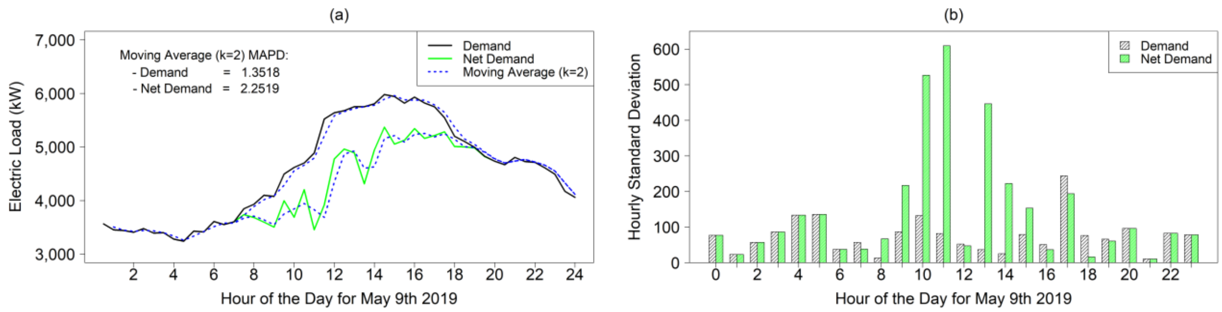

Fig. 4. (a) Demand, net demand, moving average and (b) hourly standard deviation during May 9th, 2019.

The search for published research detailing accurate PELDs forecasting methodologies for facilities with BTMREG revealed that future load forecasts have been a core activity for utilities since the electricity industry began in the late 1800's (Hong, 2014). Utilities rely on electric load forecasts to plan their supply and generating capacities (Dutta and Mitra, 2017; Hong and Fan, 2016; Alfares and Mohammad, 2002), to inform revenue projections, rate design, energy trading, and more (Hong and Fan, 2016). The capacity of electric utilities to ensure a reliable service to their clients depends heavily on these load forecasts (also referred to as demand forecasts). Electric load forecasting methods have been extensively researched over the past few decades. The literature provides an ample range of studies featuring various methodologies and models for this purpose (Yildiz et al. (2017); Hong and Fan (2016); Garulli et al. (2015); Alfares and Mohammad, 2002). Alfares and Mohammad (2002) conducted a review of more than 100 works published between the comprehensive review by Moghram and Rahman (1989) and February 2000. Alfares and Mohammad (2002) classified the published methodologies into the first nine categories shown in Table 1. The researchers also provided a brief description along with the advantages and disadvantages identified for each category. The authors observed what they described as a clear trend towards new, stochastic, and dynamic forecasting techniques. Fuzzy logic, expert systems and ANNs were specific techniques highlighted by the authors. They also highlighted a trend towards hybrid methods that combine two or more techniques. Hong and Fan (2016) published a tutorial review based on more than 25 representative load forecasting papers (13 of which were literature review papers) published between the work by Abu-El-Magd and Sinha (1982) and November 2015. The techniques evaluated by the authors are included within the categories specified in Table 1. One of the authors' conclusions was that a universally best load forecasting technique does not exist. Hong and Fan (2016) concluded that the data and jurisdictions are the factors that determine the appropriate technique and not the other way around. Yildiz et al. (2017) reviewed more than 50 commercial building load forecasting works published between 1984 and March 2016 and identified the techniques within the categories specified in Table 1. The authors concluded that the machine learning models reviewed (ANN, SVRM, and CART) had a superior forecasting performance than the regression models included in the review. Forecasting daily peak electric load proved to be a more difficult task than forecasting day ahead hourly electric load for Yildiz et al. (2017). The wide range of electric load forecasting methodologies and techniques currently found in the literature can be simplified into a general approach. This general approach entails the estimation of a load model from past data, and then using this model to predict future loads (Garulli et al., 2015).

Table 1

Categorization of techniques found in electric load forecasting literature reviews.

Category	**Alfares and Mohammad (2002)**	**Hong and Fan (2016)**	**Yildiz et al. (2017)**
1) Regression models *(Including Semi-Parametric Additive Models)*	X	X	X
2) Exponential smoothing	X	X	
3) Iterative reweighted least-squares	X		
4) Adaptive load forecasting	X		
5) Stochastic time series	X		

6) ARMAX models based on genetic algorithms *(Including other autoregressive models)*	X	X	X
7) Fuzzy logic	X	X	
8) Artificial neural network (ANN)	X	X	X
9) Knowledge-based expert systems	X		
10) Support vector regression and machine (SVRM)		X	X
11) Gradient boosting machine		X	
12) Thermal models			X
13) Classification and regression trees (CART)			X

PELDs forecasting methodologies are scarce and can quickly become less effective if left unattended while the internal power distribution systems of facilities are constantly evolving and becoming considerably more complex. Worldwide initiatives to decarbonize the electric grid and reduce its associated greenhouse gas emissions have caused a significant increase in the number of facilities adopting REG systems (IEA, 2019a). Worldwide investment to increase building energy efficiency and minimize the financial and environmental impact of rising energy consumption totaled USD$ 139 billion in 2018 (IEA, 2019b). Saxena et al. (2019) demonstrated how facilities that pair PELDs forecasts with demand response actions could reduce their peak loads and achieve financial savings. The operating costs of the power stations that supply these peak electric loads tend to be very expensive and passed down to the consumers. In addition, these power stations typically have a low fuel efficiency and a high negative environmental impact when they burn fossil fuels (IER, 2020). Therefore, PELDs forecasts are not only useful to avoid peak demand charges, but also to reduce negative environmental impacts. However, as far as we were able to assess, published research detailing accurate PELDs forecasting methodologies applicable to the increasing number of facilities adopting BTMREG, as well as published studies comparing the performance of PELDs forecasting methodologies with and without BTMREG are not available.

3. Methodology overview

This section will provide an overview of the methodology developed for the current study. The methodology developed to determine the performance of both load forecasting and PELD forecasting methodologies was predominantly based on the previous work by Saxena et al. (2019). These researchers established two general approaches for PELD prediction. We will refer to the first approach as the threshold-based approach. This approach can be separated into two phases. During the first phase, regression-based load forecasting models are used to generate day ahead load forecasts. During the second phase, these forecasts are compared to a pre-calculated monthly threshold (Dlim) in order to classify each day as either a PELD or a Non-PELD. The second approach will be referred to as the classification-based approach. For this approach, classification models are used to classify an upcoming day as either a PELD or a Non-PELD. Saxena et al. (2019) combined the results of some of the evaluated individual models into one ensemble (or hybrid) approach and tested the methodology using electric load data from a circuit in a university in the USA without BTMREG. As an addition to the previous work by Saxena et al. (2019), the methodology for the current study includes an additional ensemble approach, it also includes the results of all individual models in the ensembles, and considers the presence of BTMREG by including electricity generation data (when applicable) and additional weather related features expected to affect REG. The proposed improved methodology is outlined in Figure 5.

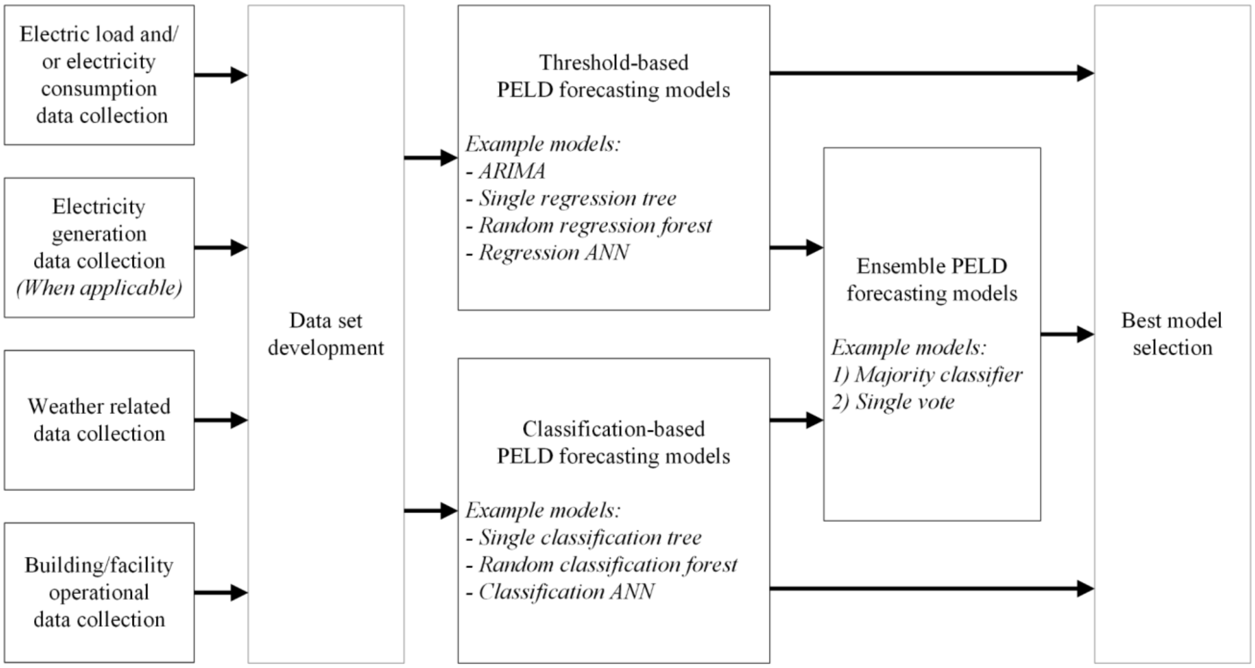

Fig. 5. PELD forecasting methodology overview.

The methodology for the current study can be outlined in five phases. Data collection, data set development, individual machine learning models implementation within each of the two general approaches (threshold and classification based), ensemble models implementation using all of the individual models as its components, and best PELDs forecasting model selection. This methodology was applied for a scenario with BTMREG and then repeated for a scenario without BTMREG. Obtaining the results for these two scenarios allowed the development of the first of its kind side-by-side empirical comparisons between the performances of both electric load and PELD forecasting models for facilities with and without BTMREG. Details about the experiment implementation of this methodology are provided in the following section.

4. Experimental setup and procedure

This section will provide details about the experimental setup and procedure to implement the methodology described in Section 3 using real data from a university in the USA. The data collection and data set development phases will be described first. A sub-section with details about the model training, validation, and testing process will follow. Two sub-sections will follow with details in regards to the development process of the models in each of the two general approaches for PELDs prediction (threshold and classification based) respectively. The section will conclude with details about the development of two ensemble PELD forecasting models.

4.1 Data collection and data set development

A data set containing 29,952 records of electric load, electricity generation, weather, operational, and calendar data at 30 minutes intervals was developed. This data set is provided as an appendix to this paper so that it may serve as an additional contribution for future research. The records in the data set cover the period between June 16th, 2018 at 00:00 hours and February 29th, 2020 at 23:30 hours. All times are represented at the official local time for the university campus in the USA selected for this study. Table 2 provides a list of the 30 variables contained in the data set along with each of the variable's description and type. Electric load and generation related data (in kW), such as that represented by variables 1, 4, and 8 in Table 2, was collected at 30 minutes intervals from a smart metered circuit at a university campus in the USA that included a solar field designed to provide up to 2 MW of BTMREG. Weather data was collected using hourly values from the publicly available local climatological data summaries corresponding to the airport weather station in closest proximity to the campus (about 6.8 km or 4.2

miles) and provided by the National Oceanic and Atmospheric Administration (NOAA) of the USA (NOAA, 2020). This weather data was later imputed using linear interpolation for continuous variables and last value carried forward for categorical variables in order to generate a 30 minutes intervals data set. Operational and calendar data, such as that represented by variables 9, 10, and 19 to 30 in Table 2, were collected from the university's heating, ventilation, and air conditioning (HVAC) management system and the university's academic calendar. The following data pre-processing steps were completed for the complete data set as described by Saxena et al. (2019) in order to ensure the quality of the data set: 1) uniformly-spaced time indices generation; 2) outlier detection and removal; and 3) missing value interpolation using linear interpolation for continuous variables and last value carried forward for categorical variables.

Table 2

Data set variables.

Variable name	**Description**	**Type**
1) Demand	Load without BTMREG present (Demand) at the time of observation registered in kW	Continuous
2) DemDlim	Calculated monthly threshold (Dlim) for Demand as described by Saxena et al. (2019) in kW	Continuous
3) DemDmaxTm1	Maximum Demand registered during the previous day in kW	Continuous
4) NetDemand	Load with BTMREG present (Net Demand) at the time of observation registered in kW	Continuous
5) NetDemDlim	Calculated monthly threshold (Dlim) for Net Demand as described by Saxena et al. (2019) in kW	Continuous
6) NetDemDmaxTm1	Maximum Net Demand registered during the previous day in kW	Continuous
7) LastDemTM1	Last Demand registered during the previous day in kW (Demand and Net Demand are the same at this point because REG is not active during this time)	Continuous

8) SolarREG	Solar REG at the time of observation registered in kW	Continuous
9) OP_CoolReq	If at the time of observation, HVAC system cooling set point < indoor air temperature; Then, OP_CoolReq = Positive difference between HVAC system cooling set point and indoor air temperature in degrees Fahrenheit (°F); Else, OP_CoolReq = 0	Continuous
10) OP_HeatReq	If at the time of observation, HVAC system heating set point > indoor air temperature; Then, OP_HeatReq = Positive difference between HVAC system heating set point and indoor air temperature in degrees Fahrenheit (°F); Else, OP_HeatReq = 0	Continuous
11) NW_DBTemp	Outdoor dry bulb temperature at the time of observation in degrees Fahrenheit (°F) recorded by NOAA	Continuous
12) NW_RelHum	Outdoor relative humidity at the time of observation to the nearest whole percentage recorded by NOAA	Continuous
13) NW_WindSpe	Outdoor wind speed at the time of observation in miles per hour (mph) recorded by NOAA	Continuous
14) NW_WeatherClassShort	Outside weather classification at the time of observation recorded by NOAA and grouped into 5 categories. *Categories: 1 = Clear/Sunny , 2 = Cloudy, 3 = Rain, 4 = Snow, 5 = Windy*	Categorical
15) DemActPEL	If at the time of observation, Demand > DemDlim; Then, DemActPEL = 1; Else, DemActPEL = 0	Categorical
16) DemActPELD	Identification of the day as 1 for actual PELD or 0 for actual Non-PELD for the Demand data as described by Saxena et al. (2019)	Categorical
17) NetDemActPEL	If at the time of observation, NetDemand > NetDemDlim; Then, NetDemActPEL = 1; Else, NetDemActPEL = 0	Categorical
18) NetDemActPELD	Identification of the day as 1 for actual PELD or 0 for actual Non-PELD for the NetDemand data as described by Saxena et al. (2019)	Categorical

19) Time	Date (MM/DD/YYYY) and time (HH:MM) in 24 hours format at the time of observation	Categorical
20) Month	Month component of Time at the time of observation. *Categories: 1, 2, 3, …, 12*	Categorical
21) HoD	Hour component of Time at the time of observation. *Categories: 0, 1, 2, …, 23*	Categorical
22) DoW	Day of the week at the time of observation *Categories: 1 = Mon, 2 = Tue, …, 7 = Sun*	Categorical
23) OP_Semester	Academic semester at the time of observation *Categories: 1 = Fall, 2 = Spring, 3 = Summer*	Categorical
24) OP_Classes	If the day is an official class day; Then, OP_Classes = 1; Else, OP_Classes = 0	Categorical
25) OP_ResHallsOpen	If the on-campus residence halls are officially open during the day; Then, OP_ResHallsOpen = 1; Else, OP_ResHallsOpen = 0	Categorical
26) OP_CampusOpen	If the campus is officially open for administrative operations during the day; Then, OP_CampusOpen = 1; Else, OP_CampusOpen = 0	Categorical
27) OP_SpringBreak	If the day is part of spring break; Then, OP_SpringBreak = 1; Else, OP_SpringBreak = 0	Categorical
28) OP_FirstDayAfterBreak	If the day is the first after a break period; Then, OP_FirstDayAfterBreak = 1; Else, OP_FirstDayAfterBreak = 0	Categorical
29) OP_Increase	If there is an event during the day that can potentially cause an increase in electric load (festival, fair, convention, concert, etc); Then, OP_Increase = 1; Else, OP_Increase = 0	Categorical
30) OP_Decrease	If there is an event during the day that can potentially cause a decrease in electric load (holiday, half-day, exams week, etc); Then, OP_Decrease = 1; Else, OP_Decrease = 0	Categorical

The calculated monthly threshold (Dlim) values for the demand scenario (DemDlim) and the net demand scenario (NetDemDlim) included in the data set, were determined using Equation 2 from the previous work by Saxena et al. (2019).

$$D_{lim,i} = \mu_i + 2 \times \sigma_i \qquad (2)$$

Where

μ_i = the mean of every electric load observation for the given month *i*, and

σ_i = the standard deviation of every electric load observation of the given month *i*.

4.2 Model training, validation, and testing process

Thirteen PELD classification models were developed and tested for this study. The testing period selected for this study included 12 months (one year) from March 1st, 2019 at 00:00 hours to February 29th, 2020 at 23:30 hours. For each month *m* in the test period, a training data used was created using a random selection of 80% of all the available data in the data set covering the period between June 16th, 2018 at 00:00 hours and the final day of the previous month, month *m-1*, at 23:30 hours. The remaining 20% of the data leading up to month *m* was used as validation data set in order to optimize any model parameters. All final ANN models were selected based on their performance on the validation set. The parameters for each ANN model were optimized by testing the values specified in Table 3. After the parameter optimization process, the model for each month *m* was retrained using all of the training and validation data available prior to the start of month *m* before forecasting month *m* for testing purposes. This procedure was followed for all models, with the exception of the seasonal ARIMA model. Because of the continuity requirement of ARIMA based models, the Seasonal ARIMA model was retrained daily at the end of each day in the testing period at 23:59 hours using all of the available data from June 16th, 2018 at 00:00 hours up to the most recent record available before the retraining time.

Table 3

Values tested for ANN parameters.

Parameter	**Values tested**
# Hidden Nodes	2 to 30 by increments of 1
Decay Rate	0.0001, 0.001, 0.01, 0.05, and 0.1
# of Iterations	200 to 5000 by increments of 200

In order to test the models, all of the models were used at the end of each day at 23:59 hours to generate 48 predictions (each at 30 minutes intervals) corresponding to the next day. Regression-based models generated load predictions while classification-based models generated a peak electric load (PEL) or Non-PEL for the month classification labels. A PEL for the month is defined as any load that is above the monthly threshold (Dlim) for the month (See variables 15 and 17 in Table 2). For final testing purposes during each month of the testing period, the load predictions generated by the regression-based models were compared to a monthly threshold (Dlim), any load found above this threshold was considered a PEL, and any day during which a PEL occurred was forecasted as a PELD. Similarly, the classification PEL and Non-PEL labels generated by the classification-based models were used to classify any day during which a PEL was forecasted as a PELD.

The process to generate the 48 predictions for October 5th, 2019 using any of the evaluated models except the seasonal ARIMA will be explained next as an example. On September 30th, 2019 at 23:59 hours, a new model to be used for the month of October 2019 is developed. The October 2019 model is initially trained using 80% of all the available data in the data set covering the period between June 16th, 2018 at 00:00 hours through September 30th, 2019 at 23:30 hours, and validated using the remaining 20% of the data. Once optimal parameters are identified, the October 2019 model is retrained using all of the training and validation data available prior to September 30th, 2019. This October 2019 model is used to generate 48 predictions, one for each 30-minute interval starting with October 5th, 2019 at 00:00 hours and ending at 23:30 hours of the same day. In the case of the seasonal ARIMA model, the model available by October 4th, 2019 at 23:59 hours would have been trained using all of the available data between June 16th, 2018 at 00:00 hours up to the most recent record available before generating the first prediction for October 5th, 2019. The 48 predictions are then converted to a single PELD binary classification. If a PEL is found, then the day is forecasted as a PELD and this prediction is compared to the actual classification of the day in order to determine the model's performance. All of the models evaluated during this research were implemented using the R language and environment for statistical computing (R Core Team, 2013).

4.3 Threshold-based PELD forecasting models

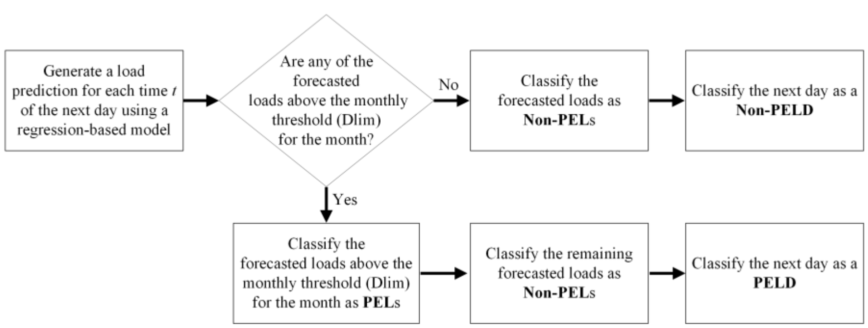

Fig. 6. Threshold-based PELD forecasting process.

Five threshold-based PELD forecasting models were developed for this study. These models were used to generate a day ahead load forecast that would later be compared to a pre-calculated monthly threshold (Dlim) in order to classify each day in the testing period as either a PELD or a Non-PELD (see Figure 6). Table 4 shows the characteristics of each of these models. Table 5 shows the values used as the monthly threshold (Dlim) for each of the months in the testing period. These values were determined using Equation 2. The focus of the current study does not include evaluating the accuracy of the monthly threshold (Dlim) prediction method suggested by Saxena et al. (2019). For this reason, the current study used ground truth monthly thresholds (Dlim) for PELD determination.

Table 4

Threshold-based PELD forecasting models characteristics.

<table>
<tr><th>Name</th><th>Description</th><th>Response</th><th>Inputs used from Table 2</th></tr>
<tr><td>M01_RegSARIMA</td><td>Seasonal ARIMA generated using the “auto.arima” function from the R package “forecast” v8.12 with a value s=336. All other parameters remained at their default value.</td><td rowspan="4">Electric load at the time of observation.

(Variable 4 for electric load with BTMREG present (net demand) or Variable 1 for electric load without BTMREG present (demand) from Table 2)</td><td>Variable 4, for electric load with BTMREG present (net demand); Variable 1, for electric load without BTMREG present (demand).</td></tr>
<tr><td>M02_RegST</td><td>Regression single decision tree generated using the function “tree” from the R package “tree” v1.0-40 with default parameters.</td><td rowspan="3">Variables 2, 3, 5, 6, 7, 9:14, and 20:30</td></tr>
<tr><td>M03_RegRF</td><td>Regression random decision forest generated using the function “randomForest” from the R package “randomForest” v4.6-14 with values ntree=1000 and importance=TRUE. All other parameters remained at their default value.</td></tr>
<tr><td>M04_RegANN</td><td>Regression feed-forward artificial neural network with a single hidden layer generated using the function</td></tr>
</table>

	"nnet" from the R package "nnet" v7.3-14 with manually selected values for size, decay, maxit, and MaxNWts, and linout = TRUE. All other parameters remained at their default value.		
M05_RegANNST	M04 but only using the variables selected by the regression single decision tree in M02 as inputs.		Variables selected by the regression single decision tree in M02.

Table 5

Monthly threshold (Dlim) values for the months in the testing period for the net demand (with BTMREG) and the demand (without BTMREG) scenarios.

Month and year	**Monthly threshold for net demand** (NetDemDlim)	**Monthly threshold for demand** (DemDlim)
Mar. 2019	5,277.62	5,584.79
Apr. 2019	5,442.61	5,759.57
May 2019	4,732.92	5,242.71
Jun. 2019	5,192.39	5,962.64
Jul. 2019	6,730.34	7,359.20
Aug. 2019	6,125.85	6,809.69
Sep. 2019	6,490.20	7,063.56
Oct. 2019	5,657.77	5,957.91
Nov. 2019	5,660.77	5,764.58
Dec. 2019	5,373.77	5,410.37
Jan. 2020	5,492.00	5,583.62
Feb. 2020	5,638.32	5,792.96

4.4 Classification-based PELD forecasting models

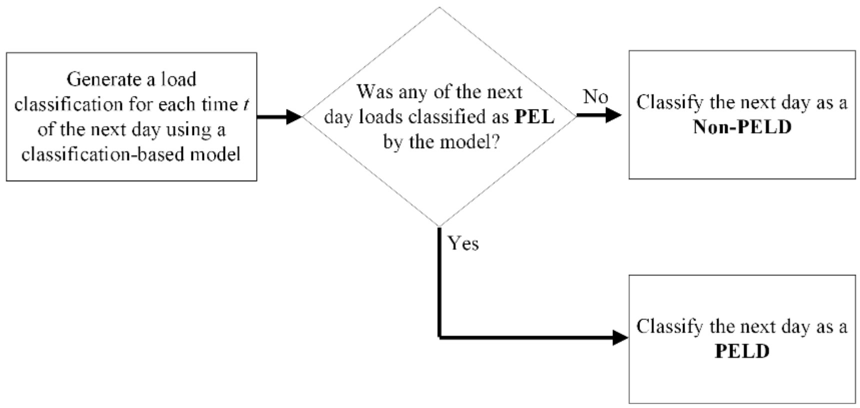

Fig. 7. Classification-based PELD forecasting process.

Six classification-based PELD forecasting models were developed to classify the electric load at time t (time of observation) as either a PEL for the month or not. Any day with a PEL present was automatically tagged as a PELD; otherwise, the day was classified as a Non-PELD (see Figure 7). Saxena et al. (2019) found a class imbalance while developing similar classification-based PELD forecasting models for a circuit without BTMREG. The current study found similar class imbalances while evaluating circuits with and without BTMREG. Table 6 shows comparisons between the amount of PELs and Non-PELs, and PELDs and Non-PELDs to illustrate the class imbalance present in the complete data set. After observing the class imbalance while developing the first two classification-based PELD forecasting models (M06_ClassST and M07_ClassRF), the full training set (before splitting into the training and validation data sets) was balanced using the synthetic minority oversampling technique (SMOTE) developed by Chawla et al. (2002) and previously applied by Saxena et al. (2019). The SMOTE technique was applied using the function “SMOTE” from the R package “DMwR” v0.4.1 with default parameters. The remaining four classification-based PELD forecasting models were developed using the balanced full training data set. Table 7 shows the characteristics of each of the six classification-based PELD forecasting models developed.

Table 6

Amount of PELs and Non-PELs, and PELDs and Non-PELDs for the net demand (with BTMREG) and the demand (without BTMREG) scenarios.

	Net demand (with BTMREG)	**Demand** (without BTMREG)
PELs	608	559
Non-PELs	29,344	29,393
Total observations	29,952	
PELs to non-PELs ratio	**19:917 (0.021)**	**43:2,261 (0.019)**
PELDs	85	65
Non-PELDs	539	559
Total observations	624	
PELDs to non-PELDs ratio	**170:1,078 (0.158)**	**5:43 (0.116)**

Table 7

Classification-based PELD forecasting models characteristics.

Name	**Description**	**Response**	**Inputs used from Table 2**
M06_ClassST	Classification single decision tree generated using the function “tree” from the R	Is the electric load at time t a Peak Electric	Variables 2, 3, 5, 6, 7, 9:14, and 20:30

	package “tree” v1.0-40 with default parameters.	Load (PEL) for the month? 1 (Yes) | 0 (No)	
M07_ClassRF	Classification random decision forest generated using the function “randomForest” from the R package “randomForest” v4.6-14 with values ntree=1000 and importance=TRUE. All other parameters remained at their default value.		
M08_ClassSTwSMOTE	M06 trained and validated using the data set balanced with the SMOTE technique.		
M09_ClassRFwSMOTE	M07 trained and validated using the data set balanced with the SMOTE technique.		
M10_ClassANNwSMOTE	Classification feed-forward artificial neural network with a single hidden layer generated using the function “nnet” from the R package “nnet” v7.3-14 with manually selected values for size, decay, maxit, and MaxNWts, linout = FALSE, and softmax = TRUE. All other parameters remained at their default value. Trained and validated using the data set balanced with the SMOTE technique.		
M11_ClassANNSTwSMOTE	M10 but only using the variables selected by the classification single decision tree in M08 as inputs.		Variables selected by the classification single decision tree in M08.

4.5 Ensemble PELD forecasting models

Two ensemble PELD forecasting models were developed by combining the results of all of the eleven independent (non-ensemble) models evaluated in Sections 4.3 and 4.4 to classify each day in the testing period as either a PELD or a Non-PELD. These models were developed based on the ensemble model proposed by Saxena et al. (2019) to classify an upcoming day as either a PELD or a Non-PELD using demand data. Many researchers agree that ensemble models often outperform the individual models that make them up (Ahmad et al., 2017; Fan et al. 2014) and the current research has continued to explore this possibility.

The first ensemble model, E01_Majority, was a majority class classifier. This model follows the same ensemble approach proposed by Saxena et al. (2019). The majority class identifier used by Saxena et al. (2019) can be represented mathematically using Equation 3.

$$C_j = \begin{cases} 1 \; if \; \sum_{i \in \mathrm{M}} X_{i,j} > \frac{|M|}{2} & \forall \mathrm{~j} \in \mathrm{~D} \\ 0 \; otherwise \end{cases} \qquad (3)$$

Where

M: Set of base models used for day classification,

D: Set of days in the billing period,

|M|: Represents the cardinality of set M,

Xi, j: Binary variable, takes a value of 1 when model i classifies day j in set D as a PELD, otherwise it takes a value of 0, and

Cj: Returns the proposed ensemble model's forecasted classification for day j as a binary result of 1 for PELD or 0 for Non-PELD.

The second ensemble model, E02_SingleVote, was a single vote classifier. This model differs from the first ensemble model in that it only needs one the component models to classify a day as a PELD in order to classify the observed day as a PELD. This methodology was included in this study to account for the possibility of having PELDs that were only detected by a minority of the models because of certain special characteristics not noticeable by the majority of the base models in the ensemble.

5. Results and discussion

5.1 Threshold-based PELD forecasting results

Figure 8 shows the monthly mean absolute percentage error (MAPE) achieved by the five threshold-based PELD forecasting models previously described in Section 4.3 during their regression-based load forecasting stage. The values for MAPE were calculated according to Equation 4.

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{|Actual_i - Forecast_i|}{|Actual_i|}\right) \times 100 \qquad (4)$$

The MAPE values are presented for both the net demand (with BTMREG) (see Figure 8.a) and the demand (without BTMREG) (see Figure 8.b) scenarios. The values in Figure 8 show how most of the evaluated models achieved better electric load forecasting performance (lower MAPE values) when applied to a scenario without BTMREG instead of a scenario with BTMREG. The results of this comparison demonstrate that it is more challenging for the regression-based electric load forecasting models evaluated to achieve high performance levels when BTMREG is present. Table 8 illustrates how the M03_RegRF and M05_RegANNST models outperformed the remaining two models at achieving the lowest average monthly MAPE values for both the net demand (with BTMREG) and the demand (without BTMREG) scenarios. These values provide further evidence of how the presence of BTMREG seems to reduce the performance of the regression-based electric load forecasting models.

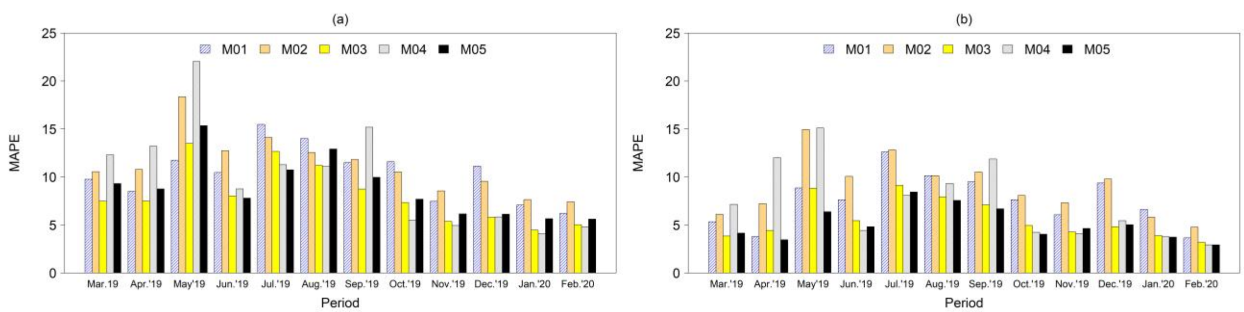

Fig. 8. MAPE achieved by the M01 to M05 models for the (a) net demand (with BTMREG) and the (b) demand (without BTMREG) scenarios.

Table 8

Average monthly MAPE values achieved by the M01 to M05 models for the net demand (with BTMREG) and the demand (without BTMREG) scenarios.

Model	**Average monthly MAPE**

	Net demand (with BTMREG)	**Demand** (without BTMREG)
M01_RegSARIMA	10.4121	7.6004
M02_RegST	11.2159	8.9645
M03_RegRF	8.2921	5.6494
M04_RegANN	9.9221	7.3715
M05_RegANNST	8.8404	5.1544

Figure 9 shows the monthly values for sensitivity achieved by the five threshold-based PELD forecasting models during their threshold-based PELD classification stage. The values for sensitivity were calculated according to Equation 5.

$$Sensitivity = \frac{TP}{TP+FN} \quad (5)$$

Where

TP = the true positives i.e. amount of correctly predicted instances of PELDs,

FP = the false positives i.e. amount of non-PELDs incorrectly predicted as PELDs, and

FN = the false negatives i.e. amount of PELDs incorrectly predicted as non-PELDs.

The sensitivity values are presented for both the net demand (with BTMREG) (see Figure 9.a) and the demand (without BTMREG) (see Figure 9.b) scenarios. The November 2019, January 2020, and February 2020 periods are not shown in Figure 9 because there were no PELD occurrences during these periods. After comparing the sensitivity values between the net demand (with BTMREG) (see Figure 9.a) and the demand (without BTMREG) (see Figure 9.b) scenarios, it was concluded that these results do not provide clear evidence to claim that the presence of BTMREG affects the performance of the models evaluated at the threshold-based PELD classification stage.

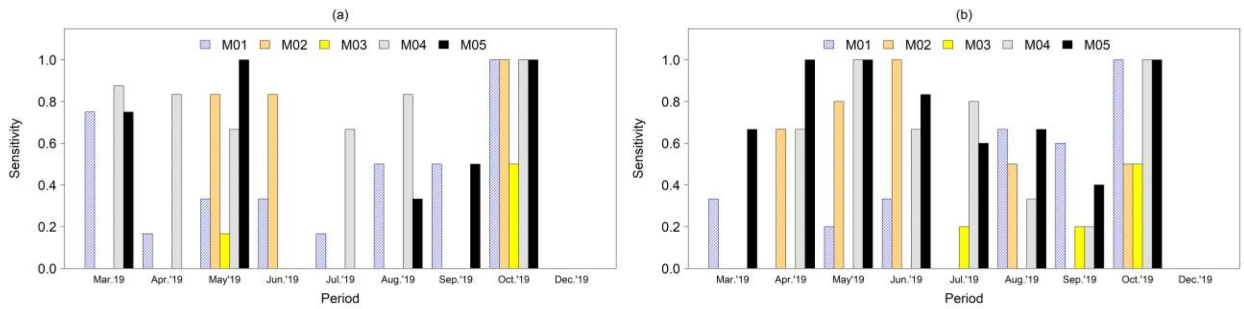

Fig. 9. Sensitivity achieved by the M01 to M05 models for the (a) net demand (with BTMREG) and the (b) demand (without BTMREG) scenarios.

Table 9 shows the average monthly sensitivity and balanced accuracy values achieved by the threshold-based PELD forecasting models during their threshold-based PELD classification stage. The balanced accuracy values were calculated according to Equation 6.

$$Balanced\ Accuracy = \frac{\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right)}{2} \qquad (6)$$

Where

TN = the True Negatives i.e. amount of correctly predicted instances of Non-PELDs; and *TP*, *FP, and FN* are the same as in Equation 5. This table illustrates how the ANN-based models M04_RegANN and M05_RegANNST outperformed the remaining models at achieving the highest values for average monthly sensitivity and balanced accuracy for both the net demand (with BTMREG) and the demand (without BTMREG) scenarios. The values in this table do not provide any clear evidence of a reduction in the performance level of the models evaluated at the threshold-based PELD classification stage caused by the presence of BTMREG.

Table 9

Average monthly sensitivity and balanced accuracy values achieved by the M01 to M05 models for the net demand (with BTMREG) and the demand (without BTMREG) scenarios.

Model	**Average monthly sensitivity**		**Average monthly balanced accuracy**	
	Net demand (with BTMREG)	**Demand** (without BTMREG)	**Net demand** (with BTMREG)	**Demand** (without BTMREG)
M01_RegSARIMA	0.4167	0.3481	0.6294	0.6102
M02_RegST	0.2963	0.3852	0.6258	0.6508
M03_RegRF	0.0741	0.1000	0.5370	0.5500
M04_RegANN	0.5417	0.5185	0.6953	0.6963
M05_RegANNST	0.3981	0.6852	0.6652	0.8236

5.2 Classification-based PELD forecasting results

Figure 10 shows the monthly values for sensitivity achieved by the six classification-based PELD forecasting models previously described in Section 4.4. The sensitivity values are presented for both the net demand (with BTMREG) (see Figure 10.a) and the demand (without BTMREG) (see Figure 10.b) scenarios. The November 2019, January 2020, and February 2020 periods are not shown in Figure 10 because there were no PELDs occurrences during these periods. These results demonstrate how the class imbalance issue described in Section 4.4 needs to be addressed in order to achieve the best sensitivity values when implementing the classification-based PELD forecasting approach regardless of the presence or absence of BTMREG. Figure 10 shows how the models using a balanced training and validation data set overwhelmingly outperformed those obtained when using the original data sets during eight or more of the months in the testing period for the net demand (with BTMREG) (see Figure 10.a) and the demand (without BTMREG) (see Figure 10.b) scenarios. After comparing the sensitivity values between the net demand (with BTMREG) (see Figure 10.a) and the demand (without BTMREG) (see Figure 10.b) scenarios, it was concluded that these results do not provide clear evidence to claim that the presence of BTMREG affects the performance of the two ensemble PELD forecasting models evaluated.

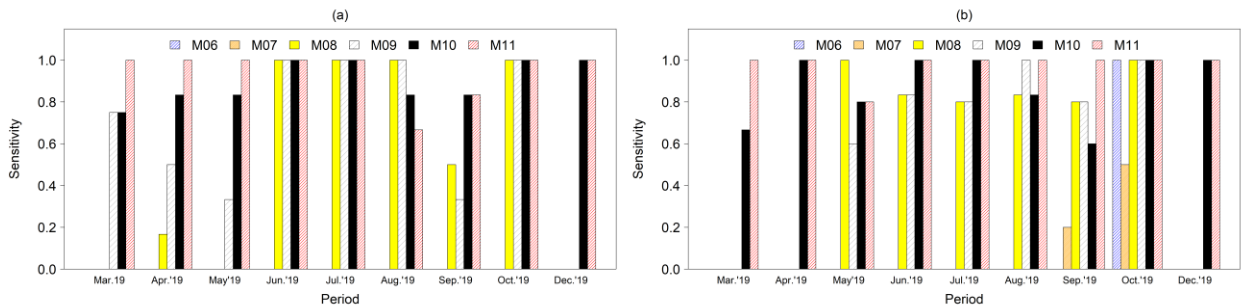

Fig. 10. Sensitivity achieved by the M06 to M11 models for the (a) net demand (with BTMREG) and the (b) demand (without BTMREG) scenarios.

Table 10 shows the average monthly sensitivity and balanced accuracy values achieved by the classification-based PELD forecasting models. This table illustrates how the ANN-based models M10_ClassANNwSMOTE and M11_ClassANNSTwSMOTE outperformed the remaining models at achieving the highest values for average monthly sensitivity and balanced accuracy for both the net demand (with BTMREG) and the demand (without BTMREG) scenarios. The values in this table do not provide any clear evidence of a reduction in the performance level of the classification-based models caused by the presence of BTMREG.

Table 10

Average monthly sensitivity and balanced accuracy values achieved by the M06 to M11 models for the net demand (with BTMREG) and the demand (without BTMREG) scenarios.

Model	Average monthly sensitivity		Average monthly balanced accuracy	
	Net demand (with BTMREG)	**Demand** (without BTMREG)	**Net demand** (with BTMREG)	**Demand** (without BTMREG)
M06_ClassST	0.0000	0.1111	0.5000	0.5517
M07_ClassRF	0.0000	0.0778	0.5000	0.5389
M08_ClassSTwSMOTE	0.5185	0.5852	0.6315	0.6770
M09_ClassRFwSMOTE	0.6574	0.5593	0.7211	0.7055
M10_ClassANNwSMOTE	0.8981	0.8778	0.8329	0.8430
M11_ClassANNSTwSMOTE	0.9444	0.9778	0.8913	0.8906

5.3 Ensemble PELD forecasting results and best model selection

Figure 11 shows the monthly values for sensitivity achieved by the two ensemble PELD forecasting models previously described in Section 4.5. This figure also includes the monthly values for sensitivity achieved by the M11_ClassANNSTwSMOTE model. This model achieved the best average monthly sensitivity and balanced accuracy values out of the eleven independent (non-ensemble) models evaluated for both the net demand (with BTMREG) and the demand (without BTMREG) scenarios (see Tables 9 and 10). Figure 11 shows the results for both the net demand (with BTMREG) (see Figure 11.a) and the demand (without BTMREG) (see Figure 11.b) scenarios. The November 2019, January 2020, and February 2020 periods are not shown in Figure 11 because there were no PELDs occurrences during these periods. These results show how both the proposed E02_SingleVote model and the M11_ClassANNSTwSMOTE model outperformed the E01_Majority model previously proposed by Saxena et al. (2019) for both the net demand (with BTMREG) and the demand (without BTMREG) scenario. The E02_SingleVote model outperformed the M11_ClassANNSTwSMOTE model on two out of nine months for the net demand (with BTMREG) scenario and on one month for the demand (without BTMREG) scenario. After comparing the sensitivity values between the net demand (with BTMREG) (see Figure 11.a) and the demand (without BTMREG) (see Figure 11.b) scenarios, it was concluded that these results do not provide clear evidence to claim that the presence of BTMREG affects the performance of the two ensemble PELD forecasting models evaluated.

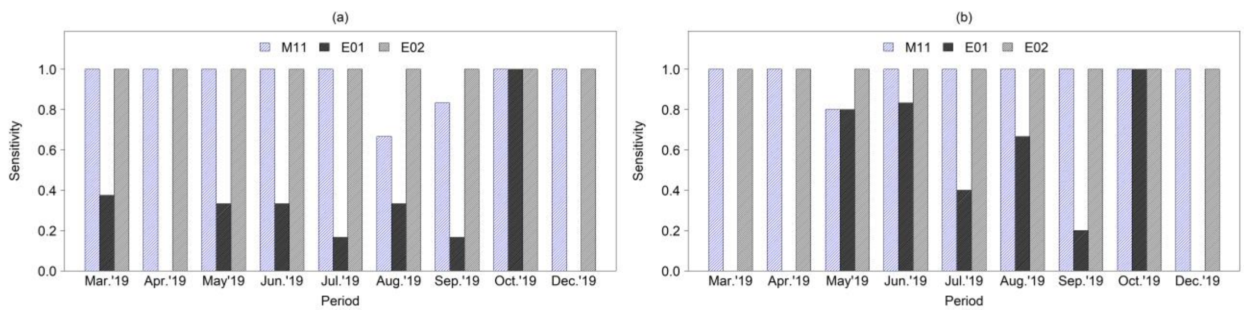

Fig. 11. Sensitivity achieved by the M11, E01 and E02 models for the (a) net demand (with BTMREG) and (b) the demand (without BTMREG) scenarios.

Table 11 shows the average monthly sensitivity and balanced accuracy values, as well as the total number of false positives and false negatives predictions produced by the two ensemble PELD forecasting models evaluated and the M11_ClassANNSTwSMOTE model. The values in this table do not provide any clear evidence of a reduction in the performance level of the classification-based models caused by the presence of BTMREG. This table illustrates how the M11_ClassANNSTwSMOTE model outperformed the remaining models at achieving the highest values for average monthly balanced accuracy. In terms of average monthly sensitivity and total number of false negatives, the M11_ClassANNSTwSMOTE model was only slightly outperformed by the E02_SingleVote model. However, the total number of false positives produced by the E02_SingleVote model is significantly greater than that produced by the other two models. Based on these results and the intent to select the most parsimonious of the models, the M11_ClassANNSTwSMOTE was selected as the best model to use for PELD prediction with BTMREG for this facility because of the model's performance and lower complexity.

Table 11

Average monthly sensitivity and balanced accuracy values, number of false positives and false negatives produced by the M11, E01, and E02 models for the net demand (with BTMREG) and the demand (without BTMREG) scenarios.

		M11 ClassANNST wSMOTE	**E01** Majority	**E02** SingleVote
Average monthly sensitivity	**Net demand** (with BTMREG)	0.9444	0.3009	1
	Demand (without BTMREG)	0.9778	0.4333	1
Average monthly balanced accuracy	**Net demand** (with BTMREG)	0.8913	0.6505	0.7046
	Demand (without BTMREG)	0.8906	0.7124	0.7333
Total number of false negatives	**Net demand** (with BTMREG)	3	34	0
	Demand (without BTMREG)	1	18	0
Total number of false positives	**Net demand** (with BTMREG)	37	0	136
	Demand	48	2	133

	(without BTMREG)			

5.4 Potential and model savings calculation

Table 12 shows the potential and model savings expected upon implementation of the selected M11_ClassANNSTwSMOTE model for both the net demand (with BTMREG) and the demand (without BTMREG) scenarios. These values were calculated using a slight variation of the method proposed by Saxena et al. (2019). Figure 12 illustrates how the potential and model savings (in kW) were calculated for the month of August 2019 within the net demand (with BTMREG) scenario as an example. Potential savings in kW after executing demand response actions for each month were determined according to Equation 7.

$$Potential\ savings\ in\ kw = HPEL - Dlim \qquad (7)$$

Where

HPEL = highest peak electric load of the month in kW, and

Dlim = monthly threshold established for the month.

This methodology assumes that all peak loads predicted in the month are reduced to the level of the monthly threshold (Dlim) established for the month. Model savings in kW were only applicable for months during which the day with the highest peak load of the month was predicted by the model as a PELD (or true positive PELD prediction). These savings were determined according to Equation 8.

$$Model\ savings\ in\ kw = \ HPEL - \max\{HFN, Dlim\} \qquad (8)$$

Where

HFN = highest non-detected (ergo not reduced) peak load (or false negative PELD prediction) of the month in kW, and HPEL and Dlim are the same as in Equation 7.

Table 12

Potential and model savings in kW, and model achievement percentage during the testing period.

	Net demand (with BTMREG)			**Demand** (without BTMREG)		
Period	**Potential savings** *(in kW)*	**Model savings** *(in kW)*	**% Model achievement**	**Potential savings** *(in kW)*	**Model savings** *(in kW)*	**% Model achievement**
Mar. 2019	247.38	247.38	100%	38.20	38.20	100%
Apr. 2019	749.38	749.38	100%	513.42	513.42	100%
May 2019	766.07	766.07	100%	775.28	0.00	0%
Jun. 2019	884.60	884.60	100%	1,045.36	1,045.36	100%
Jul. 2019	1,657.66	1,657.66	100%	1,281.79	1,281.79	100%
Aug. 2019	1,247.15	1,008.00	81%	835.31	835.31	100%
Sep. 2019	1,169.79	753.00	64%	731.44	731.44	100%
Oct. 2019	2,163.22	2,163.22	100%	2,701.08	2,701.08	100%
Dec. 2019	131.22	131.22	100%	94.62	94.62	100%
Aggregate	**9,016.47**	**8,360.53**	**93%**	**8,016.50**	**7,241.22**	**90%**

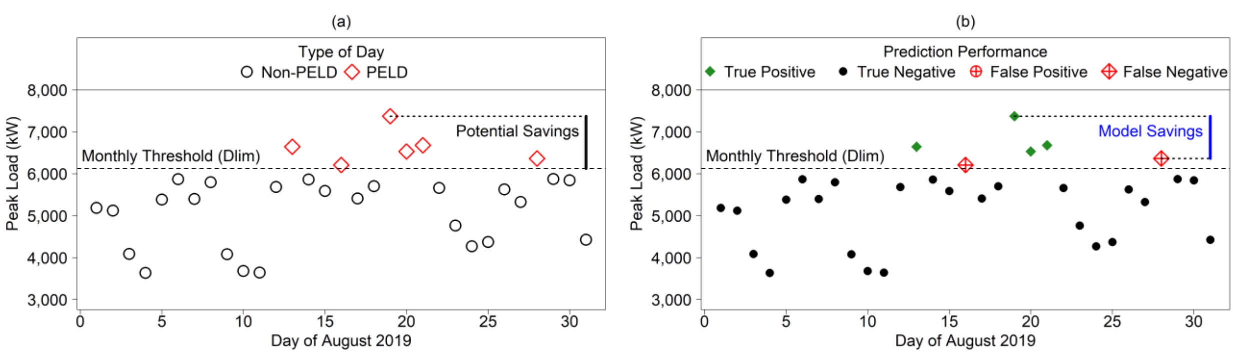

Fig. 12. (a) Potential savings and (b) model savings calculations (in kW) for the net demand (with BTMREG) scenario during August 2019.

Potential and model savings is US$ were calculated by applying a US$17.00 per kW peak load rate to the previously calculated potential and model savings in kW (see Table 13). This peak load rate was obtained from the utility that serves the university campus chosen for this study. This was still the approximate active peak load rate at the time of this paper's submission. The results presented in Tables 12 and 13 demonstrate how the selected M11_ClassANNSTwSMOTE model would have achieved 93% of the potential savings in kW and US$ 142,129.01 savings in electricity costs for the university selected for the current study within the net demand (with BTMREG) scenario. The results also show how there are more potential and model savings to be achieved after adopting BTMREG. At first glance, this is a very counterintuitive finding because by definition a customer's load profile is reduced when BTMREG is present (net demand scenario) as we have seen in Figures 3 and 4. Figure 13 illustrates how this finding can be explained by the fact that the demand reduction targets set for demand response actions (based on the monthly threshold (Dlim)) when BTMREG is present (net demand), are typically lower than the targets set when BTMREG is not present (demand). The values for monthly threshold (Dlim) for the complete testing period can be compared by looking back at Table 5. In addition, there is always the possibility of peak loads within the net demand (with BTMREG) scenario to be as high as those within the demand (without BTMREG) scenario if there is a considerable drop in BTMREG levels.

Table 13

Potential, model, and missed savings in US$ during the testing period.

	Net demand (with BTMREG)			**Demand** (without BTMREG)		
Period	**Potential savings** *(in US$)*	**Model savings** *(in US$)*	**Missed savings** *(in US$)*	**Potential savings** *(in US$)*	**Model savings** *(in US$)*	**Missed savings** *(in US$)*
Mar. 2019	4,205.46	4,205.46	0.00	649.40	649.40	0.00
Apr. 2019	12,739.46	12,739.46	0.00	8,728.14	8,728.14	0.00
May 2019	13,023.19	13,023.19	0.00	13,179.76	0.00	13,179.76
Jun. 2019	15,038.20	15,038.20	0.00	17,771.12	17,771.12	0.00

Jul. 2019	28,180.22	28,180.22	0.00	21,790.43	21,790.43	0.00
Aug. 2019	21,201.55	17,136.00	4,065.55	14,200.27	14,200.27	0.00
Sep. 2019	19,886.43	12,801.00	7,085.43	12,434.48	12,434.48	0.00
Oct. 2019	36,774.74	36,774.74	0.00	45,918.36	45,918.36	0.00
Dec. 2019	2,230.74	2,230.74	0.00	1,608.54	1,608.54	0.00
Aggregate	**153,279.99**	**142,129.01**	**11,150.98**	**136,280.50**	**123,100.74**	**13,179.76**

Fig. 13. Model savings calculations (in kW) for the (a) net demand (with BTMREG) and (b) the demand (without BTMREG) scenarios during July 2019.

Figure 14 provides more insight into this finding by illustrating the demand, net demand, solar generation, monthly thresholds (Dlim), and model savings (in kW) during the day with the highest peak electric load for the month of July 2019, the 19th. The figure shows how the peak electric load in the scenario without BTMREG (demand) is higher than the peak electric load in the scenario with BTMREG (net demand). This figure also shows how the peak electric load in the scenario with BTMREG (net demand) was caused by a drop in solar generation. However, more model savings (1,911 kW vs 1,282 kW) are achieved because the presumptive demand reduction target set for demand response actions (based on the monthly threshold (Dlim)) is lower when BTMREG is present (net demand). The results shown in Tables

12 and 13 also indicate that the highest savings at the university selected for this study are achieved during the summer months (June to August) and the first two months of autumn (also referred to as fall), September and October. This can be explained by the fact that these are typically the months with the highest outside temperatures and consequently the highest energy usage for cooling purposes at the university selected for this study.

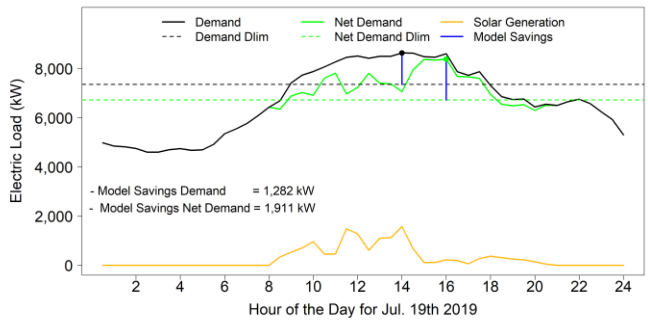

Fig. 14. Demand, net demand, solar generation, monthly thresholds (Dlim), and model savings (in kW) during July 19th, 2019.

6. Conclusions and potential future research

The research described in this paper has provided three main contributions in order to address the lack of published studies detailing accurate PELDs forecasting methodologies applicable to the increasing number of facilities adopting BTMREG, as well as the lack of published studies comparing the performance of these methodologies in both the presence and absence of BTMREG. The most interesting insight provided by these contributions to the authors is that counterintuitively, there can be more potential and model savings to be achieved by facilities using PELD forecasting methodologies after adopting BTMREG. The results show how implementing these methodologies after BTMREG adoption becomes even more important than before the adoption in order to achieve financial savings. At first, many researchers and practitioners might not consider this outcome because by definition, a customer's load profile is reduced when BTMREG is adopted (net demand scenario) which can translate into less opportunities for load reduction.

The first of the three main contributions is the development and testing of a PELD forecasting methodology applicable to both consumers with and without BTMREG. This methodology was tested using ARIMA, CART, random regression and classification forest, ANN, and ensemble (also known as hybrid) based models. However, the methodology is model agnostic and different models can be tested in future research efforts. The experimental results showed that an ANN based model using features selected by a CART based model (M11_ClassANNSTwSMOTE) and one of the ensemble models (E02_SingleVote) achieved the highest average monthly sensitivity values for both the net demand (with BTMREG) and the demand (without BTMREG) scenarios. Based on the average monthly sensitivity and balanced accuracy values, the number of false positives and negatives produced by the model, and the intent to select the most parsimonious of the models, the M11_ClassANNSTwSMOTE was selected as the preferred model to use for PELD prediction for this facility with BTMREG present. This model showed superior performance and reduced complexity. Furthermore, this model demonstrated the capacity to have achieved 93% of the potential savings in kW and US$ 142,129.01 savings in electricity costs during a yearlong testing period for the scenario with BTMREG. Given these results, it was concluded that practitioners interested in achieving the best model performance using parsimonious models should start with the implementation of classification-based models. Based on the results obtained from these models, more elaborated approaches such as threshold-based PELD classification and ensemble approaches might not be needed.

The second contribution is the documentation of the first of their kind side-by-side empirical comparisons between the performance of ARIMA, CART, random regression and classification forest, ANN, and ensemble (also known as hybrid) based models at forecasting electric load and PELDs in both scenarios (with and without BTMREG). The results obtained while testing the proposed methodology in the scenario without BTMREG serve as additional validation of the work published by Saxena et al. (2019) about forecasting PELDs without BTMREG. The results obtained through the side-by-side empirical comparisons in the scenario with BTMREG provided four important insights in regards to past, present, and potential future research. First, both a random forest (M03_RegRF) and an ANN based regression model (M05_RegANNST) outperformed ARIMA and CART regression-based models at predicting future electric load levels for both the net demand (with BTMREG) and the demand (without BTMREG) scenarios. Second, comparing the results of the scenario with BTMREG and the scenario without BTMREG, empirical evidence suggesting that the presence of BTMREG affects the performance of the models was only observed for the regression-based models evaluated. The results obtained from the classification-based models as well as the ensemble models evaluated did not show evidence of an effect on the performance of these models due to the presence of BTMREG.

The third and fourth insights provide important details about the methodology to consider for future research based on past publications and the current results. The third insight was that class imbalance issues in the data set need to be addressed in order to achieve the best performances when implementing the classification-based PELD forecasting approach regardless of the presence or absence of BTMREG. The fourth insight was that the single vote ensemble approach outperformed the current majority vote approach proposed by Saxena et al. (2019) but produced a significantly greater number of false positive predictions when compared to the other models evaluated. The use of ensemble forecasting for PELD forecasting can be further explored by evaluating other ensemble forecasting methodologies.

A first of its kind PELD forecasting model savings comparison for scenarios with and without BTMREG was presented as the third and final contribution of this research. We have already discussed the first insight provided by this contribution at the beginning of this section. This was also the most interesting insight to the authors and it was the discovery of the possibility for more potential and model savings to be achieved by facilities using PELD forecasting methodologies when BTMREG is adopted. The second insight provided by this contribution was that the months with the highest outside temperatures and consequently the highest energy usage for cooling purposes were also the moths with the greatest savings to be achieved at the university selected for this study.

There are still many research questions to address in regards to PELDs forecasting methodologies for future research. How does the resolution of the data set (30 mins. vs 60 mins. vs x mins) affect the performance of the models? What is the optimal size of the training data set for each model? What are the effects of training the models with just the hours when peak loads occur? Will the addition of new variables and/or models improve the forecasting performance? How effective is the methodology for other types of REG sources such as wind and hydro? These are just some of the many remaining research questions that could be addressed by future studies in order to increase buildings' energy efficiency and reduce their energy related costs and environmental impact.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Figure 1

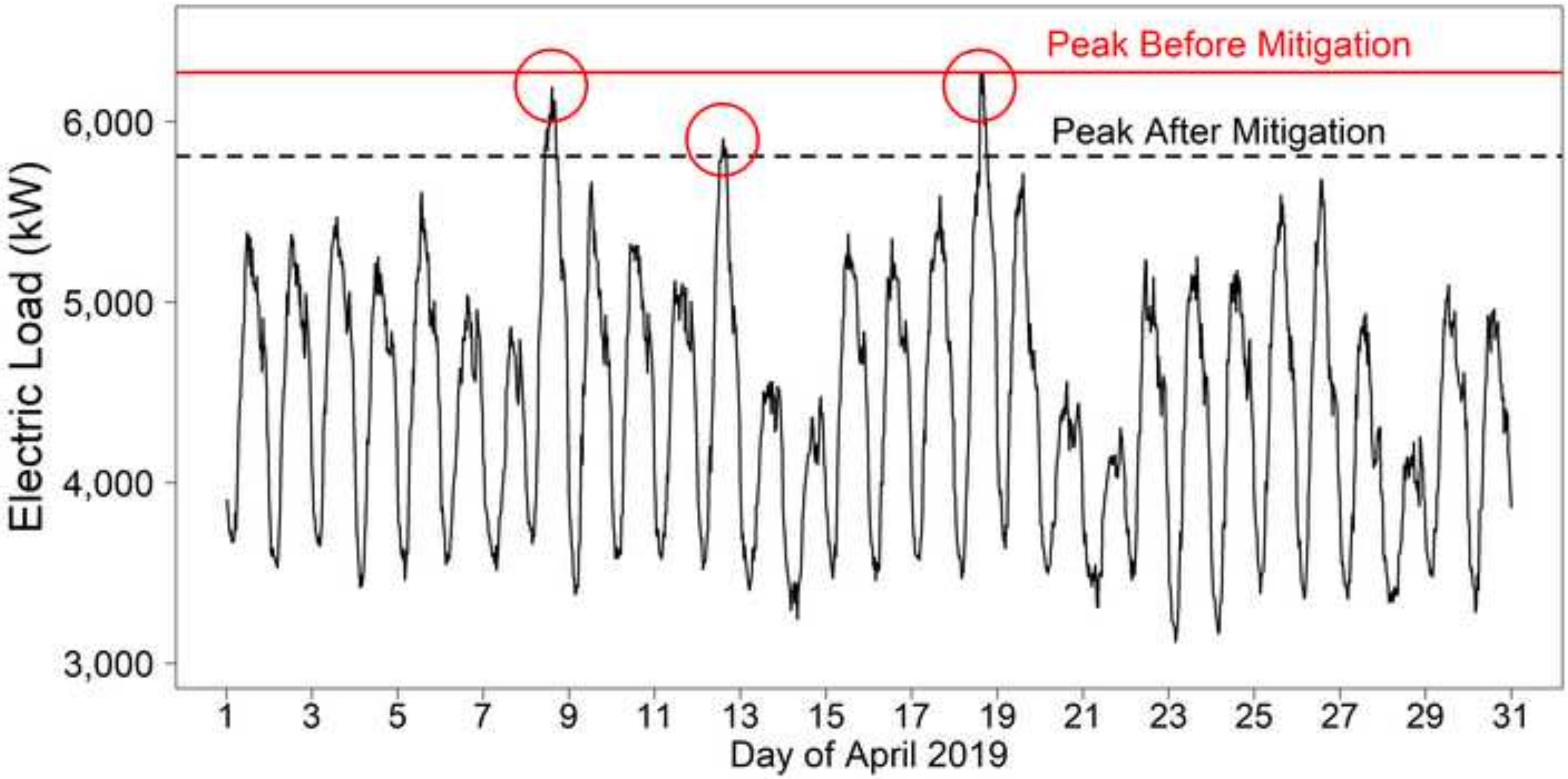
Peak Before Mitigation
Peak After Mitigation
Electric Load (kW)
6,000
5,000
4,000
3,000
1
3
5
7
9
11
13
15
17
19
21
23
25
27
29
31
Day of April 2019

Figure 2

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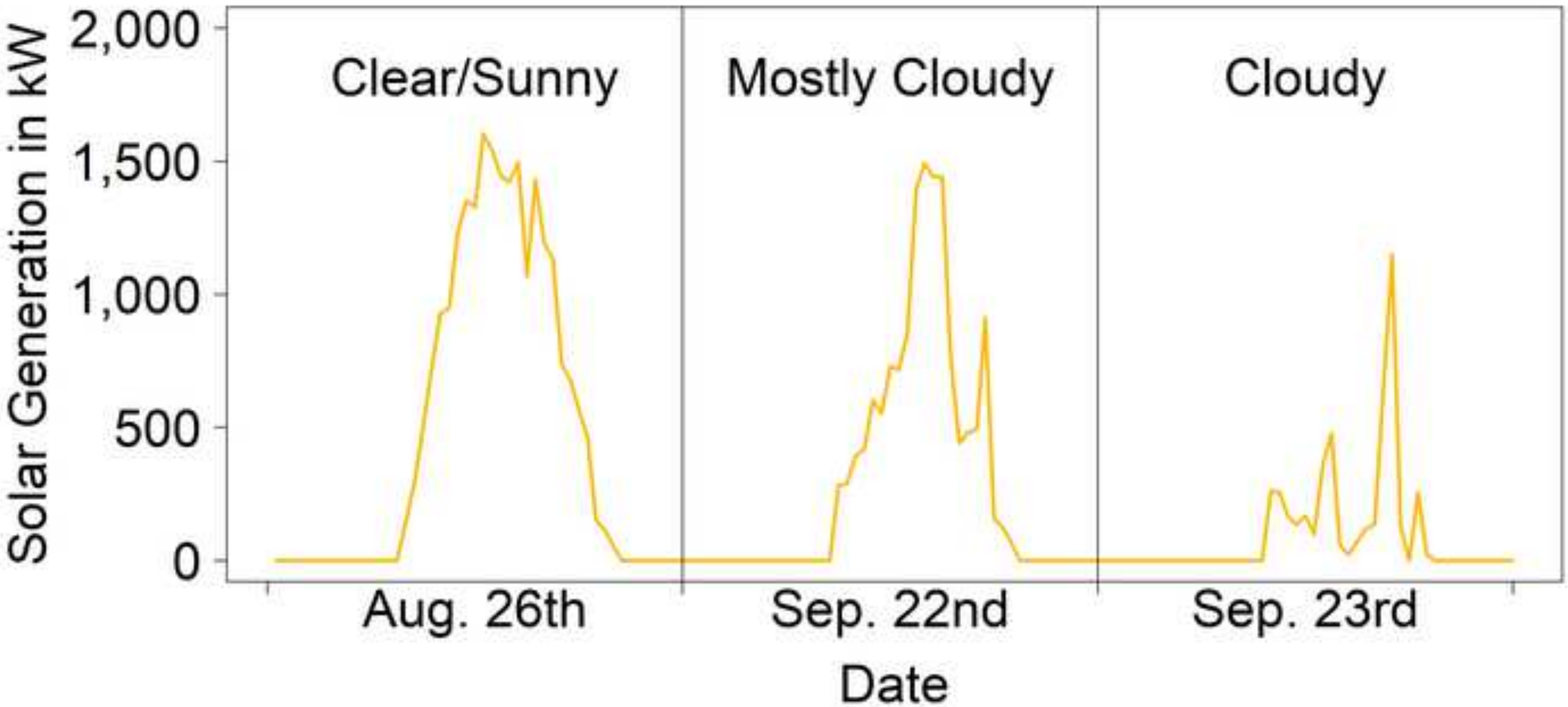


Figure 3

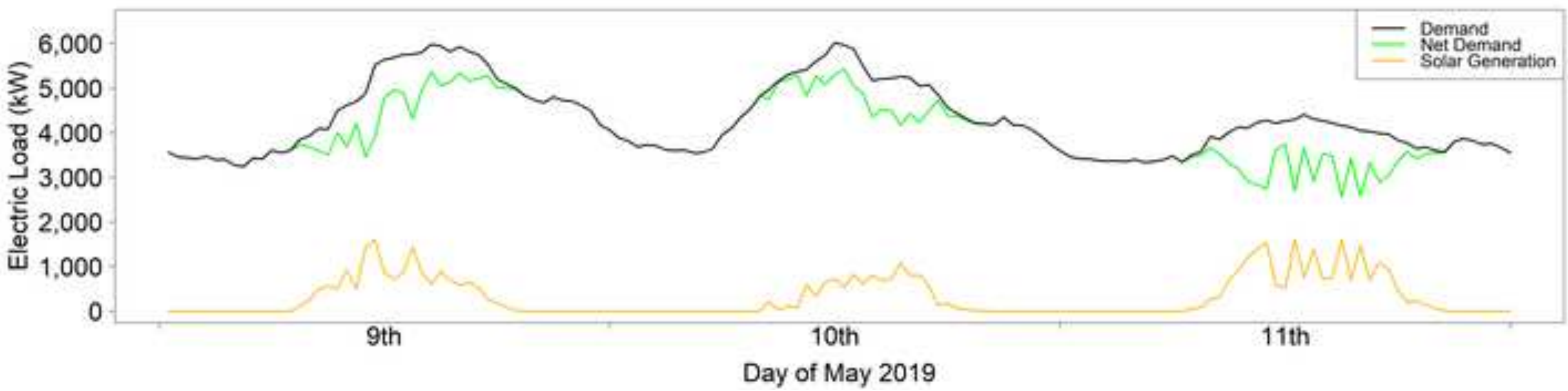

Demand
Net Demand
Solar Generation
Electric Load (kW)
6,000
5,000
4,000
3,000
2,000
1,000
0
9th
10th
11th
Day of May 2019

Figure 4

Click here to access/download;Figure;Fig04.tif

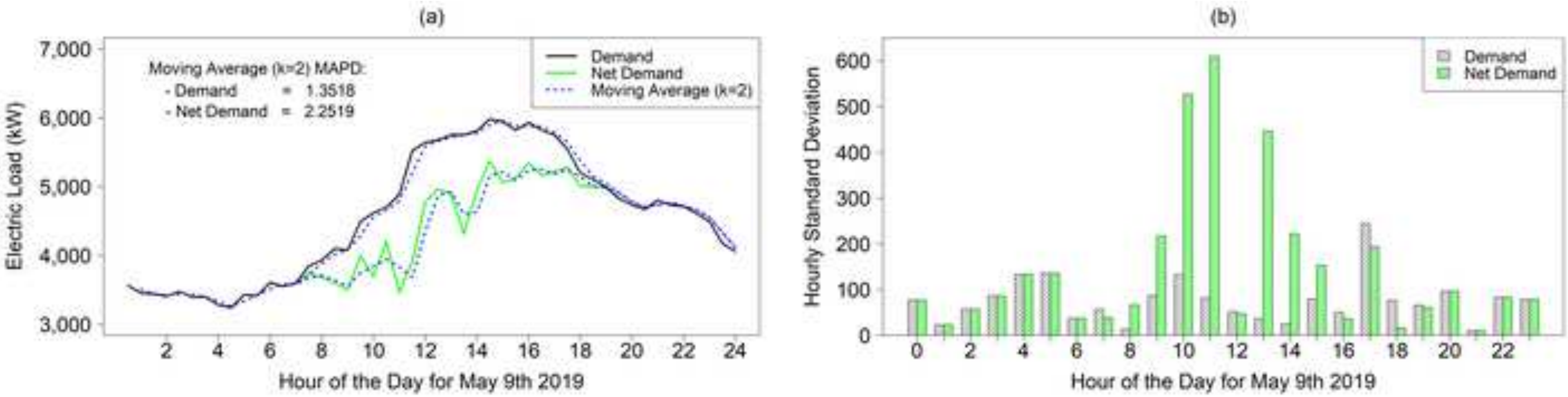
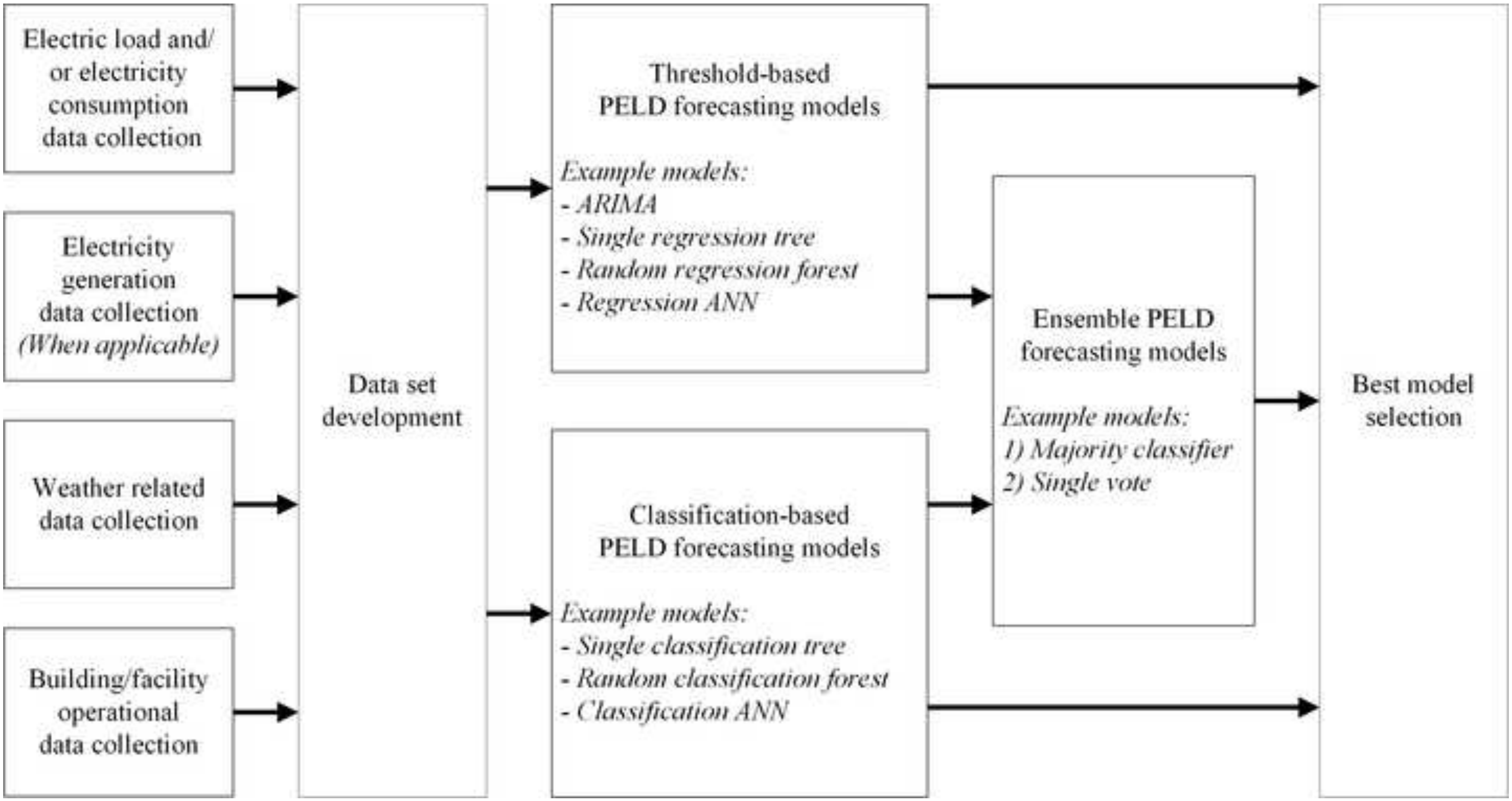


Figure 5



Electric load and/ or electricity consumption data collection
Electricity generation data collection (When applicable)
Weather related data collection
Building/facility operational data collection
Data set development
Threshold-based PELD forecasting models
Example models:
- ARIMA
- Single regression tree
- Random regression forest
- Regression ANN
Classification-based PELD forecasting models
Example models:
- Single classification tree
- Random classification forest
- Classification ANN
Ensemble PELD forecasting models
Example models:
1) Majority classifier
2) Single vote
Best model selection

Figure 6

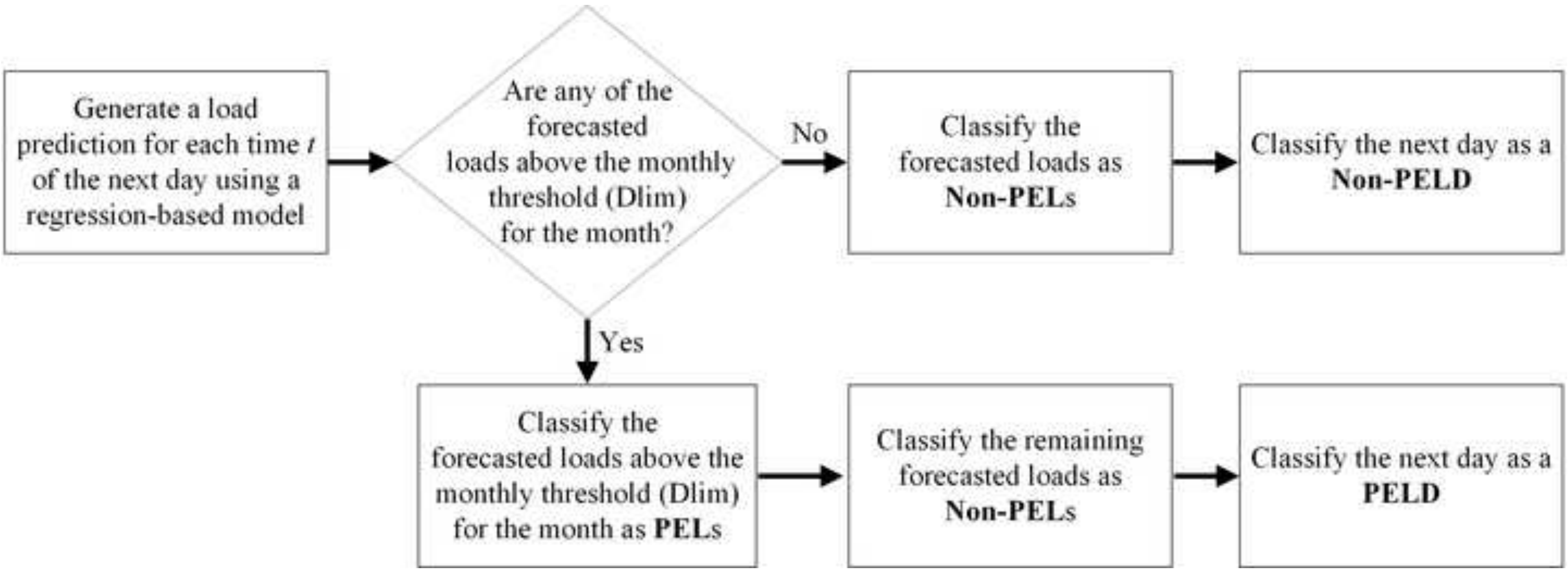

Generate a load prediction for each time t of the next day using a regression-based model
Are any of the forecasted loads above the monthly threshold (Dlim) for the month?
No
Classify the forecasted loads as Non-PELs
Classify the next day as a Non-PELD
Yes
Classify the forecasted loads above the monthly threshold (Dlim) for the month as PELs
Classify the remaining forecasted loads as Non-PELs
Classify the next day as a PELD

Figure 7

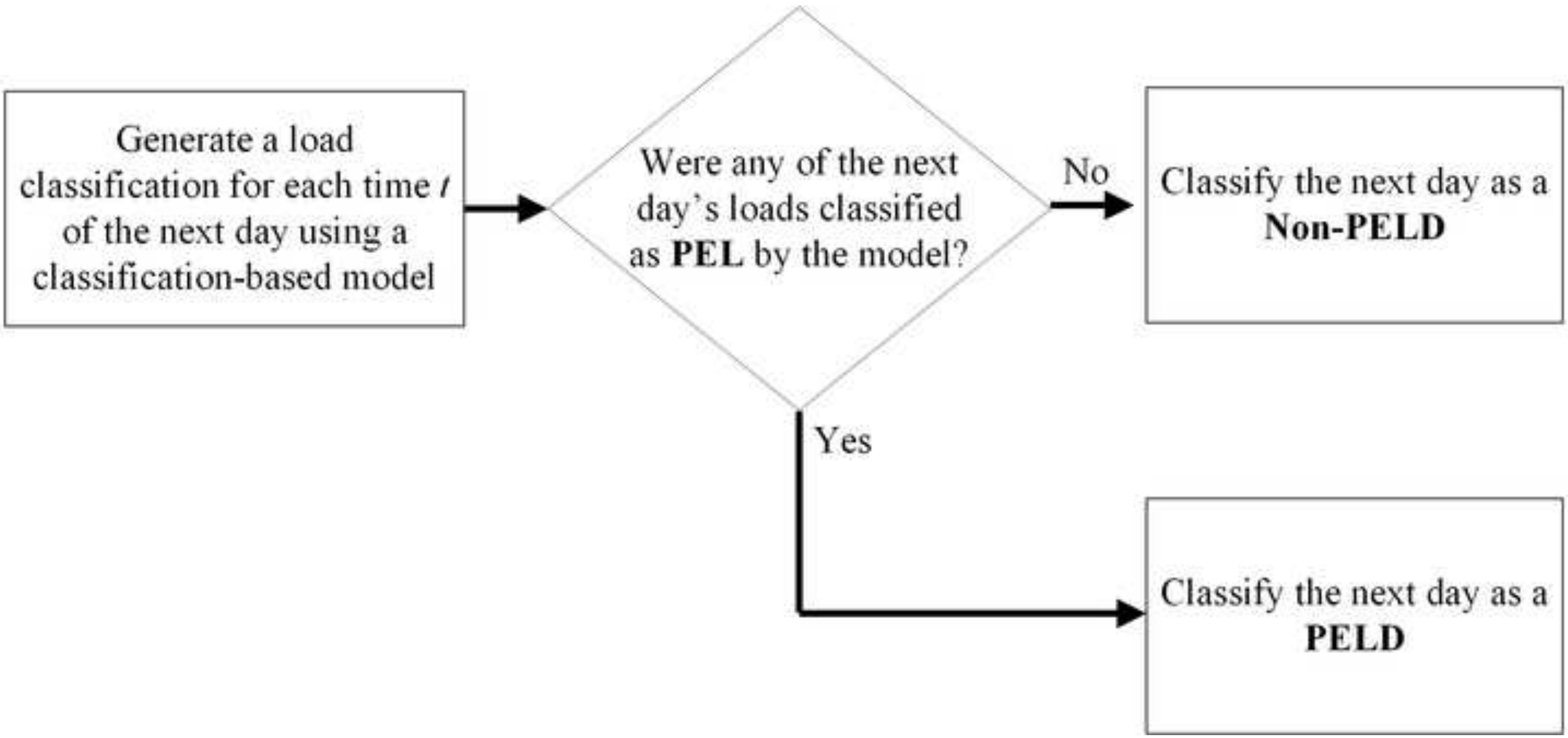

Generate a load classification for each time *t* of the next day using a classification-based model
Were any of the next day's loads classified as **PEL** by the model?
No
Classify the next day as a **Non-PELD**
Yes
Classify the next day as a **PELD**

Figure 8

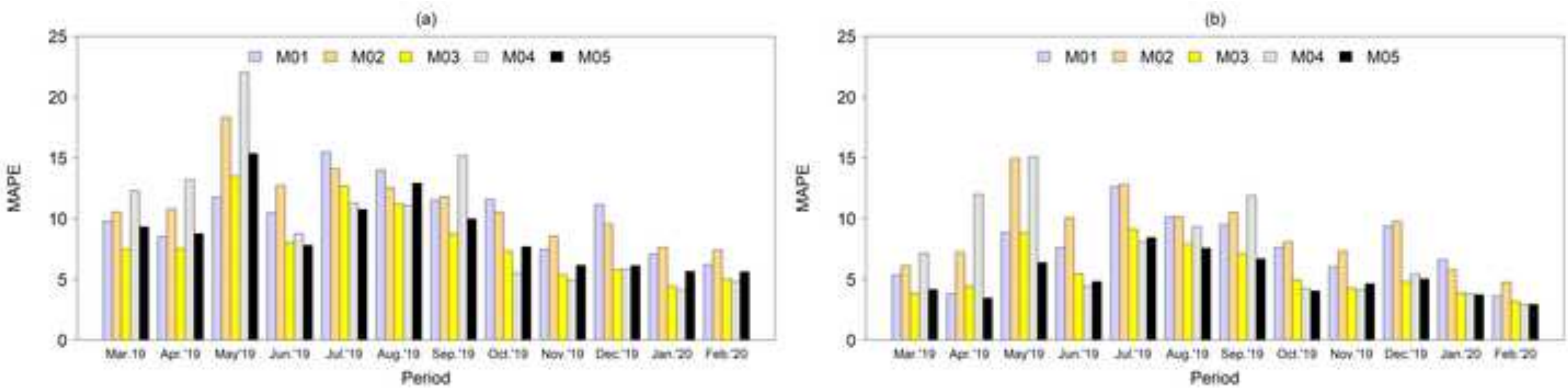

(a)
(b)
MAPE
Period
M01
M02
M03
M04
M05
0
5
10
15
20
25
Mar.'19
Apr.'19
May'19
Jun.'19
Jul.'19
Aug.'19
Sep.'19
Oct.'19
Nov.'19
Dec.'19
Jan.'20
Feb.'20

Figure 9

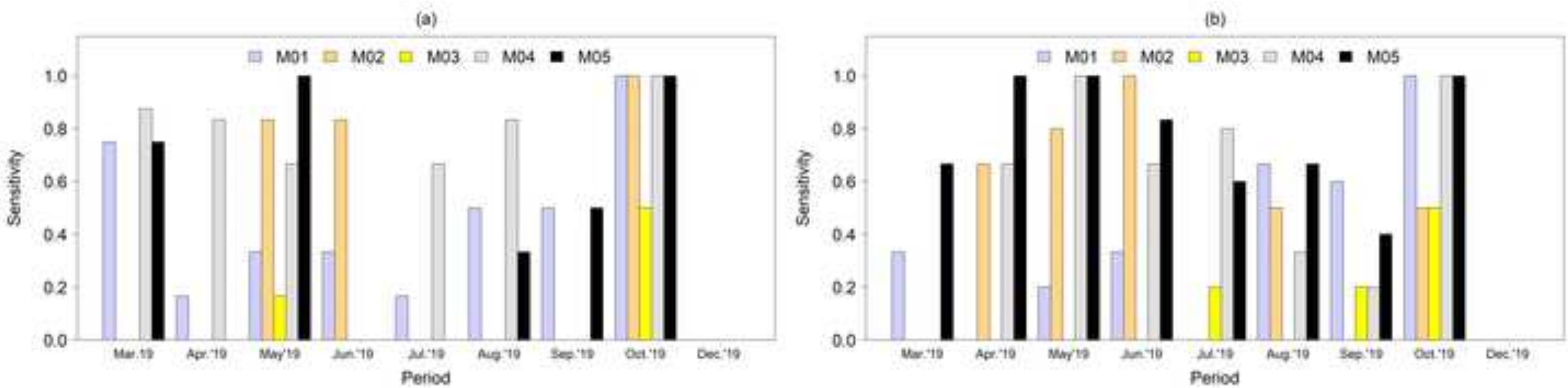

(a)
M01
M02
M03
M04
M05
Sensitivity
1.0
0.8
0.6
0.4
0.2
0.0
Mar.'19
Apr.'19
May'19
Jun.'19
Jul.'19
Aug.'19
Sep.'19
Oct.'19
Dec.'19
Period
(b)
M01
M02
M03
M04
M05
Sensitivity
Period

Figure 10

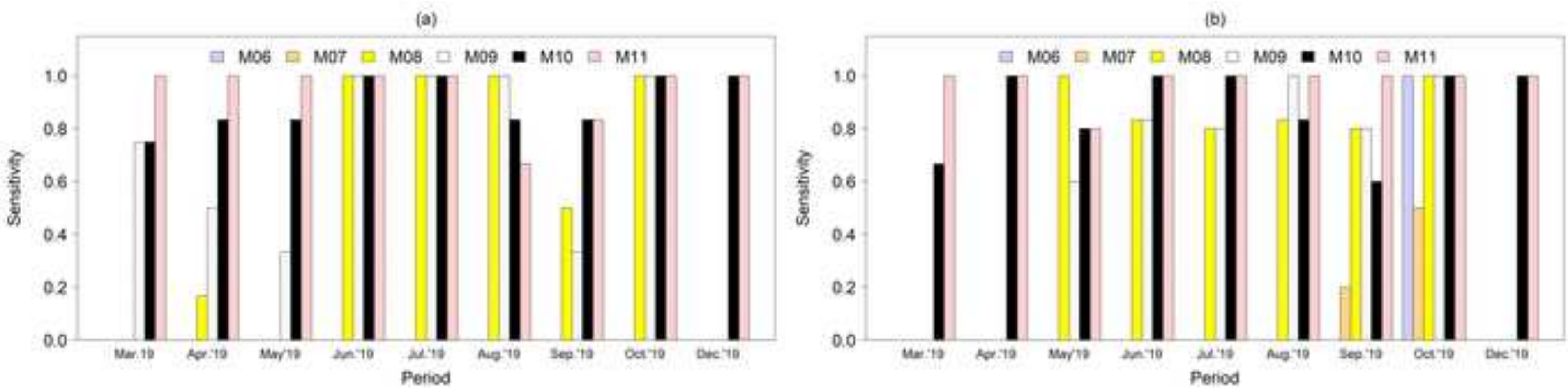

(a)
M06
M07
M08
M09
M10
M11
1.0
0.8
0.6
0.4
0.2
0.0
Sensitivity
Mar.'19
Apr.'19
May'19
Jun.'19
Jul.'19
Aug.'19
Sep.'19
Oct.'19
Dec.'19
Period
(b)
M06
M07
M08
M09
M10
M11
1.0
0.8
0.6
0.4
0.2
0.0
Sensitivity
Mar.'19
Apr.'19
May'19
Jun.'19
Jul.'19
Aug.'19
Sep.'19
Oct.'19
Dec.'19
Period

Figure 11

Click here to access/download;Figure;Fig11.tif

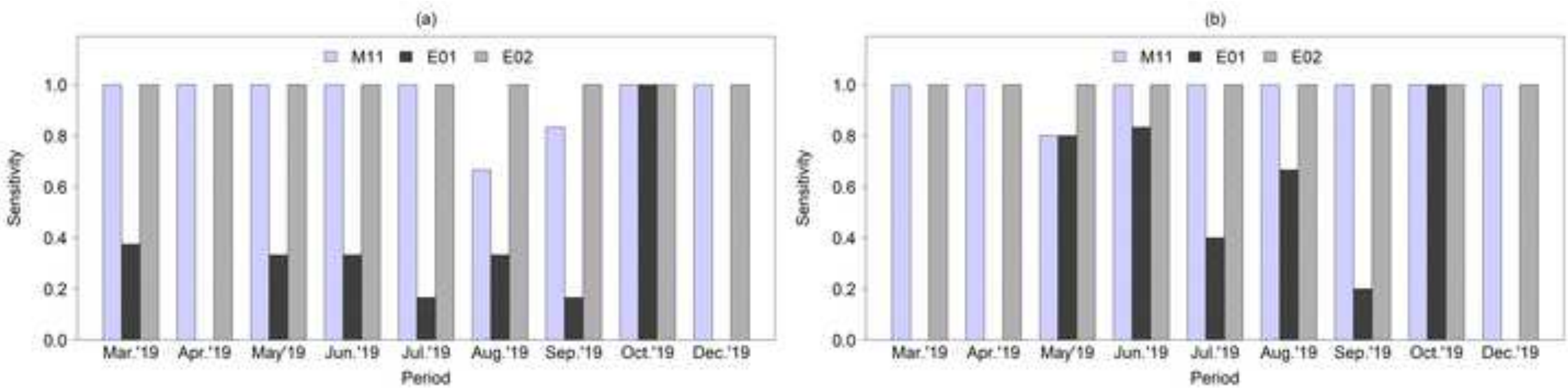


Figure 12

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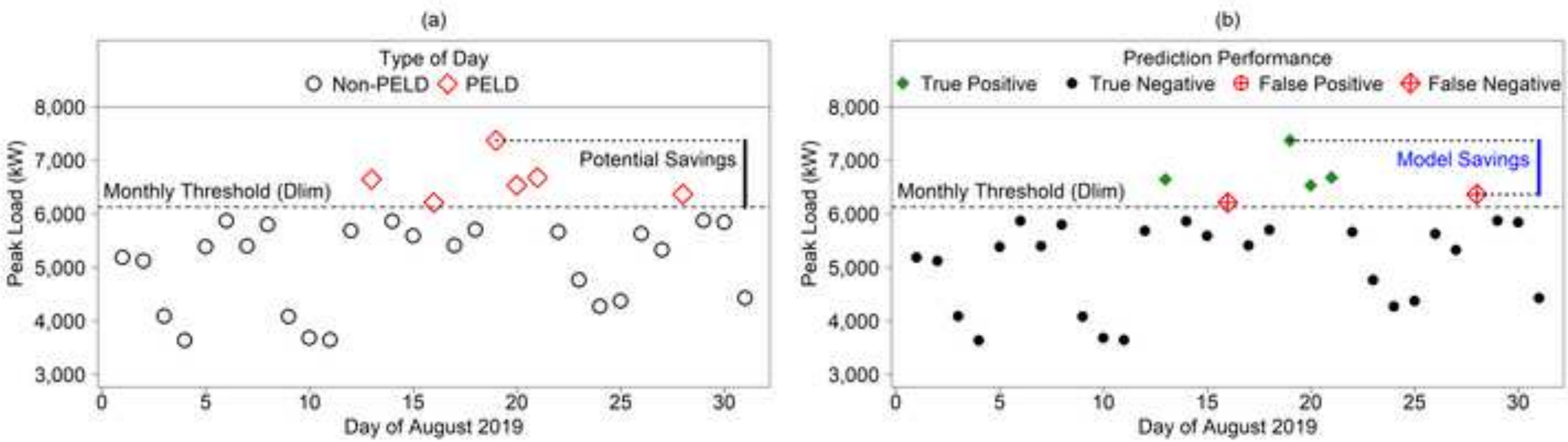


Figure 13

Click here to access/download;Figure;Fig13.tif

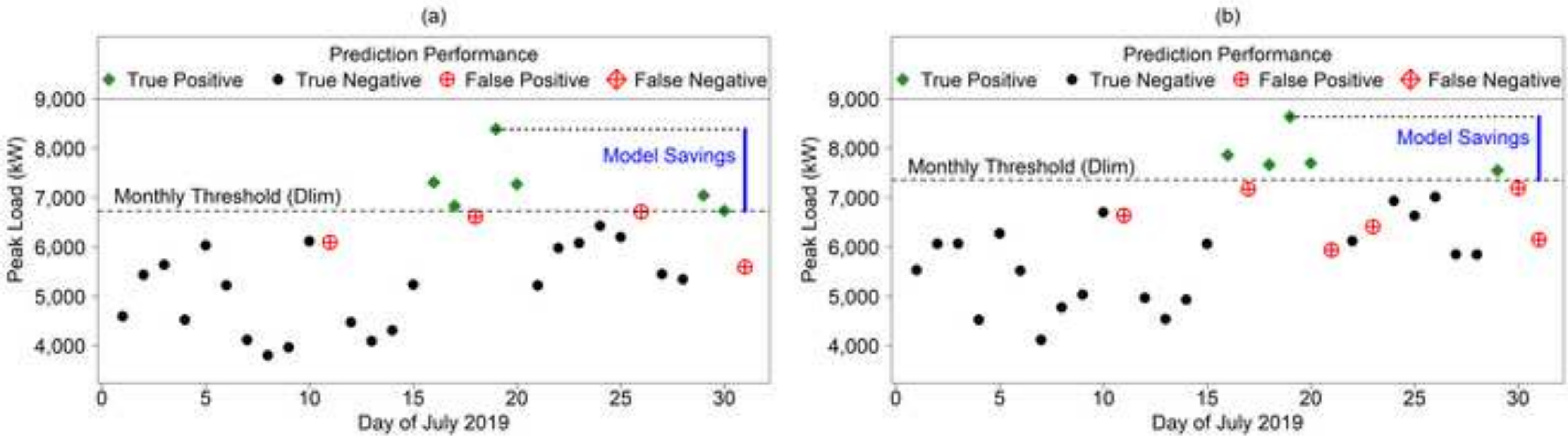
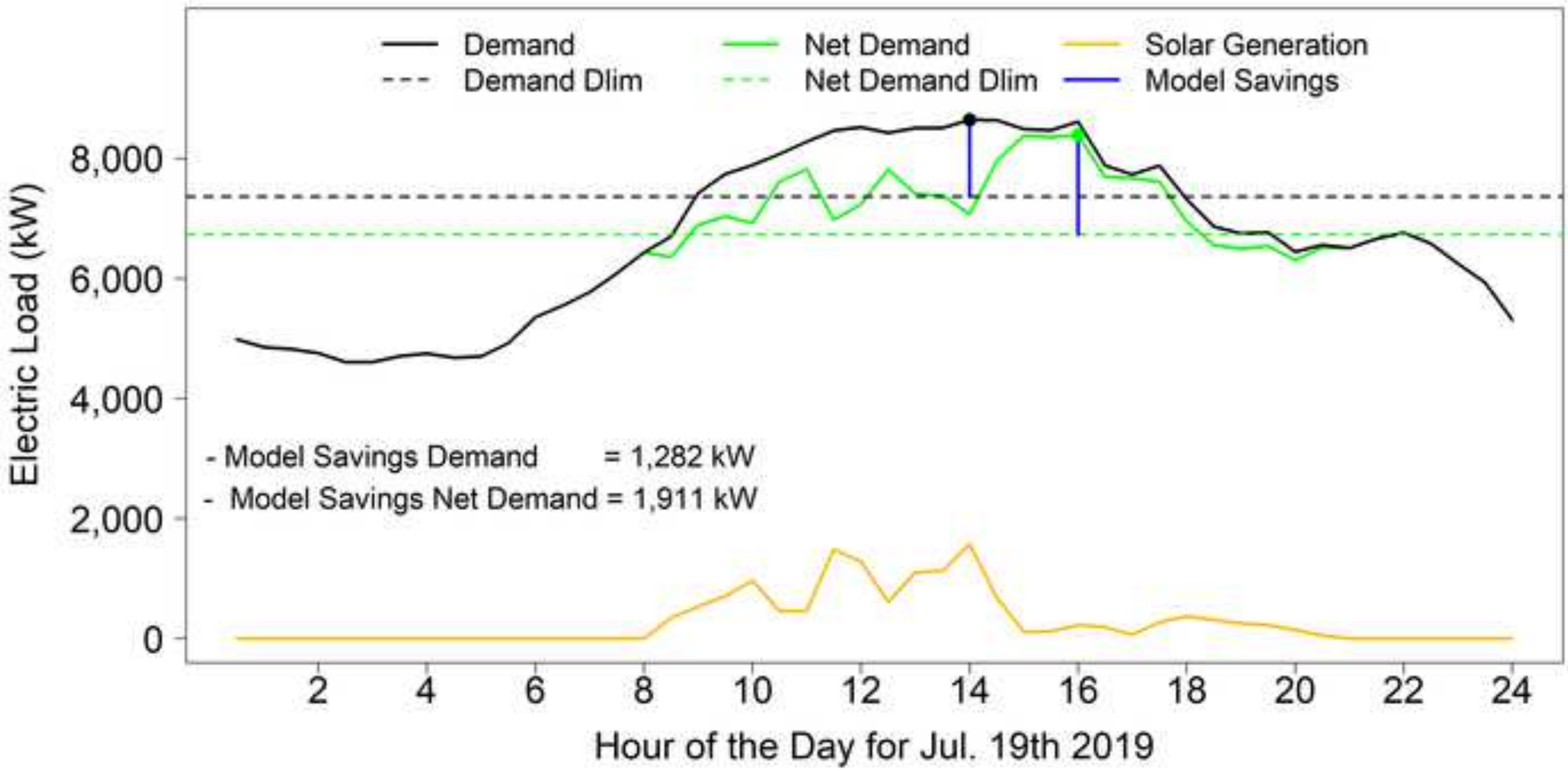
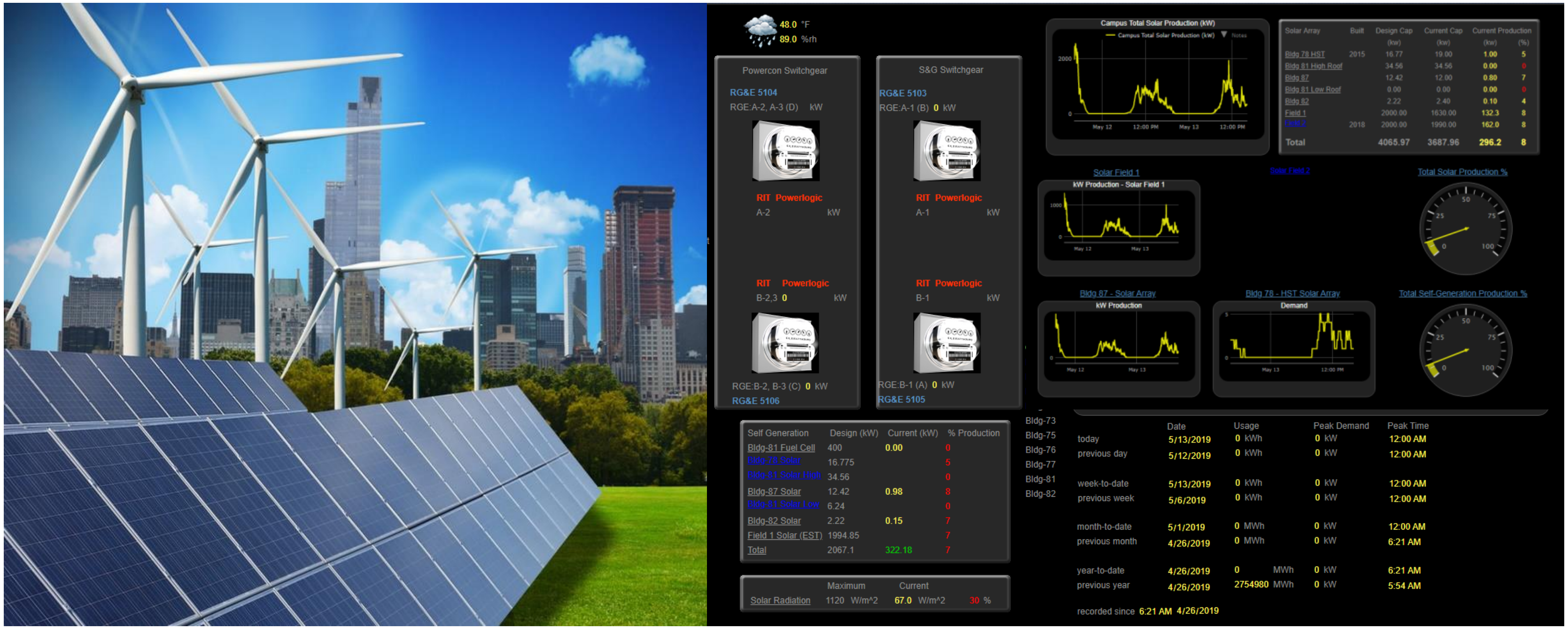


Figure 14


Demand
Demand Dlim
Net Demand
Net Demand Dlim
Solar Generation
Model Savings
8,000
6,000
4,000
2,000
0
Electric Load (kW)
- Model Savings Demand = 1,282 kW
- Model Savings Net Demand = 1,911 kW
2
4
6
8
10
12
14
16
18
20
22
24
Hour of the Day for Jul. 19th 2019

Actionable Peak Electric Load Day Forecasting Methodology Applicable to Facilities with Behind the Meter Renewable Electricity Generation



[I01]

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Wednesday Oct. 28th 2020

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Thank you!

Topics

- Motivation
- Research Goals
- Methodology
- Findings
- Main Contributions

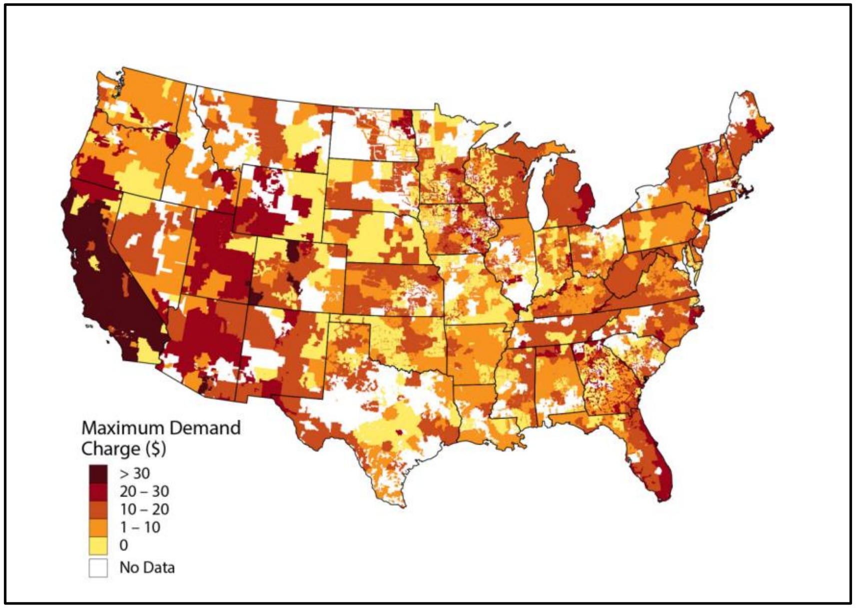
Renewable Energy Generation
in Rochester, NY. [I02]

Motivation

1. 39% of the total energy consumed in the USA in 2019 was for residential and commercial use. (USEIA, 2020)

2. Buildings : 28% of global energy-related carbon dioxide (CO2) emissions in 2018. (IEA, 2019)

3. Peak load charges can amount to up to 70% of electricity costs. (Dutta and Mitra, 2017; McLaren et al., 2017; Hledik, 2014)

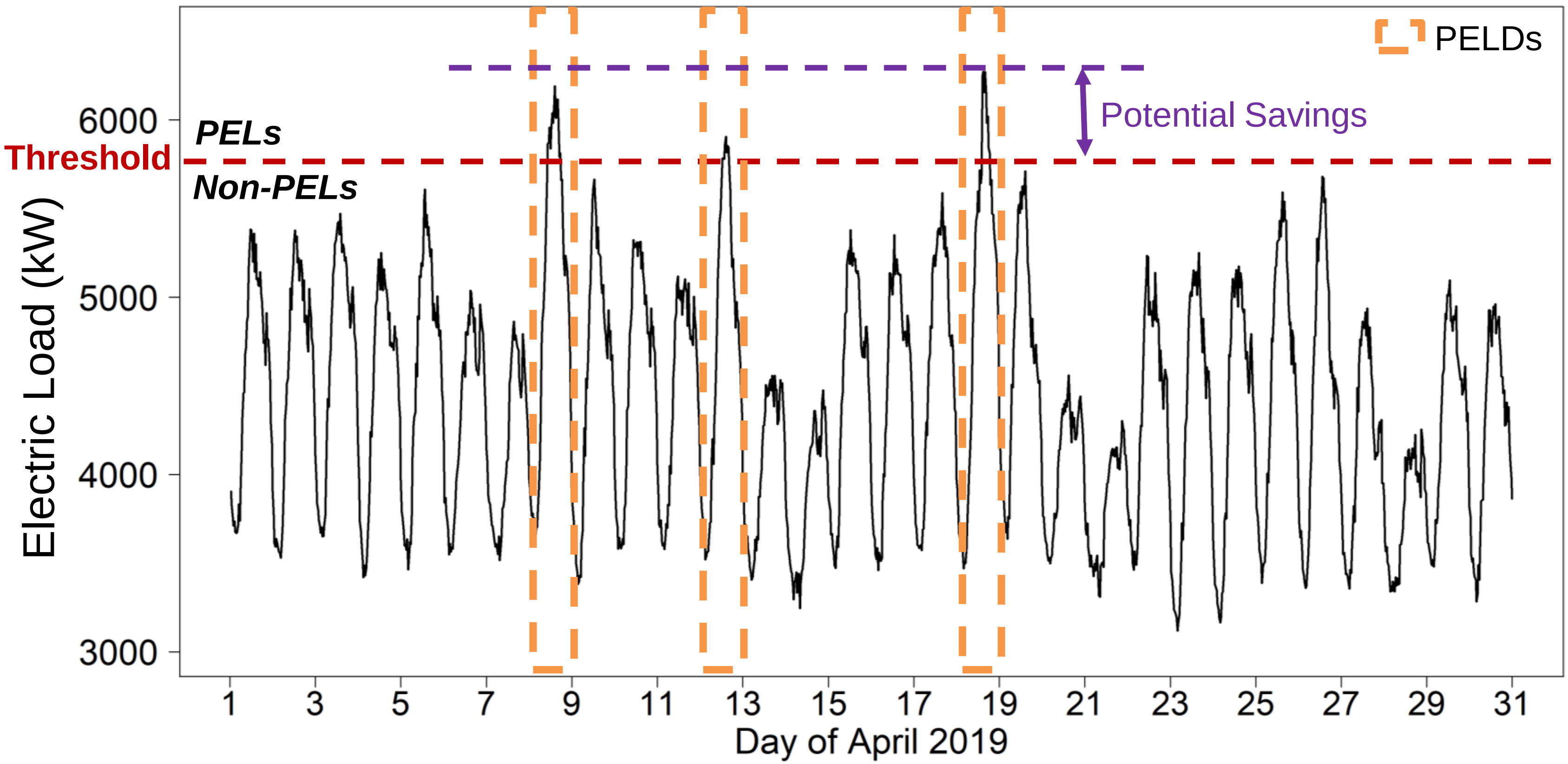


Maximum peak load charge rates by utility service territory in 2017. [I03]

Motivation

Peak Electric Loads (PELs) : Highest loads registered during the month.

Peak Electric Load Days (PELDs) : Days of the month when PELs occurred.



Motivation

4. The impact of peak electric loads can be reduced by acting on the intelligence provided by load forecasts and PELD forecasts. (Saxena et al., 2019)

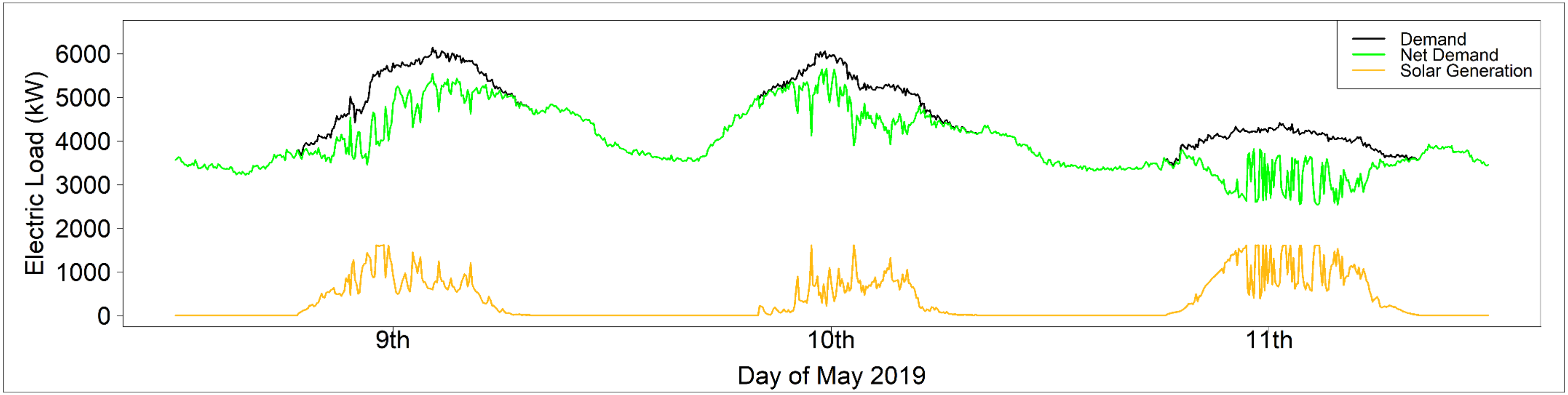
5. The share of renewable energy in global power capacity increased to 33% in 2018. (REN21, 2019)

[I04]

Motivation

6. Renewable electricity generation (REG) output is as variable as weather itself. (Staffell and Pfenninger, 2018; Chaiamarit and Nuchprayoon, 2014)

7. This characteristic of REG challenges the accuracy of both electric load forecasts (Tushar et al., 2018) and PELD forecasts (Aponte and McConky, 2019) .



Electric demand, net demand, and solar generation during May 9th-11th, 2019.

Motivation

8. The challenges faced by the increasing number of facilities adopting behind the meter renewable electricity generation (BTMREG) worldwide to accurately forecast PELDs have not been addressed by the published literature.

Facility with BTMREG in Rochester, NY. [I05]

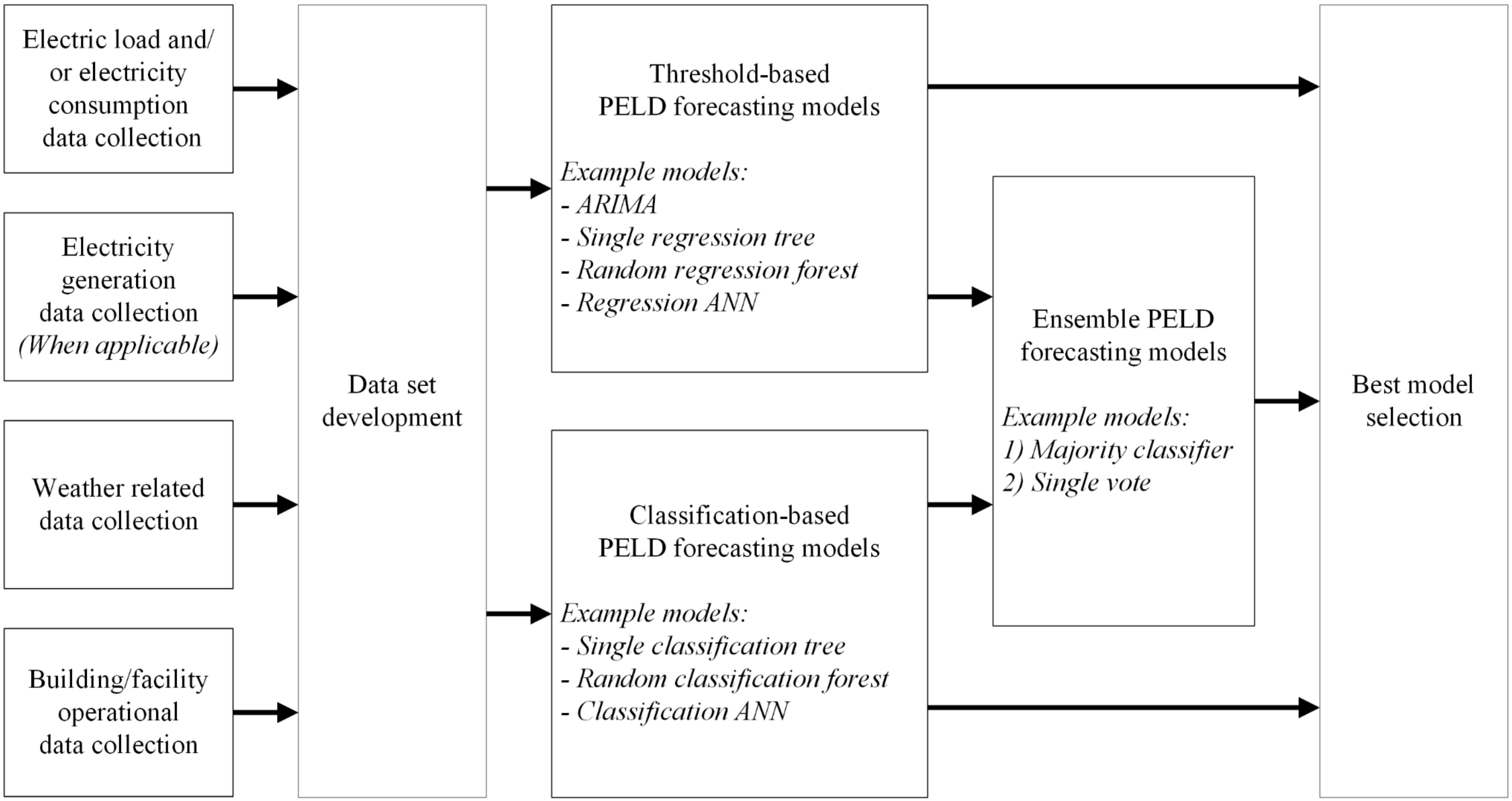
Research Goals

1. Accurately predict if an upcoming day will be a PELD for the month for scenarios with and without BTMREG.

2. Identify any differences between the performances of several electric load and PELD forecasting models for scenarios with and without BTMREG.

3. Identify any differences between the expected potential and model savings generated by a PELD forecasting methodology for scenarios with and without BTMREG.

Methodology



Based on the previously published work of Saxena et al. (2019)

Methodology

About the dataset:

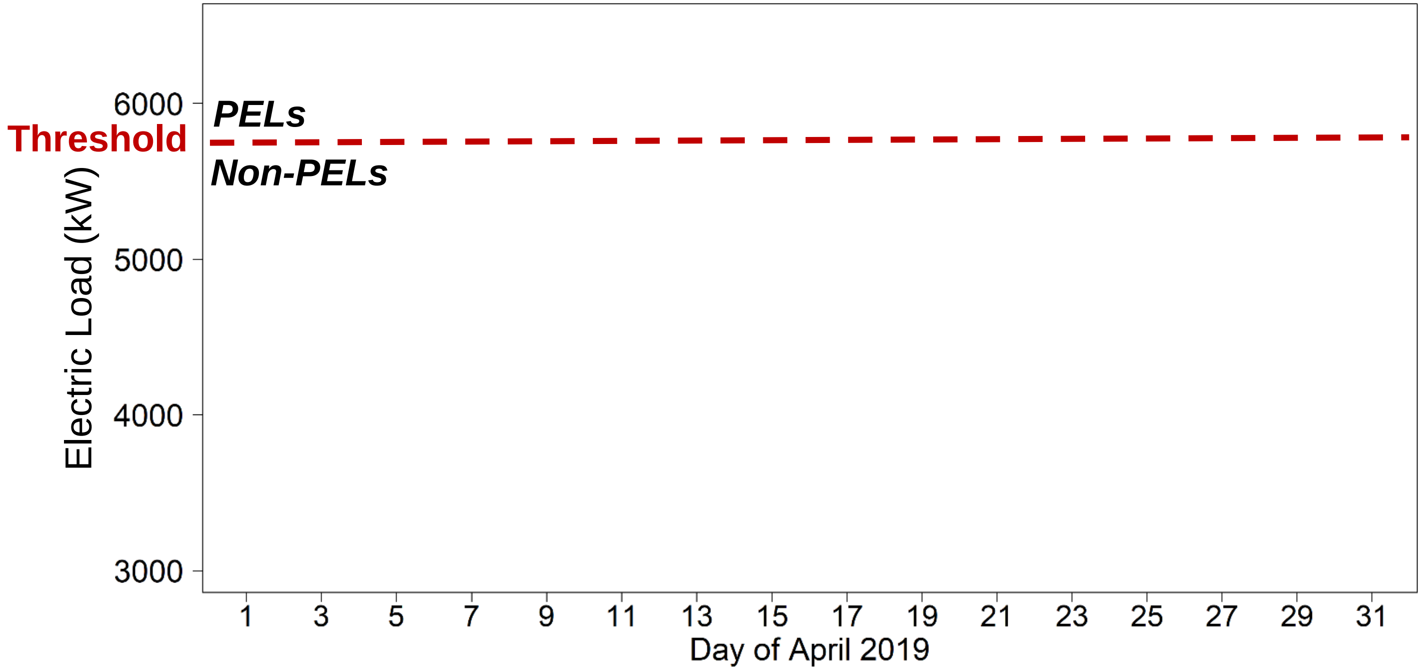
- 29,952 records @ 30-minutes frequency
- 32 variables in total
- Complete period: Jun. 16th, 2018 – Feb. 29th, 2020

  (Approx. 1 year and 9 months)
- Testing period: Mar. 1st, 2019 – Feb. 29th, 2020 (1 year)
- Electric load and electricity generation data from facility's smart meters
- Operational data (HVAC and Calendar) provided by the facility
- National Oceanic and Atmospheric Administration (NOAA) weather data

Methodology

Threshold-based PELD forecasting process

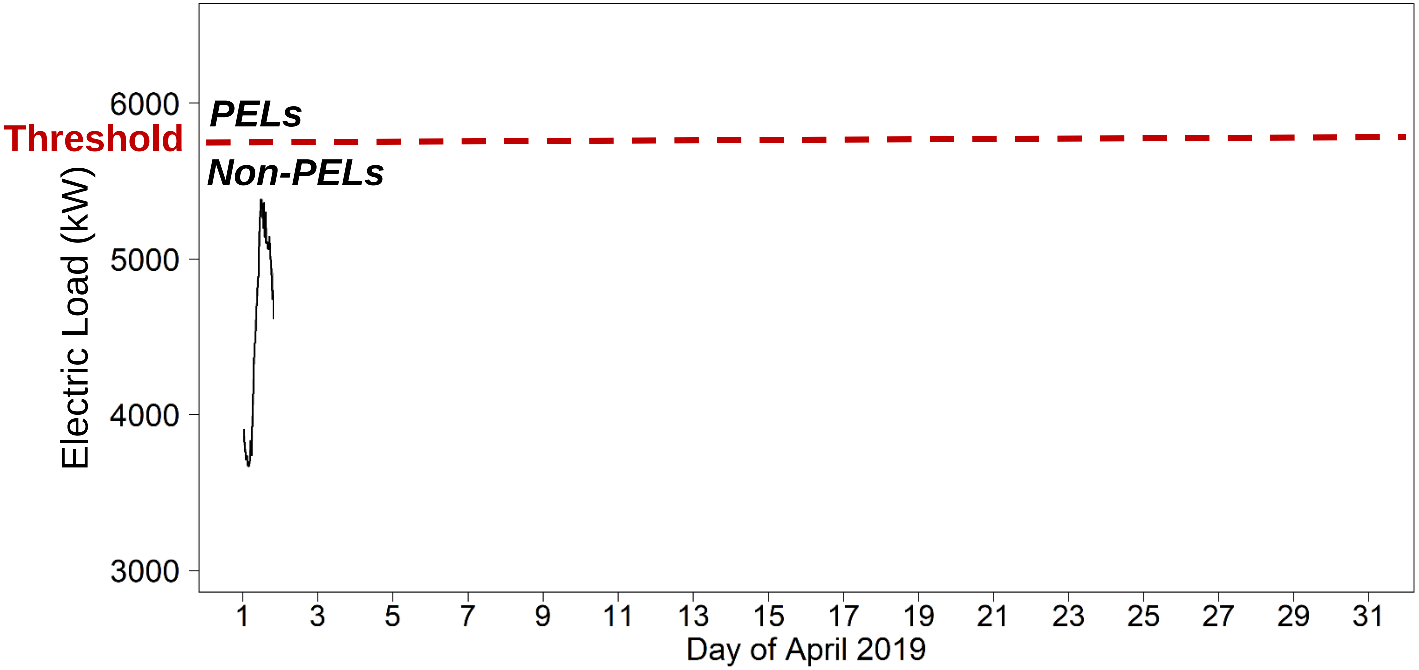
1) A threshold is determined at the beginning of the month.



Methodology

Threshold-based PELD forecasting process

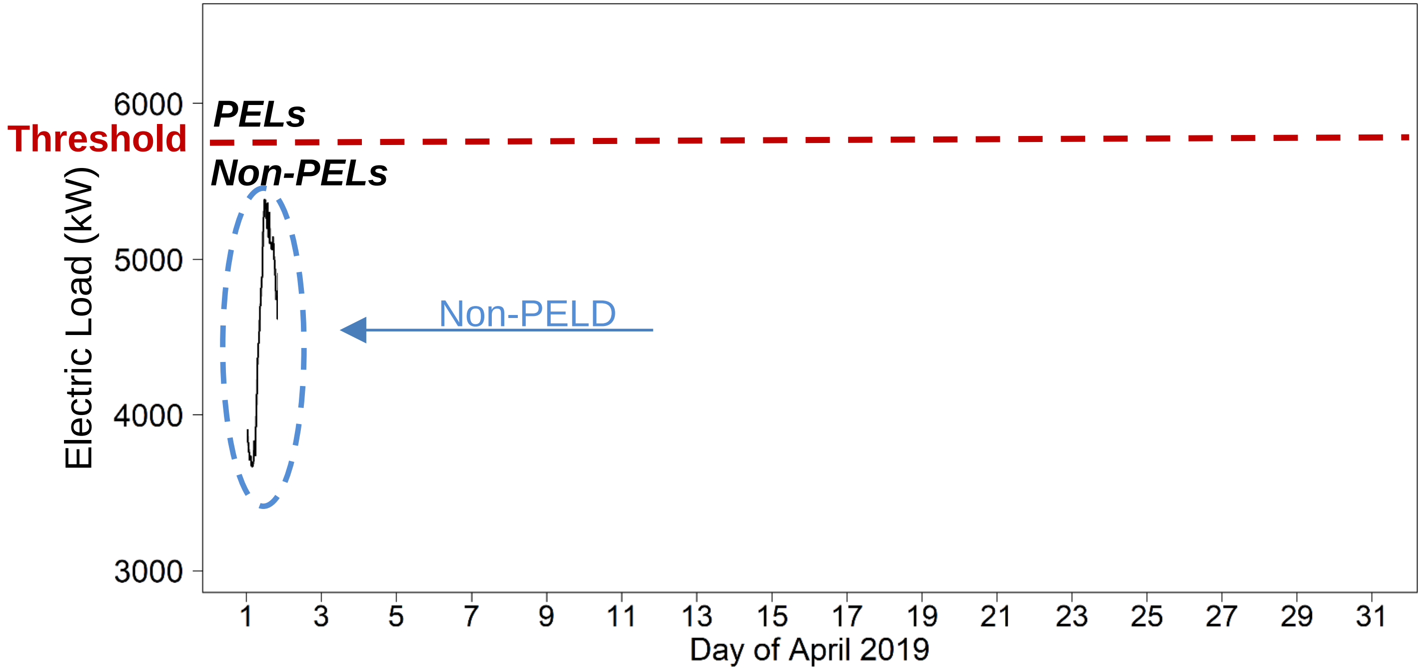
2) Every day at midnight, a regression-based model generates a day ahead (24 hours) electric load forecast based on historical data.



Methodology

Threshold-based PELD forecasting process

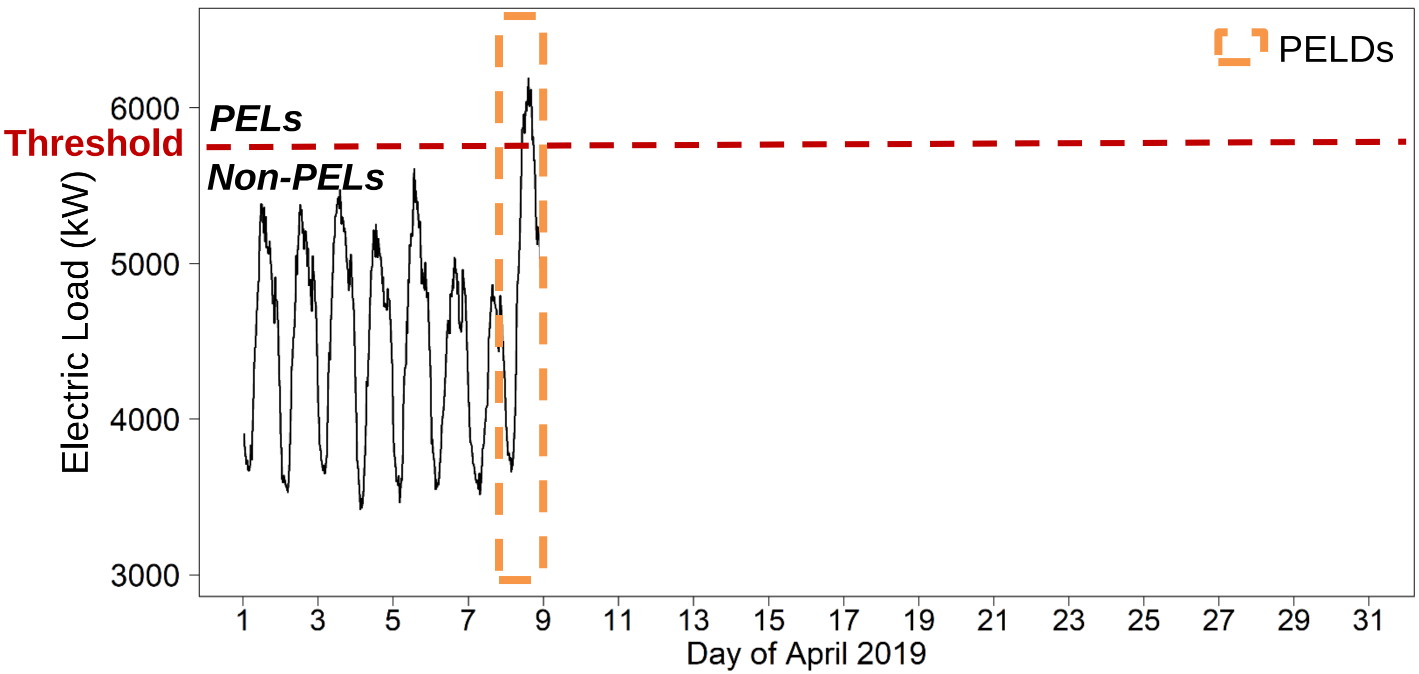
3) All forecasted loads are compared to the threshold and if any is found to be above it, then it is classified as a PEL and the day as a PELD.



Methodology

Threshold-based PELD forecasting process

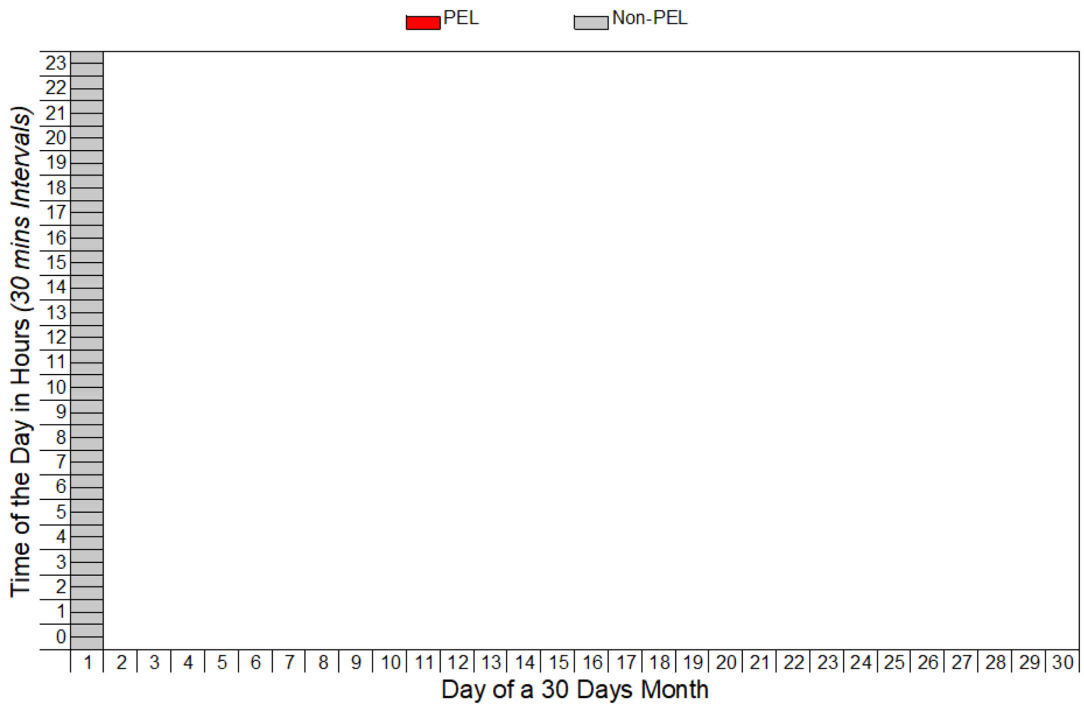
3) All forecasted loads are compared to the threshold and if any is found to be above it, then it is classified as a PEL and the day as a PELD.



Methodology

Classification-based PELD forecasting process

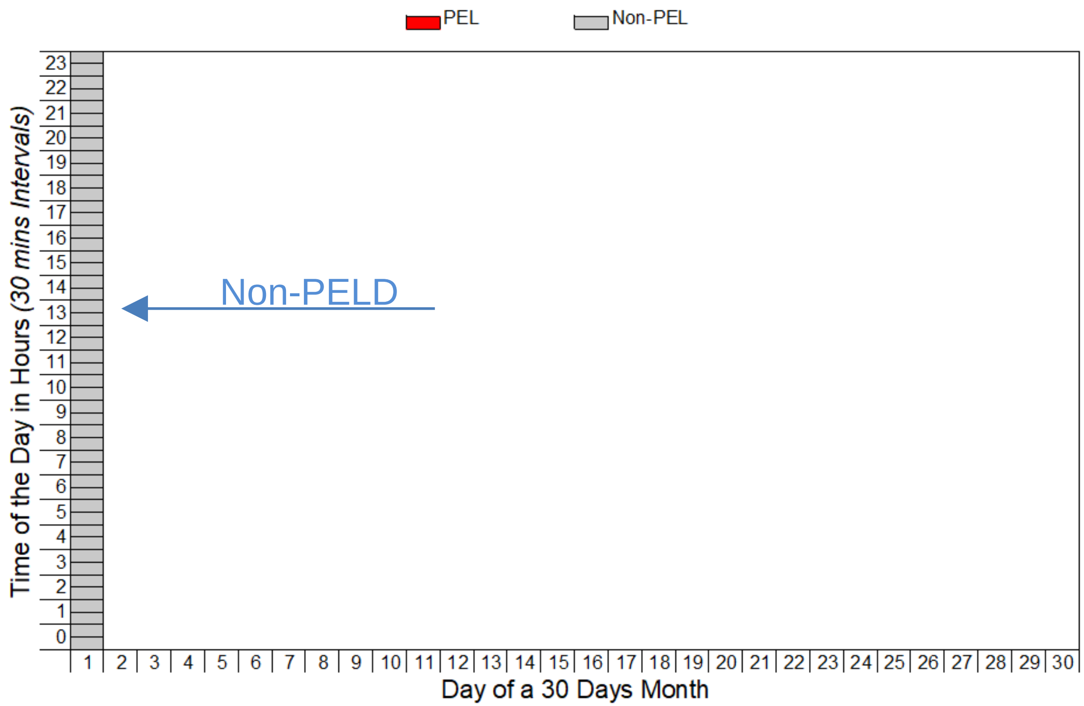
1) Every day at midnight, a classification-based model generates a day ahead (24 hours) classification of each load as either a PEL or a Non-PEL based on historical data and known features about the upcoming day.



Methodology

Classification-based PELD forecasting process

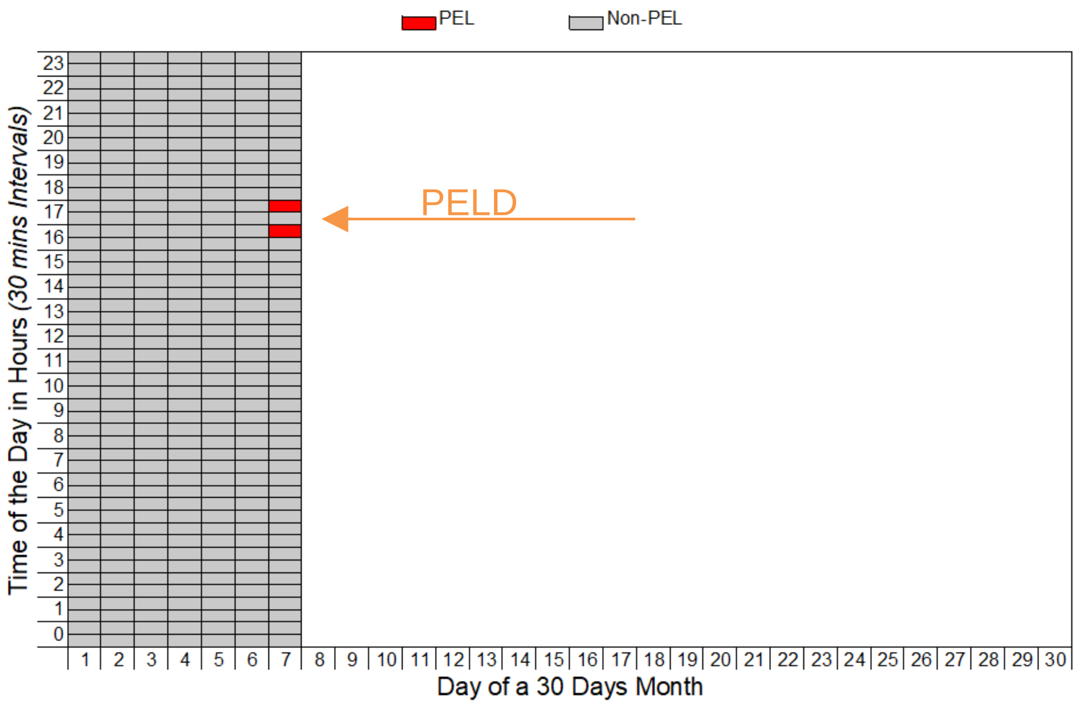
2) If any of the loads of the day is classified as a PEL by the classification-based model, then the day is classified as a PELD.



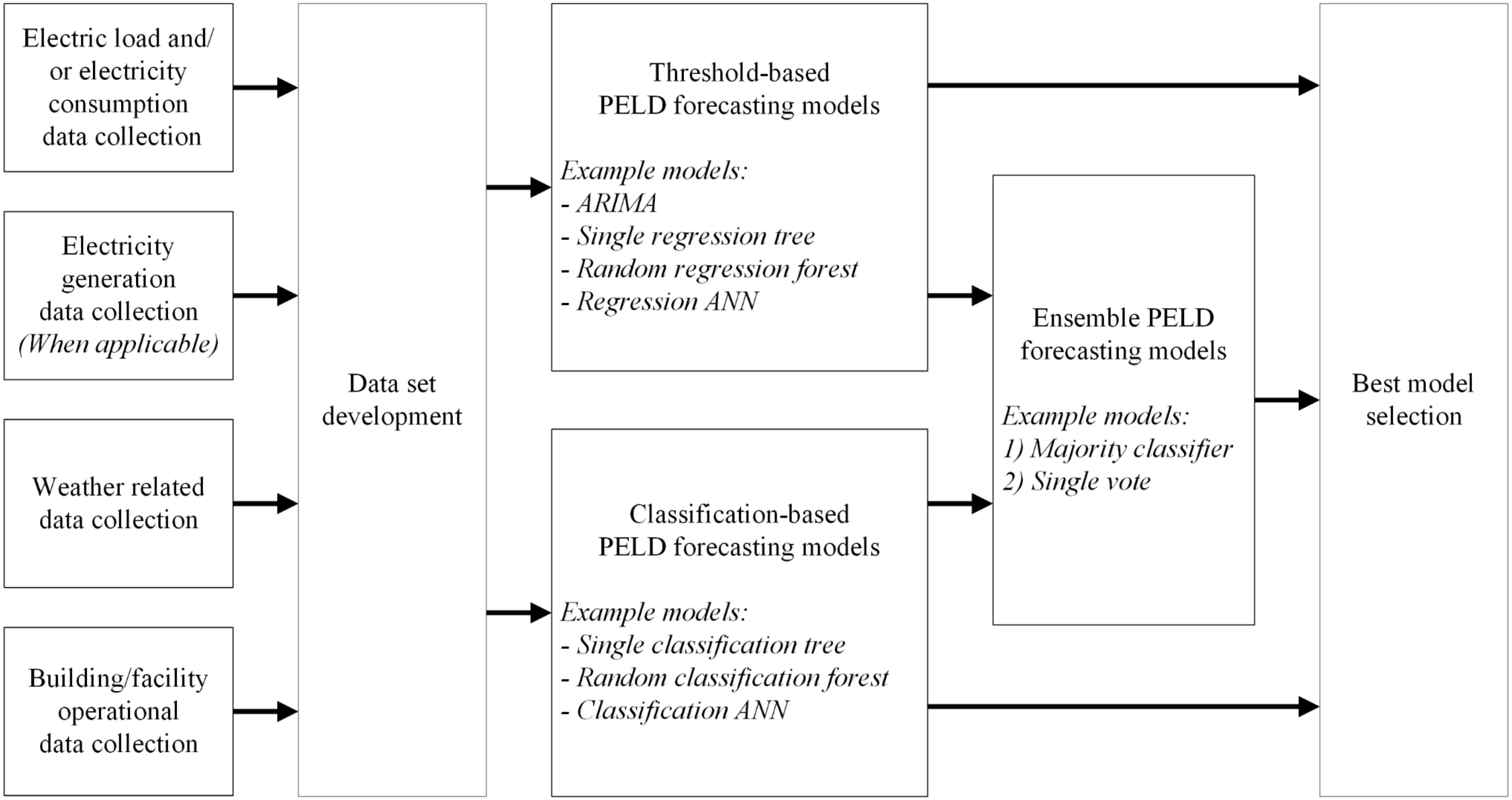
Methodology

Classification-based PELD forecasting process

2) If any of the loads of the day is classified as a PEL by the classification-based model, then the day is classified as a PELD.

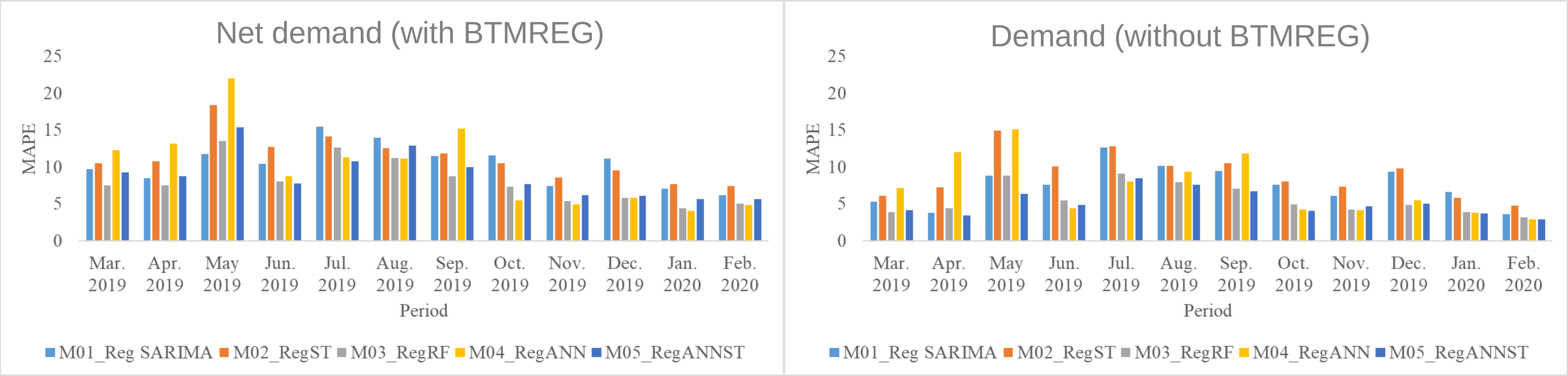


Methodology



Based on the previously published work of Saxena et al. (2019)

Findings: Threshold-Based Approach



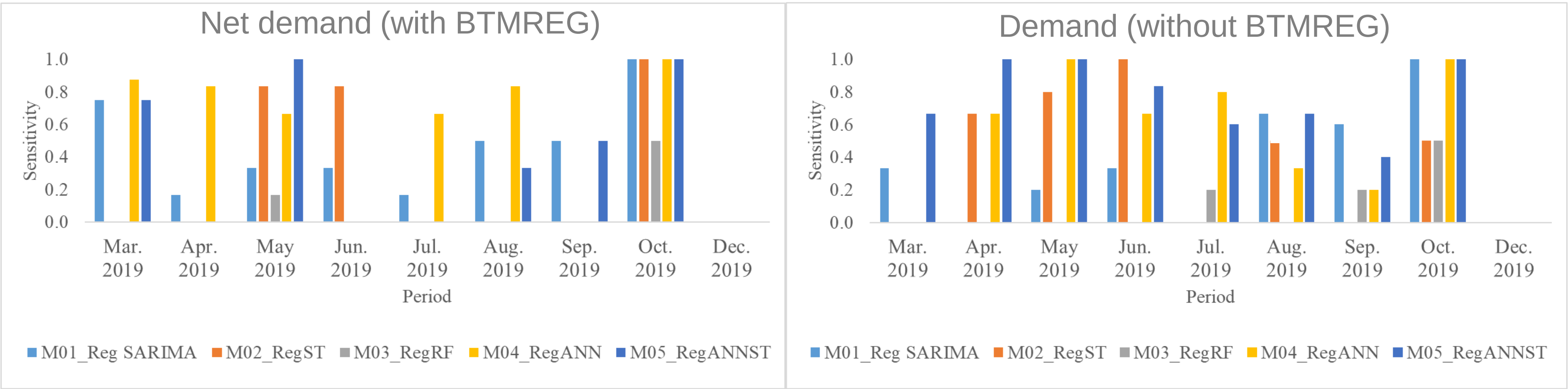
MAPE achieved by the M01 to M05 models.

Model	**Average monthly MAPE**	
	Net demand (with BTMREG)	**Demand** (without BTMREG)
M01_Reg SARIMA	10.4121	7.6004
M02_RegST	11.2159	8.9645
M03_RegRF	8.2921	5.6494
M04_RegANN	9.9221	7.3715
M05_RegANNST	8.8404	5.1544

1. BTMREG seems to affect the performance of the regression-based electric load forecasting models evaluated.

R·I·T

Findings: Threshold-Based Approach

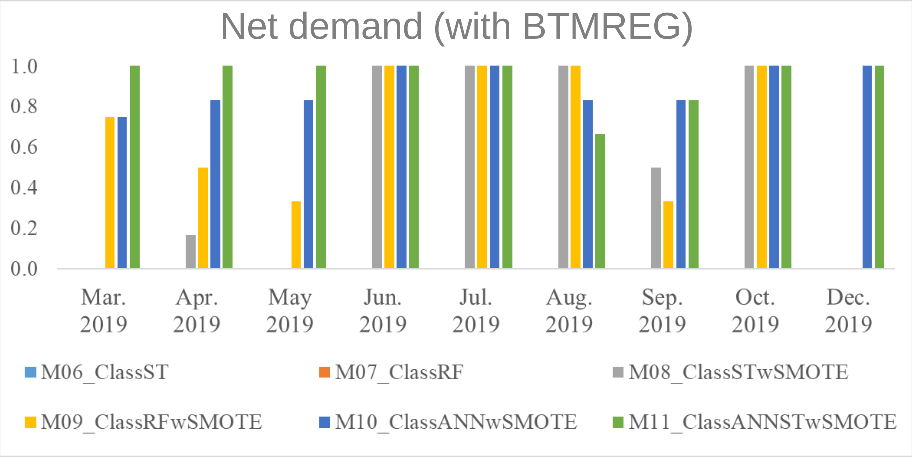


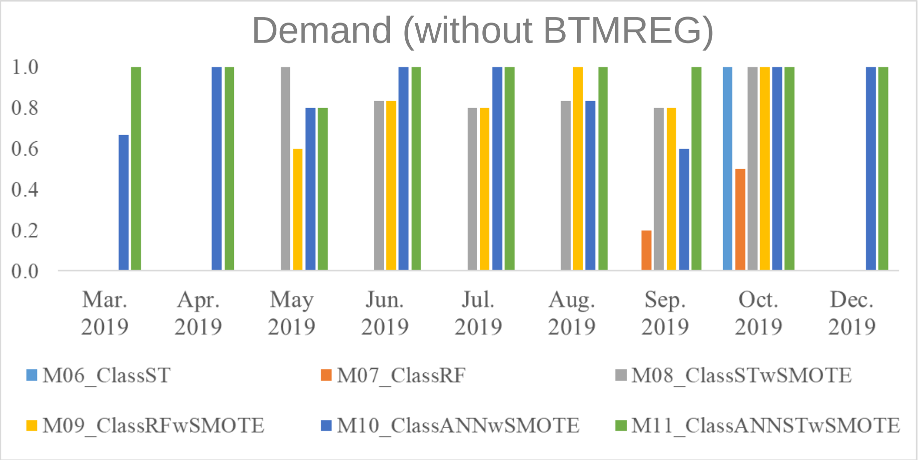
Sensitivity achieved by the M01 to M05 models.

Model	**Average monthly sensitivity**		**Average monthly balanced accuracy**	
	Net demand (with BTMREG)	**Demand** (without BTMREG)	**Net demand** (with BTMREG)	**Demand** (without BTMREG)
M01_Reg SARIMA	0.4167	0.3481	0.6294	0.6102
M02_RegST	0.2963	0.3852	0.6258	0.6508
M03_RegRF	0.0741	0.1000	0.5370	0.5500
M04_RegANN	0.5417	0.5185	0.6953	0.6963
M05_RegANNST	0.3981	0.6852	0.6652	0.8236

2. BTMREG seems to not affect the performance of the models evaluated at the threshold-based PELD classification stage.

Findings: Classification-Based Approach



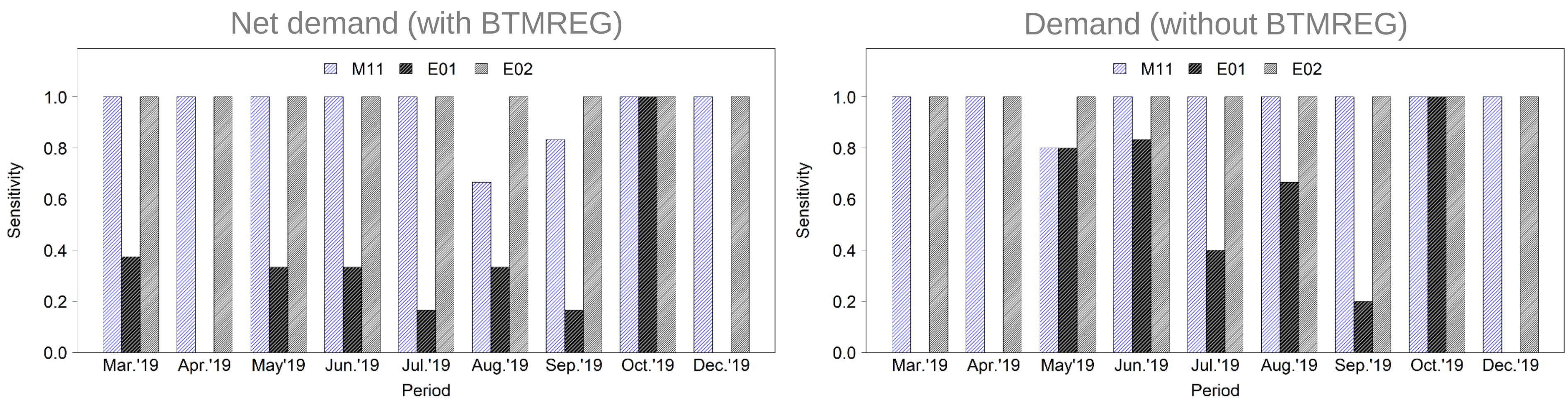


Sensitivity achieved by the M06 to M11 models.

Model	Average monthly sensitivity		Average monthly balanced accuracy	
	Net demand (with BTMREG)	**Demand** (without BTMREG)	**Net demand** (with BTMREG)	**Demand** (without BTMREG)
M06_ClassST	0.0000	0.1111	0.5000	0.5517
M07_ClassRF	0.0000	0.0778	0.5000	0.5389
M08_ClassSTwSMOTE	0.5185	0.5852	0.6315	0.6770
M09_ClassRFwSMOTE	0.6574	0.5593	0.7211	0.7055
M10_ClassANNwSMOTE	0.8981	0.8778	0.8329	0.8430
M11_ClassANNSTwSMOTE	0.9444	0.9778	0.8913	0.8906

3. Addressing the class imbalance is important regardless of BTMREG.
4. BTMREG seems to not affect the performance of the classification-based models evaluated.

Findings: Ensemble Approach



Sensitivity achieved by the M11, E01, and E02 models.

5. The E02_SingleVote model and the M11_ClassANNSTwSMOTE model outperformed the E01_Majority model under both scenarios.

6. The E02_SingleVote model outperformed the M11_ClassANNSTwSMOTE model on two out of nine months for the net demand (with BTMREG) scenario and on one month for the demand (without BTMREG) scenario.

Findings: Ensemble Approach

		M11 ClassANNSTwSMOTE	E01 Majority	E02 SingleVote
Average monthly sensitivity	**Net demand** (with BTMREG)	0.9444	0.3009	1
	Demand (without BTMREG)	0.9778	0.4333	1
Average monthly balanced accuracy	**Net demand** (with BTMREG)	0.8913	0.6505	0.7046
	Demand (without BTMREG)	0.8906	0.7124	0.7333
Total number of false negatives	**Net demand** (with BTMREG)	3	34	0
	Demand (without BTMREG)	1	18	0
Total number of false positives	**Net demand** (with BTMREG)	37	0	136
	Demand (without BTMREG)	48	2	133

7. The M11 ClassANNSTwSMOTE model was selected as the best model overall for this facility with BTMREG based on:
   - High performance
   - Lower complexity

8. BTMREG seems to not affect the performance of the ensemble models evaluated.

Findings: Best Model Savings

	Net demand (with BTMREG)			**Demand** (without BTMREG)		
Period	**Potential savings** *(in kW)*	**Model savings** *(in kW)*	**% Model achievement**	**Potential savings** *(in kW)*	**Model savings** *(in kW)*	**% Model achievement**
Mar. 2019	247.38	247.38	100%	38.20	38.20	100%
Apr. 2019	749.38	749.38	100%	513.42	513.42	100%
May 2019	766.07	766.07	100%	775.28	0.00	0%
Jun. 2019	884.60	884.60	100%	1,045.36	1,045.36	100%
Jul. 2019	1,657.66	1,657.66	100%	1,281.79	1,281.79	100%
Aug. 2019	1,247.15	1,008.00	81%	835.31	835.31	100%
Sep. 2019	1,169.79	753.00	64%	731.44	731.44	100%
Oct. 2019	2,163.22	2,163.22	100%	2,701.08	2,701.08	100%
Dec. 2019	131.22	131.22	100%	94.62	94.62	100%
Aggregate	**9,016.48**	**8,360.54**	**93%**	**8,016.51**	**7,241.22**	**90%**

9. The M11_ClassANNSTwSMOTE model would have achieved 93% of the potential savings in kW and US$ 142,129.18 (8,360.54 kW x 17 US$/kW) savings in electricity costs.

Findings: Best Model Savings

	Net demand (with BTMREG)			**Demand** (without BTMREG)		
Period	**Potential savings** *(in kW)*	**Model savings** *(in kW)*	**% Model achievement**	**Potential savings** *(in kW)*	**Model savings** *(in kW)*	**% Model achievement**
Mar. 2019	247.38	247.38	100%	38.20	38.20	100%
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Oct. 2019	2,163.22	2,163.22	100%	2,701.08	2,701.08	100%
Dec. 2019	131.22	131.22	100%	94.62	94.62	100%
Aggregate	**9,016.48**	**8,360.54**	**93%**	**8,016.51**	**7,241.22**	**90%**

10. There are more potential and model savings to be achieved when BTMREG is present for the facility evaluated.

Main Contributions

1. Development and testing of a PELD forecasting methodology applicable to both consumers with and without BTMREG.

   A model selected after implementing the methodology for a facility with BTMREG demonstrated the capacity to have achieved 93% of the potential savings in kW and US$ 142,129.18 savings in electricity costs during a yearlong testing period.

Main Contributions

2. Documentation of the first of its kind side-by-side empirical comparisons between the performance of ARIMA, RCT, random regression and classification forest, ANN, and ensemble based models at forecasting electric load and PELDs for scenarios with and without BTMREG.

   Evidence suggesting an impact on model performance due to the presence of BTMREG was only observed for the regression-based models evaluated. The classification-based and ensemble models evaluated did not show such evidence.

Main Contributions

3. A side-by-side comparison of the potential and model savings achieved by implementing the PELD forecasting methodology in a scenario with BTMREG versus a scenario without BTMREG.

   Experimental results suggest that the variability (intermittency) of BTMREG can create opportunities for more potential and model savings to be achieved.

Thank you for your attention!
Please feel free to ask questions.

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Images

[I01] Image source: Eviart/Shutterstock https://cdn.mos.cms.futurecdn.net/wJULFMBFtPPCHYCjbdaeGZ-1024-80.jpeg.webp [Retrieved: October, 15th 2020]

[I02] Image source: http://www.hewittyoung.com/wp-content/uploads/2017/06/Solar_close_371.jpg [Retrieved: October, 15th 2020]

[I03] Image source: McLaren, J., Mullendore, S., Gagnon, P., & Laws, N. (2017). Identifying Potential Markets for Behind-the-Meter Battery Energy Storage: A Survey of U.S. Demand Charges. Golden CO: National Renewable Energy Laboratory, NREL/BR-6A20-68963, https://www.nrel.gov/docs/fy17osti/68963.pdf [Retrieved: 24 September 2020]

[I04] Image source: https://i2.wp.com/www.un.org/sustainabledevelopment/wp-content/uploads/2015/09/Icons-FINAL.png?fit=1227%2C750&ssl=1 [Retrieved: October, 15th 2020]

[I05] Image source: Craig W. Shaw, Stratus Imaging https://cdn.rit.edu/images/news/2018-12/gisfuelcellresearch_cropped.jpg [Retrieved: October, 15th 2020]