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Electricity peak shaving for commercial buildings using machine learning and vehicle to building (V2B) system

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HIGHLIGHTS

- A novel system is presented that predicts day-ahead demand profile and optimizes EV charging/discharging to minimize peak demand.
- The system is designed to comply with preplanned EV trip schedules and minimum state of charge (SOC) requirements.
- Four machine learning methods are tested to predict day ahead demand profile of a case study building at 15-minute intervals.
- Five peak demand reduction scenarios are analyzed using combination of EVs, a stationary battery, and a PV system.
- The results show up to 36 % reduction in peak demand using two EVs, one stationary battery, and PV system of 40 kW capacity.

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ABSTRACT

Reducing electricity peak demand is essential to maintain the balance between supply and demand side in electricity power markets, as well as reduce utility costs and environmental impacts. With growth in adoption of Electric Vehicles (EVs), there is an emerging opportunity to balance electrical power demand of buildings by storing electricity in EVs during low demand periods and discharging electricity into buildings during peak demand periods. Due to uncertainty in time and magnitude of peak demand, decision makers are always faced with a challenging task to identify optimal schedules for charging and discharging EVs to minimize peak electricity demand. This paper presents the development of a novel system that is capable of predicting day-ahead building electricity demand profile and identifying optimum schedule of charging and discharging EVs to minimize electricity peak demand. The system is designed to comply with planned EV trip schedules and minimum state of charge (SOC). The system consists of (1) machine Learning (ML) model to predict electrical power demand, and (2) demand management optimization model to identify optimal schedule for charging and discharging EVs. Four methods are explored to develop the ML model, including histogram-based gradient boosting, random forest, deep artificial neural network (DNN), and long short-term memory (LSTM). A case study of multi-tenant commercial building is analyzed to evaluate the performance of the system and demonstrate its new capabilities. The results of the case study shows that LSTM has the best performance in terms of mean absolute error, root mean square error, and mean absolute percentage error with average values of 7.44, 17.78, and 20.08 %, respectively. Five scenarios for shaving peak electricity demand, including combinations of two electric vehicles, a stationary battery, and a PV system are investigated. Scenarios including the stationary battery and the PV system are considered to evaluate the full potential of peak demand reduction in the case study building. The results of the demand management optimization model show up to 36 % reduction in peak demand using two EVs, one stationary battery, and PV system of 40 kW capacity. The key contributions that this study adds to existing knowledge are: (1) developing machine learning models to predict day-ahead electricity demand in 15-minute intervals, (2) integrating machine learning and optimization algorithms in identifying EV charging and discharging schedules to minimize utility cost by shaving peak energy demand, and (3) considering planned EV trips and minimum SOC requirements in identifying optimal charging and discharging of EVS to shave peak energy demand in buildings. The implementation of this system provides practical solutions for managing electricity demand in commercial buildings using EVs. By reducing energy consumption and promoting the

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innovative use of EVs, this system offers a sustainable approach to managing electricity demand in commercial buildings.

1. Introduction

Reducing electricity peak demand is essential to maintain the balance between supply and demand side in electricity power markets. If demand during peak time exceeds existing generating capacity, utility companies need to purchase electricity at high rates from other companies to supplement their generating capacity or build new generating plants which can escalate environmental impacts. To incentivize users to reduce their peak demand, specifically in commercial buildings, utility companies often include a demand charge that can account for 30 % to 70 % of utility bills [1]. Therefore, managing electricity peak demand in buildings can result in reduction of electricity costs and environmental impacts.

Improving energy efficiency and electricity demand peak shaving has gained importance in recent years due to the growth in energy demand, global warming, and escalation of electricity prices [2]. In this regard, several researchers focused on developing models for building electricity peak shaving using different approaches such as demand management systems [3–5], onsite renewable power sources [6–8], and energy efficiency measures [9–12]. With the growing adoption of Electric Vehicles (EVs), there is an emerging opportunity to balance electrical power demand of buildings by storing electricity in EVs during low demand periods and discharging electricity into buildings during peak time. However, due to the uncertainty in time and magnitude of peak demand, decision-makers face a challenging task in identifying optimal schedules for charging and discharging of EVs to minimize electricity costs. This highlights the importance of developing new and innovative models capable of predicting demand profile of buildings to identify optimal schedules for charging and discharging EVs.

2. Literature review

Existing research is investigated in two major categories: (1) building electricity demand forecasting, and (2) electricity power peak shaving models. The following literature review sections discuss these categories in detail.

2.1. Building electricity power demand forecasting

Building electricity power demand prediction is a key step in demand side management as well as other domains such as fault detection and diagnosis, deployment of distributed and renewable generation resources, and control optimization [13–15]. Moreover, the availability of data on electricity usage in buildings provides a great opportunity for leveraging machine learning methods to predict building electricity consumption. In this regard, various prediction models were developed in the literature using methods such as regression, and machine learning and deep learning. For example, a number of studies applied regression methods to forecast the electricity demand of buildings [13,16,17]. The linear structure of regression models can facilitate direct physical interpretation of features affecting the electricity demand, such as ambient temperature [18,19]. However, regression methods are reported to have significant shortcomings in prediction of electricity demand due to nonlinear and non-stationary structure of electricity time series [20]. Other studies applied methods such as Autoregressive Integrated Moving Average (ARIMA) [21–23], multiplicative error [24], Fourier series [25,26], and Kalman filtering [14,15,27,28]. These methods consider the current and future energy usage as a function of the past energy usage history. Despite the capability of these methods in predicting short-term load patterns, they are unreliable in case of non-stationary conditions or nonlinear data [20]. Machine learning methods such as Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANNs) are used to forecast electricity power demand of buildings [29–37]. ANNs are reported by several studies to be more effective in electricity demand prediction compared to other approaches [29,38,39]. For example, Yildiz et al. developed a number of models using ARIMA, ANN, SVM, and RF methods to forecast hour-ahead electricity demand of a university building with time resolution of 1 h. The results of the study showed that ANN outperformed other methods with mean absolute percentage errors of 1.75 % [13]. Similarly, Dong et al. developed six different machine learning models including: ANN, SVM, support vector regression (SVR), least-square support vector machine (LS-SVM), Gaussian process regression (GPR) and Gaussian mixture model (GMM) to predict day ahead electricity demand of four residential buildings with time resolution of 1 h. According to the study, ANN had the best performance compared to other methods with mean absolute percentage errors up to 27.52 % [40].

Despite the contribution of the aforementioned studies in predicting energy demand for buildings, there are still limitations and challenges to be addressed. On one hand, the above studies mainly focused on residential sector. It should be noted that factors affecting the electricity demand such as number of occupants, operational schedule, building equipment, and building scale are significantly different in commercial buildings compered to residential sector. Therefore, there is a need for further studies on commercial building electricity prediction. On the other hand, there are limited studies on day-ahead electricity demand prediction for commercial buildings while considering time resolution shorter than 1 h which is required for peak demand management systems.

2.2. V2B electricity power peak shaving models

Several studies developed decision making models to identify optimal schedule for charging and discharging of EVs to minimize electricity costs [41–48]. For example, Ioakimidis et al. presented an optimization model using interior point algorithm to peak-shave and valley-fill the power consumption profile of a university building by scheduling charging and discharging of EVs. It should be noted that the power consumption profile in this study is assumed to be constant over the course of the days and seasons, and therefore, the variation of building demand with respect to changes in weather conditions as well as number of occupants are not considered. The results of this study showed up to 20 % reduction in electricity peak demand [49]. Kuang et al. presented an optimization model using mixed integer linear programming to identify optimal energy exchange among building, EV charging station and power grid to minimize electricity costs. They studied the impact of driver behaviors such as availability of EVs, and initial and desired state of battery on the economic performance of V2B across different building types [50]. In a similar study, Mahmud et al. presented a decision-tree-based algorithm for coordinated control of EVs, photovoltaic units, and battery energy storage systems to reduce peak load in residential buildings. They concluded that the large battery capacity available in EVs play a significant role in managing peak domestic loads and peak grid demand [51]. Other studies focus on presenting collaborative charging and discharge frameworks to facilitate the implementation of V2B [52–58]. For example, Tanguy et al. presented a collaborative charging approach where EVs are charged for free in exchange for shaving electricity peak demand of buildings. They presented a linear programming optimization model to identify the optimal schedule for charging and discharging of EVs. They used the power consumption profile of a university building for a duration of 1 year as input for the developed optimization model. The results of this

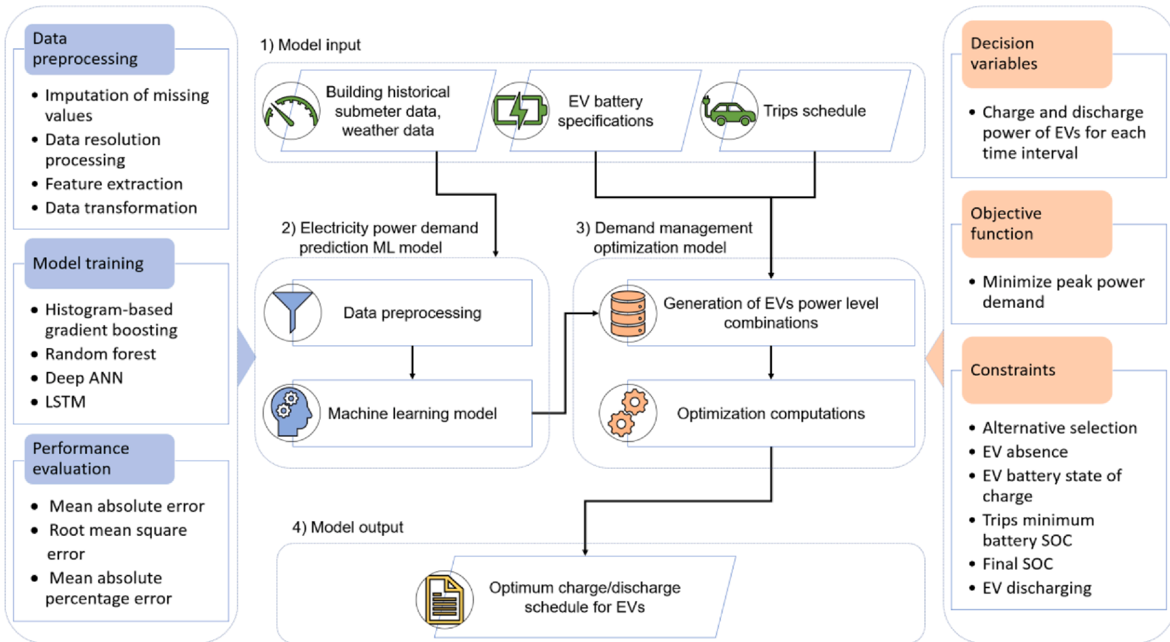

Fig. 1. System Architecture.

study indicated that collaborative charging can be financially viable for both the institution hosting the system and the participants [53]. A similar study conducted by Moura et al. presented a collaborative charging approach to align the electricity and parking values. They presented a bi-level multi-objective optimization model to identify the optimal tariffs and charging and discharging schedules to simultaneously minimize the costs for the building and EV owners [59].

Despite the contribution of former studies, there are limited or no reported studies that focused on the prediction of day-ahead electricity consumption profile to identify optimum schedule of charging and discharging EVs for minimizing electricity peak demand. Moreover, there are limited models that can provide detailed charging and discharging schedule for EVs that take into account trip schedules and battery state of charge (SOC) requirements.

3. Research objectives and methodology

The objective of this study is to develop a new system that is capable of predicting day-ahead electricity consumption profile to identify optimum schedule of charging and discharging EVs to minimize electricity peak demand. The system consists of (1) a machine learning model to predict day-ahead electricity power demand of existing commercial buildings, and (2) a demand management optimization model to identify optimal schedules for charging and discharging of EVs.

The input data of the present system includes: (1) building historical electricity submeter data from Building Management System (BMS) in addition to weather data such as temperature; (2) EV battery specification such as capacity, minimum SOC, SOC before trips, and maximum power of EV charging and discharging; and (3) data of planned day trips and anticipated electricity consumption for each EV, as shown in Fig. 1. To calculate demand costs, utility companies typically measure building's power demand in 15-minute intervals throughout the billing cycle. The highest peak demand during the billing cycle is then identified, and the building is charged based on that peak demand. Accordingly, the granularity of electricity submeter data is considered at 15-minute resolution to enable the present system to accurately predict electricity demand.

The goal of the demand prediction model is to identify electricity consumption profile one day ahead based on factors that impact electricity consumption in buildings, including historical submeter data and weather data. Machine Learning methods are used to predict electrical power demand of existing commercial buildings due to their capability of predicting non-stationary and nonlinear time series data with high accuracy. The building power demand prediction model is developed in three main steps: (i) data preprocessing where data is cleaned and prepared; (ii) model training where different ML models are developed; and (iii) model evaluation where the accuracy of the developed ML models is analyzed.

The demand management model is designed to schedule charging and discharging of EVs to minimize peak demand in commercial buildings by shifting loads from high demand time intervals to low demand periods. It should be noted that the optimization model identifies the optimum schedule for charging and discharging of EVs based on predicted building power demand profile from the demand prediction model, as shown in Fig. 1. The optimization model is developed in three main steps: (i) identifying decision variables; (ii) formulating objective function and constrains; and (iii) implementing optimization computations. The research team used binary linear programing to execute the model computations due to its capability of identifying global optimum solutions in a short computational time. A case study of a commercial building is analyzed to demonstrate the capabilities of the developed model.

The present system is designed to show its output in tabular and graphical formats. The output data includes: (i) charge and discharge schedule of EVs with respect to trip schedules and battery level constraints; and (ii) analysis of building electricity demand profile before and after preforming the V2B peak demand reduction.

This study presents an innovative approach for tackling the challenges associated with managing electricity demand in commercial buildings. Specifically, the present study introduces three key contributions, including: (1) developing machine learning models to predict day-ahead electricity demand using 15-minute intervals, (2) integrating machine learning and optimization algorithms in identifying EV charging and discharging schedules to minimize utility cost by shaving peak energy demand, and (3) considering planned EV trips and minimum SOC requirements in identifying optimal charging and discharging of EVS to shave peak energy demand in buildings. This system provides decision-makers in commercial buildings valuable support for electricity demand management by leveraging EVs, thereby minimizing operational expenses and promoting sustainable building energy practices.

Table 1
Histogram-based gradient boosting (HistGB).

Parameters	Values
Learning rate	0.1
Maximum depth	3
Loss function	Mean Squared Error
Minimum samples to split an internal node	2
Minimum samples for leaf nodes	1

Table 2
Random forest (RF).

Parameters	Values
Number of estimators (Trees)	100
Criterion function	Mean squared error
Minimum samples to split an internal node	2
Minimum samples for leaf nodes	1
Number of estimators (Trees)	100

Table 3
Deep Artificial Neural Network (DNN).

Layer Number	Layer type	Output Shape	Activation Function
1	Dense	256	ReLU
2	Batch Normalization	256	–
3	Dense	128	ReLU
4	Batch Normalization	128	–
5	Dense	64	ReLU
6	Batch Normalization	64	–
7	Dense	32	ReLU
8	Dense	1	Linear

Table 4
Long Short-Term Memory (LSTM).

Layer Number	Layer type	Output Shape	Activation Function
1	LSTM	100	Hyperbolic Tangent
2	Dense	50	ReLU
3	Dense	10	ReLU
4	Dense	1	Linear

4. Building power demand prediction model

4.1. Data Pre-processing

Data pre-processing prepares the raw sensor data that might be incomplete, faulty, and unstable. This is a necessary step in ML to prepare data to be used to train and test the developed models. Data pre-processing is performed in five steps: (1) Imputation of missing values, (2) Data resolution processing, (3) Feature extraction, (4) Feature selection, and (5) Data transformation. The data preprocessing steps are discussed in detail in the case study section.

4.2. Model development

Four electricity demand prediction models are developed using various machine learning methods. These methods include: (1) Histogram-based gradient boosting (HistGB), (2) Random forest (RF), (3) Deep Artificial Neural Network (DNN), and (4) Long Short-Term Memory (LSTM). The parameters and architecture of these 6 models are shown in Table 1 to 4, respectively. The mathematical formulation of these algorithms are not discussed here as they can be found in machine learning resources [60–62]. It should be noted that the deep learning models are developed using Adam optimizer with loss function of mean squared error for 200 epochs. Moreover, machine learning models including Histogram-based gradient boosting and Random Forest are implemented using python programing language and scikit-learn library. Moreover, DNN and LSTM models are implemented using Keras interface for Tensorflow in python.

4.3. Predictive performance evaluation

Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) are used to evaluate the performance of the developed models. MAE is used as it reflects a uniform error over the dataset and provides a general insight over the performance of the Models. Similarly, MAPE is used as it provides a measure of relative error where error is measured with respect to magnitude of target value. Root Mean Square Error (RSME) is used as it is sensitive to the magnitude of errors where larger errors have a disproportionately large effect on calculated RSME value. MAE, MAPE, and RSME can be calculated based on true values y and predicted values $\hat{y}$ as shown in equation (1), equation (2), and equation (3), respectively.

$$\mathrm{MAE}(y,\hat{y}) = \frac{1}{N_t}\sum_{i=1}^{N_t}|y-\hat{y}| \tag{1}$$

$$MAPE = \frac{1}{N_t} - \sum_{i=1}^{N_t}\frac{|y-\hat{y}|}{y} \tag{2}$$

$$\mathrm{RSME}(y,\hat{y}) = \sqrt[2]{\sum\nolimits_{i=1}^{N_t}\frac{(y-\hat{y})^2}{N_t}} \tag{3}$$

where N_t is total number of samples in the test dataset, and $\bar{y}$ is average value of y_i.

5. Optimization model development

5.1. Decision variables

The optimization model integrates a set of decision variables that identify optimal schedule of charging and discharging EVs. To this end, a set of decision variables is designed to model charge and discharge power of EVs for each of time intervals in a day. To enhance the computational efficiency, possible charge and discharge power for EVs are considered as discrete values that are determined based on user specified increments. The above discrete values are referred to as EV power levels. To model the optimization problem in a linear form, all possible combination of power levels of EVs are generated. The power level combinations for EVs are designed as vectors EVP_n with length of M representing total number of EVs. The value of $EVP_n(m)$ corresponds to the power level of EV number m in combination number n. The possible power levels for each EV are designed to range from maximum discharging power (MDP) with negative sign to maximum charging power (MCP) with positive sign, where zero indicates no charge or discharge, as shown in equation (4). For example, considering 2 EVs with $MDP = -15kW$ and $MCP = 15kW$ and user specified increments 5 kW,

$m = 2$	$EVP_1(1) = -15$	$EVP_2(1) = -15$	$EVP_3(1) = -15$	$EVP_4(1) = -15$	$EVP_5(1) = -15$	...	$EVP_{45}(1) = 15$	$EVP_{46}(1) = 15$	$EVP_{47}(1) = 15$	$EVP_{48}(1) = 15$	$EVP_{49}(1) = 15$
	$EVP_1(2) = -15$	$EVP_2(2) = -10$	$EVP_3(2) = -5$	$EVP_4(2) = 0$	$EVP_5(2) = 5$	...	$EVP_{45}(2) = -5$	$EVP_{46}(2) = 0$	$EVP_{47}(2) = 5$	$EVP_{48}(2) = 10$	$EVP_{49}(2) = 15$

Fig. 2. Example for possible values of..$EVP_n(m)$

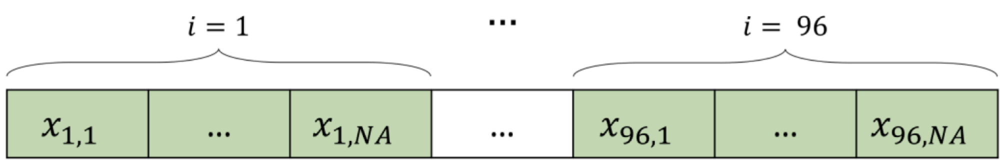

Fig. 3. Optimization model decision variables.

the model generates 49 (7 possible power level for EV number 1 × 7 possible power level for EV number 2) combination of power levels, as shown in Fig. 2. In the above example, $EVP_2(2) = -10\,kW$, $EVP_4(2) = 0\,kW$, and $EVP_{49}(2) = +15\,kW$ represent 10 kW discharge, no charge/discharge, and 15 kW charge for EV number 2 in combination 2, 4, and 49, respectively.

$$EVP_n(m) \in [MDP_m, \cdots, 0, \cdots, MCP_m] \tag{4}$$

The above EV power level combinations are modeled for each of the time intervals using $x_{i,n}$ which is a binary decision variable that represents the selection of power level combination alternative n for time interval i, as shown in Fig. 3. Decision variable $x_{i,n}$ is designed to range from the first combination alternative $x_{i,1}$ to alternative $x_{i,NA}$, representing the total number of alternatives NA for time interval i, as shown in Fig. 2. i is designed to range from, $i = 1$ to $i = 96$ representing the number of intervals with duration of 15 min in 24 h. For example, $x_{3,5} = 1$ represents the selection of the 5th power level alternative for the 3rd time interval.

5.2. Objective function

The objective function of the developed model is designed to minimize the variance of building power load. Minimizing the variance of building power load results in reducing the peak demand by shifting high power load to low power load intervals. Building power variance can be calculated by adding up the variance of power demand in all time intervals as shown in Eq. (5). The variance of power demand for interval i can be calculated based on building load and EV charge or discharge loads, as shown in Eq (6). It should be noted that building loads for all the time intervals are predicted using the machine learning component of the present system, including total power usage of fixtures and equipment in the building.

$$BPV = \sum_{i=1}^{96}\sum_{n=1}^{NA} V_{i,n} \times x_{i,n} \tag{5}$$

$$V_{i,n} = \left[BP_i + \sum_{m=1}^{M} EVP_n(m) - BP_{min}\right]^2 \tag{6}$$

where BPV is Building Power Variance; 96 is the number of intervals with duration of 15 min in 24 h; NA is total Number of Alternative combinations for EV power levels; $V_{i,n}$ is Variance of power demand for combination alternative n in time interval i; BP_i is building power load in time interval i; M is number of EVs; $EVP_n(m)$ is charge/discharge power load of EV number m in combination alternative n; and BP_{min} is minimum predicted power of building in the entire time intervals.

5.3. Optimization constraints

Six types of constraints are integrated in the model to ensure the feasibility of the generated solutions: (1) Alternative selection constraints; (2) EV absence constraints; (3) EV battery State of Charge (SOC) constraints; (4) Trips minimum battery SOC constraints; (5) Final SOC constraints; and (6) EV discharging constraints. The alternative selection constraints are designed to ensure that only one EV power level combination is selected for each of the time intervals, as shown in Eq (7). EV absence constraints are integrated in the model to ensure that the impact of EVs on building power load are set to zero when they are on trips and not available, as shown in Eq (8).

$$\sum_{n=1}^{NA} x_{i,n} = 1, \forall i = 1, \cdots, 96 \tag{7}$$

$$\sum_{n=1}^{NA} EVP_n(m) \times x_{i,n} = 0 \, if A_{m,i} = 0, \ \forall m = 1, \cdots, M, \quad \forall i = 1, \cdots, 96 \tag{8}$$

where $A_{m,i}$ is set to 1 if EV number m is available during time interval i; Otherwise, $A_{m,i}$ is set to 0.

EV battery SOC constraints are designed to ensure that the battery levels for each EV satisfy the minimum specified SOC level and maximum level of 100 in all time intervals, as shown in Eq (9).

$$MSOC_m \le ISOC_m - TRSOT_{m,I} + \sum_{i=1}^{I}\sum_{n=1}^{NA} \frac{EVP_n(m) \times D_i \times 100}{EVC_m} \times x_{i,n} \le 100$$

$$\forall m = 1, \cdots, M, \quad \forall I = 1, \cdots, 96 \tag{9}$$

where $MSOC_m$ is minimum specified SOC for EV number m; $ISOC_m$ is the initial SOC of EV number m; $TRSOT_{m,I}$ is total reduction in SOC of EV number m due to performed trips before time interval I; D_i is duration of time interval i in hours (15 min = 0.25 h); and EVC_m is the capacity of EV number m in kWh.

Minimum trips battery SOC constraints are integrated in the model to ensure that each of the EVs reserve the minimum level of SOC before each of their trips, as shown in Eq (10). Similarly, Final SOC constraints are integrated in the model to ensure that each of EVs are charged to achieve the specified minimum battery levels at the end of the last time interval.

$$MTSOC_m \le ISOC_m - TRSOT_{m,t} + \sum_{i=1}^{t-1}\sum_{n=1}^{NA} \frac{EVP_n(m) \times D_i \times 100}{EVC_m} \times x_{i,n} \tag{10}$$

$$FSOC_m \le ISOC_m - TRSOT_{m,96} + \sum_{i=1}^{96}\sum_{n=1}^{NA} \frac{EVP_n(m) \times D_i \times 100}{EVC_m} \times x_{i,n}$$

$$\forall m = 1, \cdots, M \tag{11}$$

where $MTSOC_m$ is minimum reserved SOC for EV number m before its trips; t is the time interval where EV trip starts; $TRSOT_{m,t}$ is total reduction in SOC of EV number m due to performed trips before time interval t; D_i is duration of time interval i in hours (15 min = 0.25 h); EVC_m is the capacity of EV number m in kWh. and $FSOC_m$ is minimum SOC for EV number m after the last time interval.

To generate practical solutions, EV discharging constraints are designed to limit the model to only allow discharging EVs for high demand intervals. The high demand power is calculated by subtracting the maximum power that EVs can supply for the building from maximum power demand of building, as shown in Eq (12).

$$0 \le \sum_{n=1}^{NA} EVP_n(m) \times x_{i,n} \ \text{if} \ \ BL_i < BL_{Max} - EVP_{Max} \ \ \forall i = 1, \cdots, 96 \tag{12}$$

where BL_{Max} is predicted maximum power demand of building; EVP_{Max}

Table 5
Statistical distributions of preprocessed features of submeter data.

Feature	Count	Mean	Standard Deviation	Min	25th Percentile	50th Percentile	75th Percentile	Max
Year	169,440	NA	NA	1	2	3	4	5
Month	169,440	NA	NA	1	3	6	9	12
Day index	169,440	NA	NA	1	8	16	23	31
Hour index	169,440	NA	NA	1	6.75	12.5	18.25	24
Interval index	169,440	NA	NA	1	24.75	48.5	72.25	96
Day of week index	169,440	NA	NA	1	2	4	6	7
Temperature (C)	169,440	12.34	11.03	−21.46	3.59	12.39	20.97	38.58
Building electricity power (kW)	169,440	49.59	32.37	15.51	22.99	38.05	68.56	204.9

is the maximum power that EVs can supply for the building.

5.4. Optimization computations

Binary linear programing is used to execute the computations of the developed optimization model due to its capability of identifying global optimum solutions in a short computational time. The model formulation is coded in MATLAB2019b and the model computations are executed using mixed integer linear programing (MILP) solver of Gurobi (GUROBI 2020).

6. Case study

A case study of multi-tenant commercial building is analyzed to evaluate the performance of the system, and demonstrate its new capabilities. The building was built in 1908 and was primarily used as a warehouse until it was renovated and converted to office spaces in the 1970 s. In 2004, the building underwent renovation to improve its energy performance and convert into a multi-tenant commercial space, and a second major energy renovation was carried out in 2014 to further upgrade the building. The upgrades in 2014 include reconfiguration of interior spaces, R-32 roof insulation, energy-efficient LED interior lighting fixtures with occupancy sensors, DX cooling with supply air temperature reset and dual temperature economizer, and demand-controlled ventilation via variable air volume (VAV) boxes. The building has a floor area of 41,000 square feet with six-story brick structure. Moreover, the building has a high visitation rate of approximately over 17,000 annual visitors. The bidirectional chargers were installed in May 2021 to store electricity in EVs during low demand time and discharge electricity into the building during peak time. In this case study, EVs are parked in the building's parking lot and are used for carshare trips.

Electricity submeter data of the building is used to predict the day-ahead electricity demand profile of the building. The electricity submeter data is collected from Building Management System (BMS) that is used to control and monitor the building fixtures and equipment including lighting systems, power systems, and HVAC systems. The submeter data collection is performed in two steps: (1) data collection from sensors/meters, and (2) data transmission and storage through the sensor network and database. The dataset used in the present study is a time series consisting of 2,541,600 records that capture electricity consumption, temperature, wind speed, and solar radiation measurements. These measurements are recorded at one-minute intervals with corresponding timestamps between January 2017 and October 2021. However, 60,480 (2.38 %) of the timestamps had null values due to network connection errors, data transmission, and sensor faults. To ensure consistency and continuity of the records for machine learning model development, forward fill imputation method is used to impute the missing values. In this method, missing values of each timestamp are imputed using the most recent known value before the missing value. To prepare the data for peak electricity demand prediction, the one-minute interval data is aggregated to a 15-minute resolution, resulting in 169,440 records. After aggregating the data to a 15-minute resolution, feature extraction is performed to transform the timestamps into six distinct columns, including year index (ranging from 1 to 5), month index (ranging from 1 to 12), day index (ranging from 1 to 31), hour index (ranging from 1 to 24), and time index in 15-minute intervals (ranging from 1 to 96). Additionally, a Boolean feature indicating business days is added to the database using the federal holiday calendar. Next, feature selection is performed using the entropy-based mutual information method discussed in a former publication by the authors

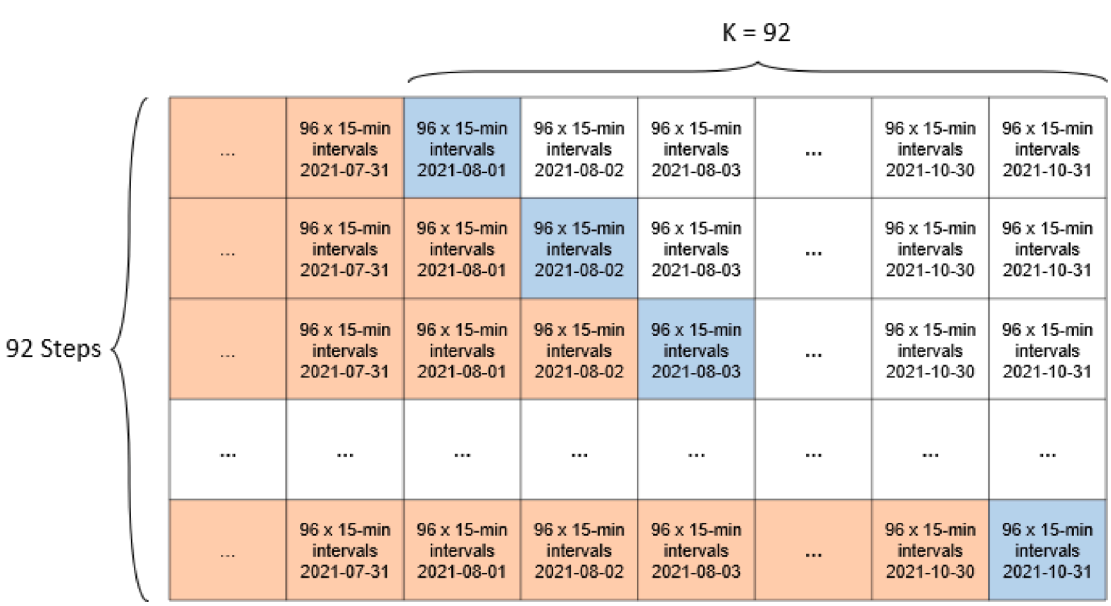

Fig. 4. Time-sensitive cross-validation.

Table 6
Comparison of predictions using various performance metrics.

Method	Aug 2021			Sep 2021			Oct 2021			Average		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
HistGB	14.41	18.93	39.40 %	12.7	16.35	38.11 %	16.69	21.77	52.27 %	14.6	19.02	43.26 %
RF	13.77	18.42	37.57 %	12.14	16.19	36.97 %	16.05	21.23	49.36 %	13.99	18.61	41.30 %
DNN	12.48	18.29	34.50 %	12.07	15.87	33.25 %	14.91	20.48	43.42 %	13.15	18.21	36.06 %
LSTM	5.84	17.71	17.63 %	8.03	15.81	21.37 %	8.46	19.83	21.23 %	7.44	17.78	20.08 %

[37]. The analysis indicates that time index, hour index, temperature, month index, year index, day index, and business days had the highest influence on electricity demand, with mutual information values of 0.25, 0.25, 0.19, 0.13, 0.11, 0.089, and 0.07, respectively. These features are used to predict the day-ahead electricity demand profile of the buildings. Finally, data normalization is applied for numerical features to enhance the predictive performance of the developed models. The statistical distributions of the preprocessed features are presented in Table 5.

A time-sensitive cross-validation method known as "Rolling Window" is used to evaluate the performance of the developed models. In this method, there are K number of consecutive series of test sets, each consisting of 96 observations for 15-minute intervals during a day, as shown in blue color in Fig. 4. The corresponding training set consists of observations that occur prior to the test set observations, as shown in orange color in Fig. 4. For example, the electricity demand profile for August 1st is predicted based on training dataset of time intervals from the beginning of the available data on January 1st, 2017 to July 31st, 2021. The same process is repeated for each subsequent day in August, September, and October 2021. In total, the process of training and testing the ML models is performed for $K = 92$ steps representing all days in August, September, and October 2021 using the above training and testing datasets, as shown in Fig. 4. Predictive performance evaluation metrics including MAE, MAPE, and RSME are computed using averages over the test sets for each month, as shown in Table 6. This validation method is used as it provides a distribution of errors for a given model on different parts of the dataset.

To avoid overfitting the data, the training and validation loss of all models are visualized for all models in August, September, and October 2021, as shown in Appendix A. The results show a consistent improvement in model performance over time, with a decreasing trend in the mean squared error loss for all models, suggesting the models have not been overfit to the data.

The model results show that LSTM outperforms other methods, including Histogram-based Gradient Boosting, Random Forest, and DNN due to its specialized architecture designed for time series data. The LSTM method show an average MAE of 7.44, an average RSME of 17.78, and an average MAPE of 20.08 %. Furthermore, MAE metrics for the LSTM model are calculated at 5.84, 8.03, and 8.46 for August, September, and October 2021, respectively. These MAE values, as shown in Table 6, indicate that LSTM has the lowest prediction uniform error over the dataset compared to other methods. Similarly, the RSME metrics for the LSTM model are calculated at 17.71, 15.81, and 19.83 for August, September, and October 2021, respectively. These RSME metrics show that LSTM has the best performance with respect to the magnitude of errors. Finally, MAPE metrics for the LSTM model are calculated at 17.63 %, 21.37 %, and 21.23 % for August, September, and October 2021, respectively. These MAPE values, as shown in Table 6, indicate that LSTM has the lowest relative error with respect to the magnitude of target values. The key difference between LSTM and the aforementioned models is the presence of a memory cell in its architecture. LSTM has three gating mechanisms responsible for controlling the flow of information into and out of the memory cell. These gating mechanisms include the forget gate, determining which information to discard from the previous time step; input gate, determining which information from the current time step should be added to the memory cell; and output gate, determining which information from the memory cell should be outputted to the next time step. The gating mechanism in LSTM enables the model to selectively remember or forget information from previous time steps, which enables the model to capture changing trends in the data. This is particularly important for electricity demand prediction, where external factors such as weather and occupancy trends can affect the demand pattern over time. Furthermore, LSTM is demonstrated to perform well in handling long-term dependencies, which is crucial for accurately predicting a building's electricity demand over an extended period. These advantages make LSTM well-suited for predicting electricity demand based on time series historical data. Comparison of predictions by developed ML models verses actual building electricity demand profile for the days of peak demand for August, September, and October 2021, are show in Fig. 5, Fig. 6, and

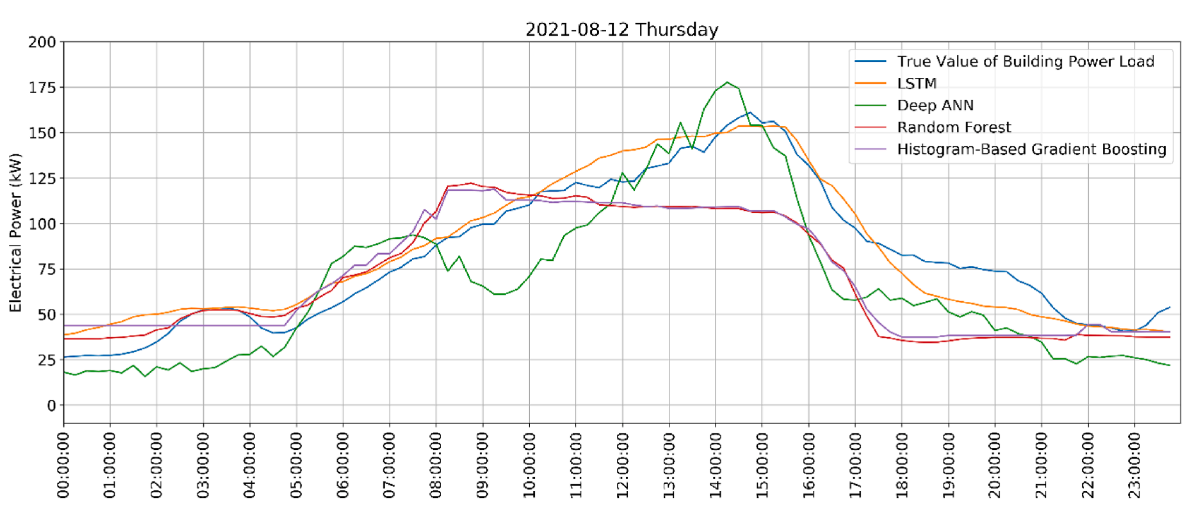

Fig. 5. ML models predictions vs true building electricity demand profile for peak day of August.

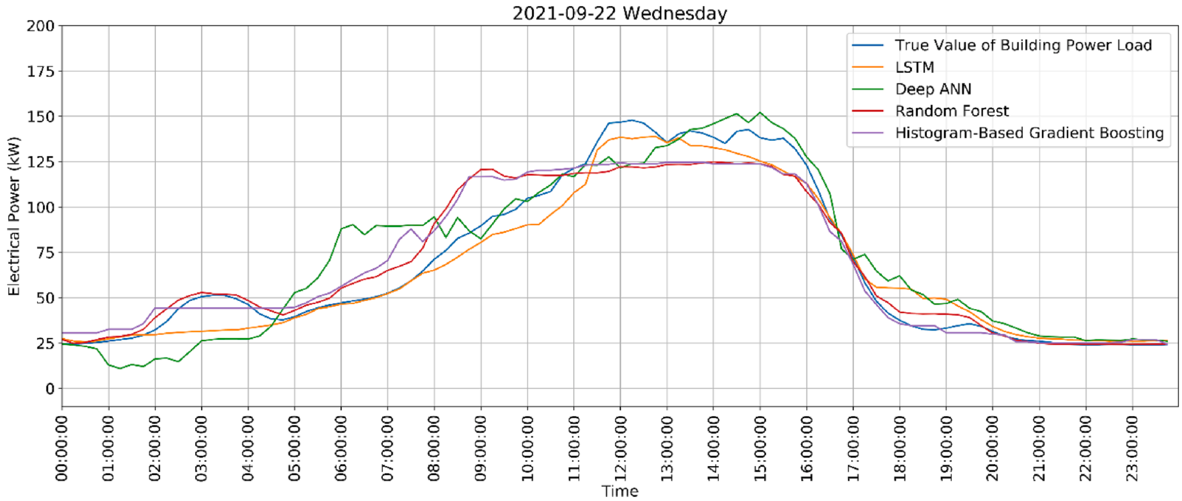

Fig. 6. ML models predictions vs true building electricity demand profile for peak day of September.

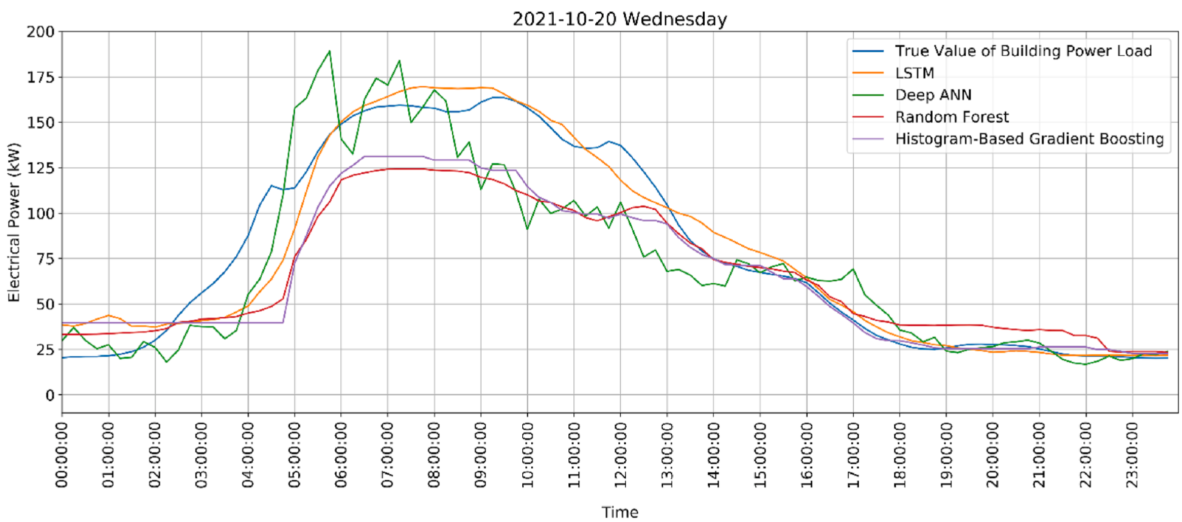

Fig. 7. Models predictions vs true building electricity demand profile for peak day ofOctober.

Table 7
Specifications of EVs and Stationary Battery.

Device	Battery Capacity (kWh)	Minimum SOC	Maximum Battery Power (kW)
EV no. 1	62	0.12	15
EV no. 2	62	0.12	15
Stationary Battery	82	0.12	10

Fig. 7, respectively. Based on the performance metrics, LSTM method is selected to predict the day ahead building electricity demand profile in the system.

The demand management optimization model is used to identify optimum schedule of charging and discharging EVs to minimize electricity peak demand for August, September, and October 2021. To identify optimum schedule of charging and discharging EVs, required data for the demand management model are collected. The demand management input data include: (i) predictions of day ahead electricity demand profile of the building using LSTM model; (ii) EV battery specification such as capacity, minimum SOC, minimum SOC before trips, and maximum power; and (iii) trips schedule along with their anticipated electricity consumption for each of EVs. Five scenarios including (1) one EV; (2) one EV and one Stationary Battery (SB); (3) two EVs; (4) two EVs and one SB; and (5) two EVs, one SB, and a Photovoltaic (PV) system are investigated. Scenarios including the SB and PV system are considered to evaluate the full potential of peak demand reduction in the case study building. SBs can be modeled similar to EVs with the difference that they have no trips and are available at all times. Maximum capacity of the PV system is calculated at 40 kW based on the available roof area. Battery capacity, minimum SOC, and maximum battery power for each of the EVs and SB are inputted in the model based on specifications of EVs and SB, as shown in Table 7. It should be noted that user specified minimum SOC before trips for all EVs is assumed 70 %.

The model identified the optimum schedule of charging and discharging EVs to minimize peak demand for all the specified scenarios and billing cycles, as shown in Table 8. For example, the model identified optimum charge and discharge schedule of EVs to achieve minimum peak demand of 146.12, 136.12, 132.89, 124.87, and 102.33 with peak demand reduction of 9.3 %, 15.5 %, 17.5 %, 22.5 %, and 36.5 % for scenarios 1 to 5 in August, respectively. It should be noted that optimum EV charge and discharge schedules are identified based on day ahead electricity demand predictions. The identified optimum charge and discharge schedules are then applied on the actual building electricity demand profile (true values) to identify peak demand reductions and

Table 8
Peak Demand Reduction and Savings Based on Results of the Present Model for Aug, Sep, and Oct 2021.

Invoice Month	Billing Cycle	Effective Demand charge ($/kW)	Scenario Number	Scenario Description	Demand (kW)	Peak Demand Reduction (kW)	Peak Demand Reduction (%)	Demand Charges	Savings
August	08/09/ 2021 09/08/ 2021	$21.89	1	One EV	146.12	15	9.3 %	$3,198.57	$328.35
			2	One EV and One SB	136.22	25	15.5 %	$2,979.67	$547.25
			3	Two EVs	132.89	28.23	17.5 %	$2,908.96	$617.95
			4	Two EVs and One SB	124.87	36.25	22.5 %	$2,733.40	$793.51
			5	Two EVs, One SB, and PV System	102.33	58.79	36.5 %	$2,240.00	$1,286.91
September	09/09/ 2021 10/07/ 2021	$22.04	1	One EV	133.12	14.77	10.0 %	$2,933.96	$325.53
			2	One EV and One SB	127.88	19.91	13.5 %	$2,818.48	$438.82
			3	Two EVs	125.32	22.47	15.2 %	$2,762.05	$495.24
			4	Two EVs and One SB	116.63	31.16	21.1 %	$2,570.53	$686.77
			5	Two EVs, One SB, and PV System	110.43	37.36	25.3 %	$2,433.88	$823.41
October	10/7/ 2021 01/5/ 2021	$17.50	1	One EV	148.49	15	9.2 %	$2,598.58	$262.50
			2	One EV and One SB	144.1	19.39	11.9 %	$2,521.75	$339.33
			3	Two EVs	141.21	22.28	13.6 %	$2,471.18	$354.90
			4	Two EVs and One SB	129.46	34.03	20.8 %	$2,265.55	$595.53
			5	Two EVs, One SB, and PV System	129.46	34.03	24.3 %	$2,163.96	$697.11

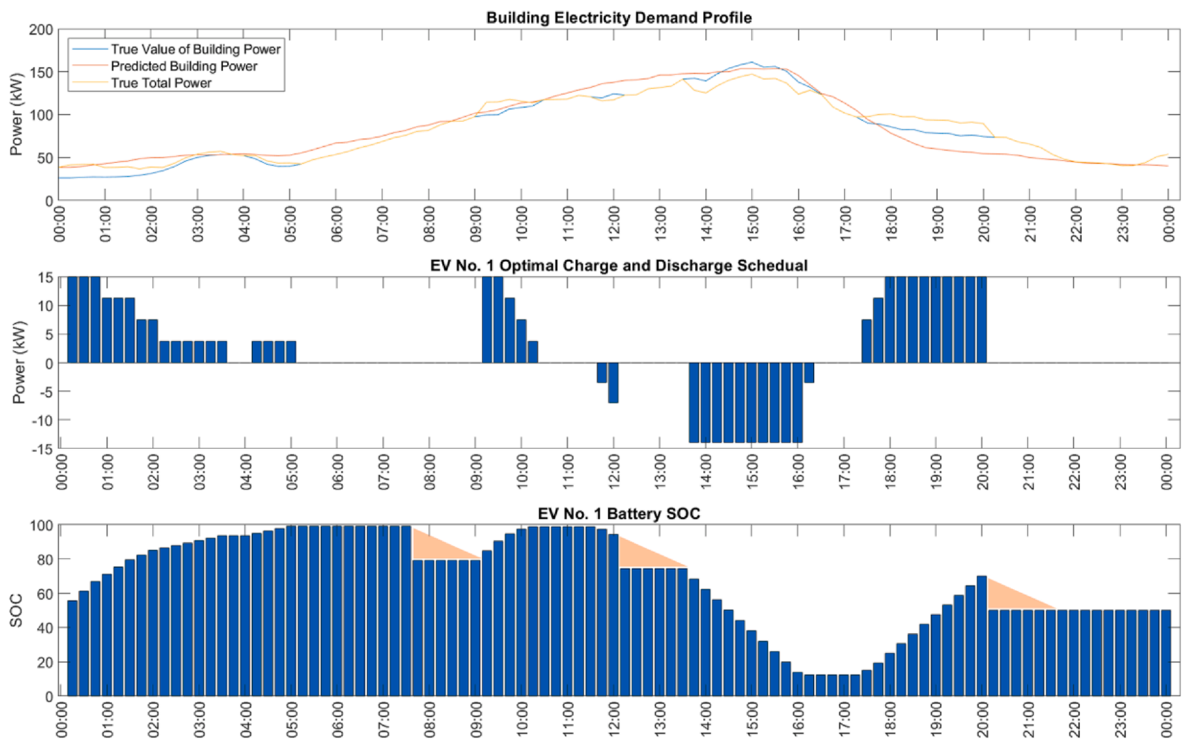

Fig. 8. Electricity demand profiles, optimal charge/discharge schedule of EVs and their SOC for scenario 1 for peak day of August 2021 (2021/08/12).

savings, as shown in Table 8. Moreover, the PV system effect on the building electricity profile is not considered in the optimization model due to uncertainty of PV power production. However, the electricity production profile of PV system is considered in calculation of actual savings for scenario 5 based on Photovoltaic Data Acquisition (PVDAQ) datasets [63].

The model is designed to generate detailed charts, including (i) Electricity demand profile before and after implementation of V2B; (ii) optimal charge and discharge of EVs and SBs in each time interval; and (iii) SOC of EVs and SBs in each time interval. For example, the model was able to identify the optimal charge and discharge schedule for Scenario 1, one EV, in August to minimize peak electricity demand, as shown in Fig. 8. On the peak day of August 2021, the EV had 3 pre-scheduled trips from 7:30am to 9:00am, 12:00pm to 1:30pm, and 8:00pm to 9:30pm. The model identified optimal charging times during the low demand periods from 12:00am to 5:00am to store electricity for the first scheduled trip, and then from 9:00am to 10:30am to store electricity for the second trip and peak shaving. The model identified the optimal discharging time from 1:45pm to 4:15pm to minimize peak demand using the battery capacity of EV. It should be noted that the model did not exceed the minimum 12 % SOC of the EV to comply with minimum SOC constraint. Furthermore, the model identified EV charging from 5:30pm to 8:15pm to reach the 75 % SOC before the last trip of the day, as shown in Fig. 8. Similarly, the model identified optimal schedule for charging and discharging EV for Scenarios 2 to 5, as shown in Figs. 9–12. The optimization computations are performed on a personal computer with Intel Core i7-10510U M, CPU 2.3 GHz processor, and 8 GB RAM. The optimization problems computations for each day of above scenarios are executed averagely in 8 s.

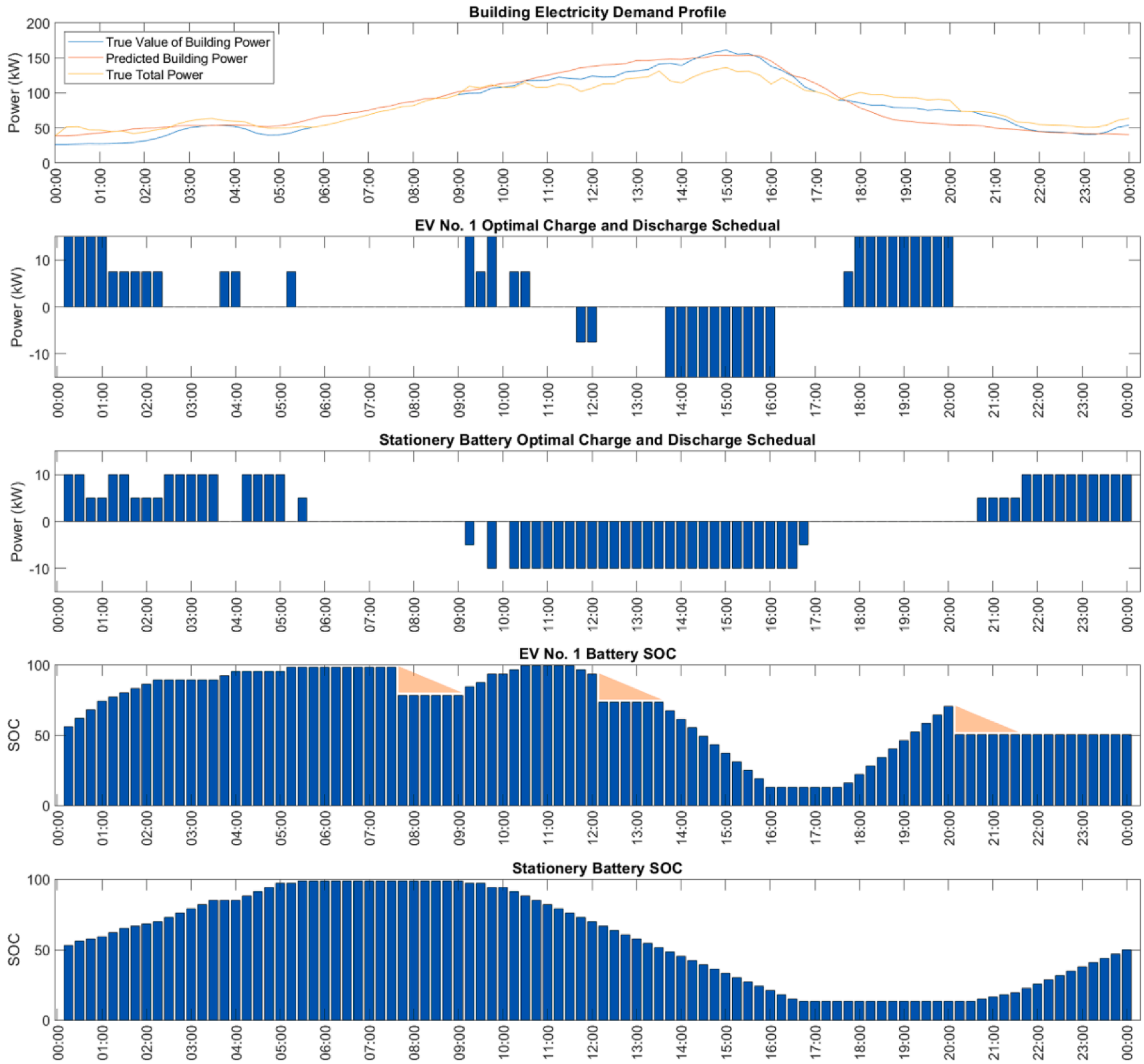

Fig. 9. Electricity demand profiles, optimal charge/discharge schedule of EVs and their SOC for scenario 2 for peak day of August 2021 (2021/08/12).

7. Discussion

This paper presents the development of a novel system that is capable of predicting building electricity demand profile and identifying optimum schedule of charging and discharging EVs to minimize electricity peak demand. The conventional method for V2B peak shaving involves setting a threshold for peak electricity demand, which prompts the discharging of EV batteries. When the power demand exceeds the specified threshold, electricity from EVs is discharged into building to reduce peak energy demand. However, conventional method may not offer the maximum energy savings as EVs might not be available during peak demand periods, or they might not have sufficient battery energy to shave peak electricity demand. For example, the implementation of the conventional method in the case study building for one EV resulted in peak demand reduction of 9.3 %, 3.2 %, and 8.9 % in August, September, and October 2021, respectively, as shown in Appendix B - Table B.1. However, the optimization model in scenario 1 achieved peak demand reduction of 9.3 %, 10 %, and 9.2 % in August, September, and October 2021, respectively. Although the results indicate that the conventional method achieved similar savings in August and October, it achieved lower savings in September due to insufficient battery SOC in the peak demand day. Moreover, additional scenarios including the 2 EVs, SB, and PV system are investigated to evaluate further reduction in peak energy demand. For two EVs scenario, the building can achieve up to 17.5 % peak demand reduction. Moreover, peak energy demand can be reduced even more effectively when stationary batteries and PV systems are combined with V2B. For two EVs, two stationary batteries, and PV system, the building can achieve up to 36.5 % reduction in peak energy demand, resulting in energy cost saving of $1286.91 in August.

The present system integrates machine learning and optimization algorithm that can provide decision makers with an effective tool reducing their electricity peak demand and associated costs. The prediction model can identify days where peak demands are likely to occur and schedule the charging and discharging of EVs to minimize energy cost. In a broader perspective, the wide adoption and utilization of V2B by commercial buildings can help utilities better balance energy supply and demand on the grid. The timing imbalance between peak and off-peak demand has worsened over the last decade as solar energy is increasingly incorporated to the grid. Addressing this timing imbalance in energy load is crucial for reducing fossil-fuel based energy generation and solar curtailment, resulting lower carbon emissions. To promote the adoption and utilization of V2B, credits and tax rebates on off-peak energy consumption can be considered. When tax credits and incentives are offered, the overall savings from V2B can increase to as much as 2.83 times on average [61]. However, the wide adoption and utilization of V2B may require more efforts and investment in grid

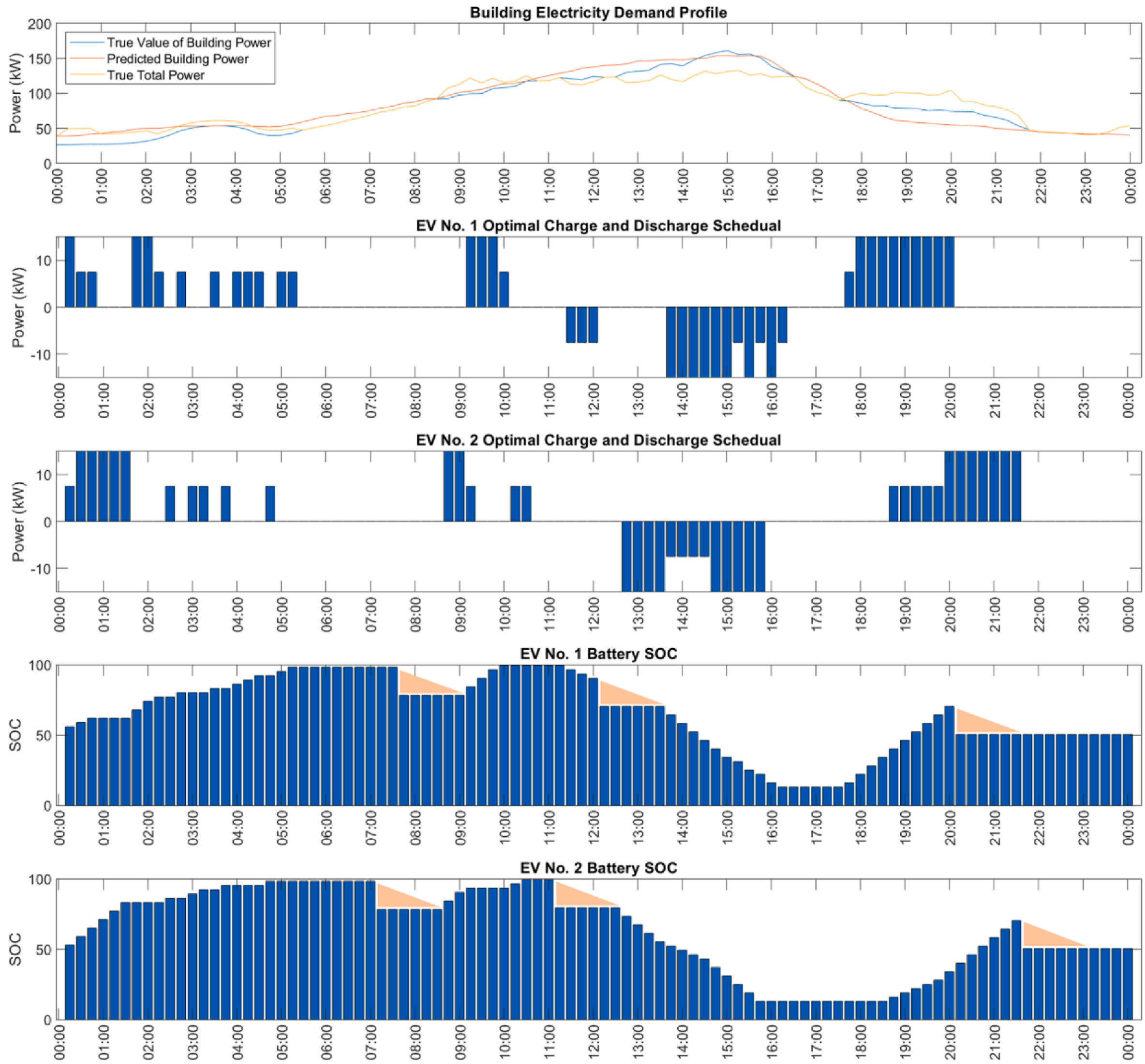

Fig. 10. Electricity demand profiles, optimal charge/discharge schedule of EVs and their SOC for scenario 3 for peak day of August 2021 (2021/08/12).

modernization and transformer upgrades to support V2B. This need for grid investment may raise concerns over cross-subsidization and inequitable distribution of costs and benefits associated with V2B. The benefits of V2B are more concentrated on the V2B users, while the costs associated with grid modernization and upgrades are likely to be dispersed among utility consumers. EV charging rates and V2B compensation rates should be determined under the consideration of the impacts of V2B on social equity, cross subsidization, and technology transfer over time. Coupling EV/V2B rates with building peak demand management strategies, such as demand rating and mandatory power factor correlation [62], could be a way to reflect the future grid upgrade costs associated with the increased loads from EVs.

8. Summary and conclusions

This paper presents the development of a novel system that is capable of predicting day-ahead building electricity demand profile to identify optimum schedule of charging and discharging EVs to minimize electricity peak demand. The system consists of (1) machine learning model to predict electrical power demand of existing commercial buildings based on building and weather data, and (2) demand management optimization model to identify optimal schedules for charging and discharging of EVs. The building power demand prediction model is developed in three main steps, including data preprocessing where data is cleaned and prepared; model training where different ML models are trained; and performance evaluation where the developed ML models are evaluated using various criteria. The demand management is developed in three main steps, including identifying decision variables; formulating objective function and constrains; and implementing optimization computations. The demand management is designed to integrate a number of constraints to comply with EVs trip schedules and battery level requirements. Machine Learning methods are selected to predict electrical power demand of existing commercial buildings due to their capability of predicting non-stationary and nonlinear time series data with high accuracy. Binary linear programing is used to execute the computations of the developed optimization model due to its capability of identifying global optimum solutions in a short computational time. A case study of multi-tenant commercial building is analyzed to evaluate the performance of the model and demonstrate its new capabilities. Four power demand prediction models are developed using histogram-based gradient boosting, random forest, deep artificial neural network, and long short-term memory (LSTM), based on historic submeter data from the case study building. Based on the model results, LSTM show the best performance in terms of mean absolute error, root mean square error, and mean absolute percentage error with average values of 7.44, 0.20, and 17.78, respectively. The case study results demonstrated the

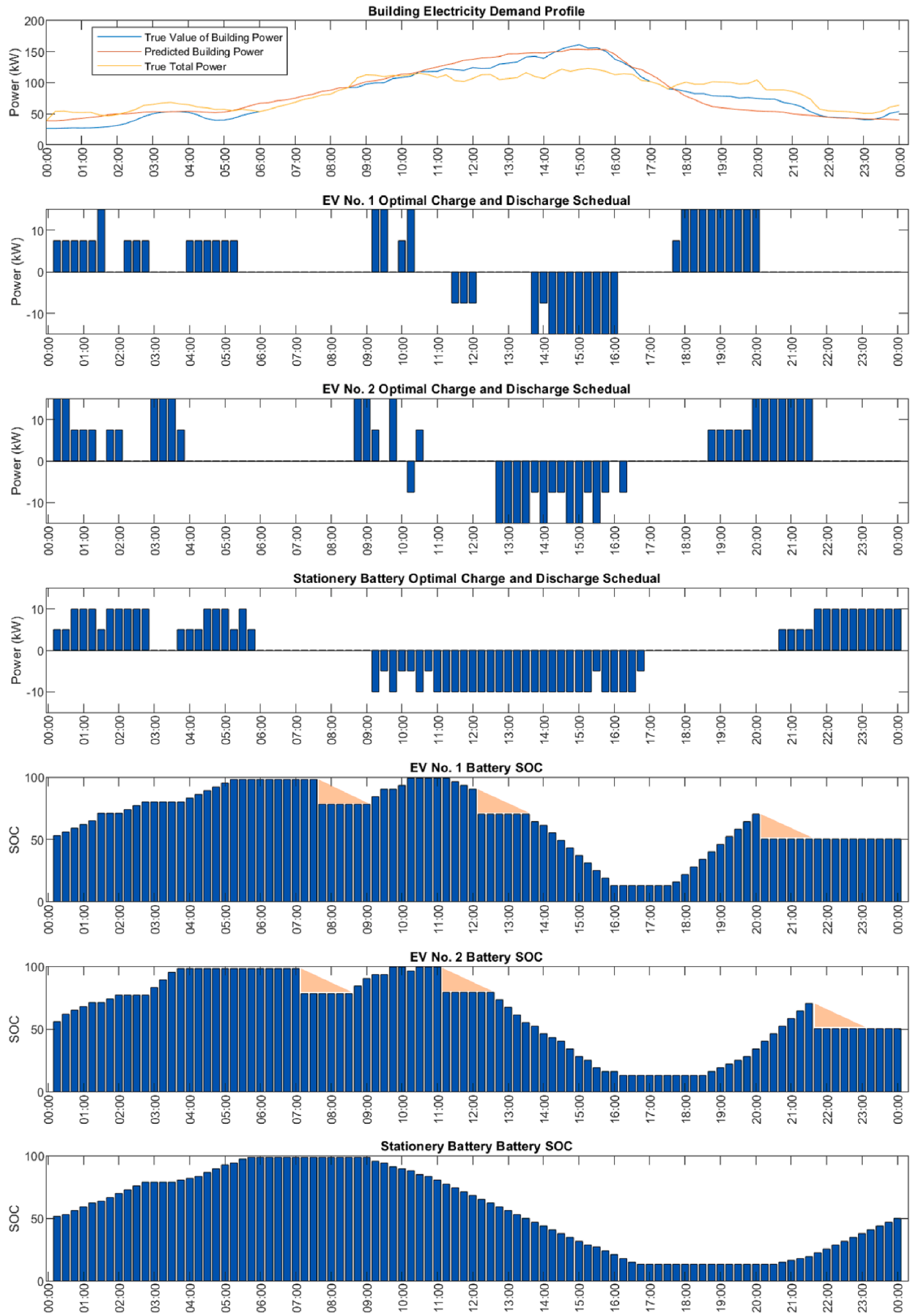

Fig. 11. Electricity demand profiles, optimal charge/discharge schedule of EVs and their SOC for scenario 4 for peak day of August 2021 (2021/08/12).

capability of the demand management model in identifying optimum schedule of charging and discharging EVs to minimize the peak demand for all the specified scenarios and billing periods. The results of the demand management optimization model showed up to 36 % reduction in peak demand using two EVs, one stationary battery, and implementation of PV system with size of 40 kW.

The novel system presented in this paper offers a practical solution to the challenges of managing peak electricity demand in commercial buildings using EVs. The present system enables building managers to identify peak demand periods and schedule the charging and discharging of EVs to ensure that they have sufficient charge for peak shaving during peak times. The system surpasses the capabilities and savings of conventional V2B system that relies on a pre-determined threshold for charging and discharging EVs. If the system is fully integrated with bidirectional chargers, commercial buildings can achieve higher peak demand reductions overall, especially when EVs are constrained by planned trips and specified minimum SOC. Ultimately, the present approach has the potential to enhance the adoption of V2B systems by

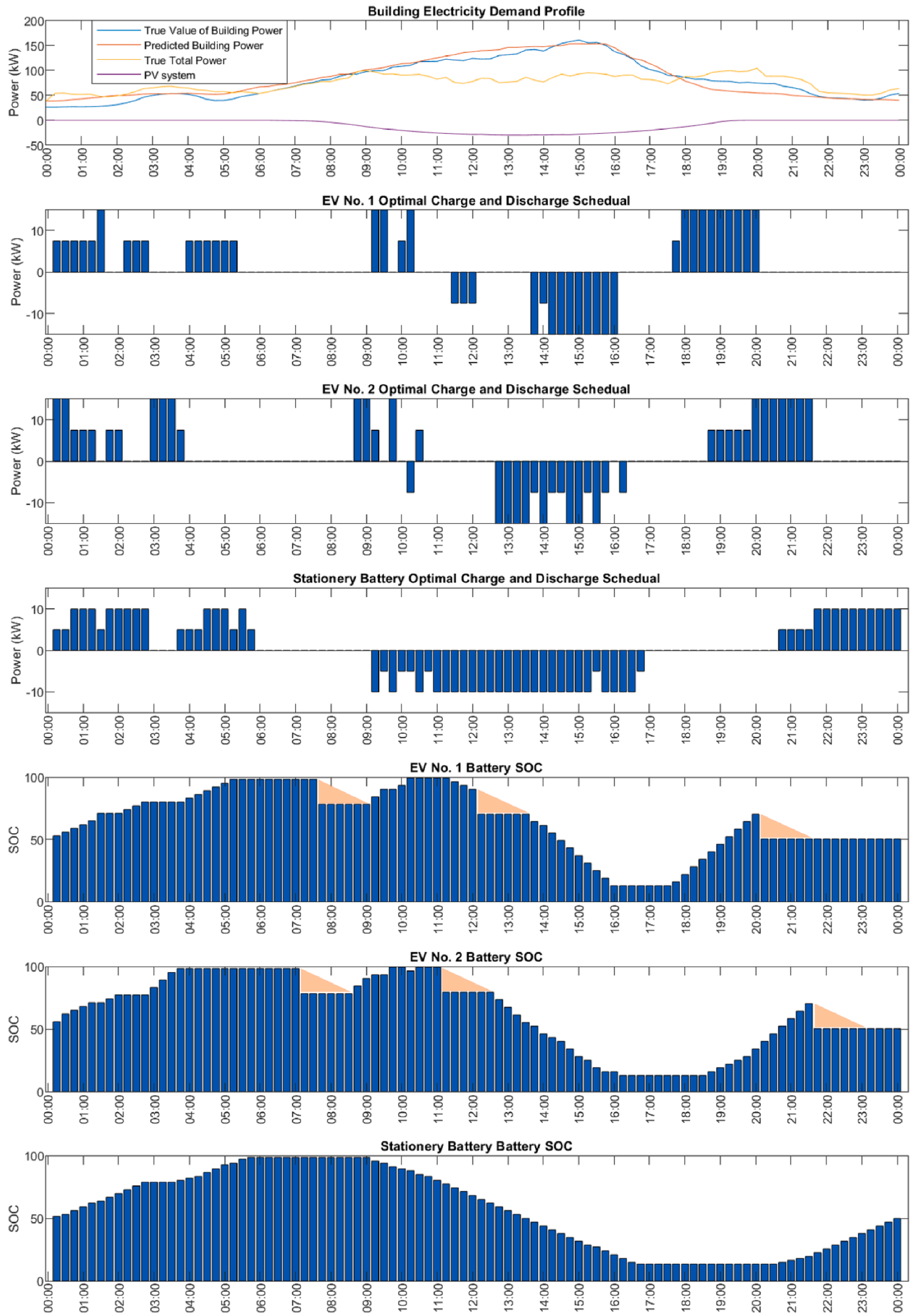

Fig. 12. Electricity demand profiles, optimal charge/discharge schedule of EVs and their SOC for scenario 5 for peak day of August 2021 (2021/08/12).

improving their ability to minimize energy cost of building through the use of EVs.

CRediT authorship contribution statement

Mahdi Ghafoori: Conceptualization, Methodology, Software, Validation, Visualization, Writing – original draft. **Moatassem Abdallah:** Supervision, Conceptualization, Methodology, Validation, Writing – review & editing. **Serena Kim:** Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Moatassem Abdallah reports a relationship with University of Colorado Denver that includes: employment.

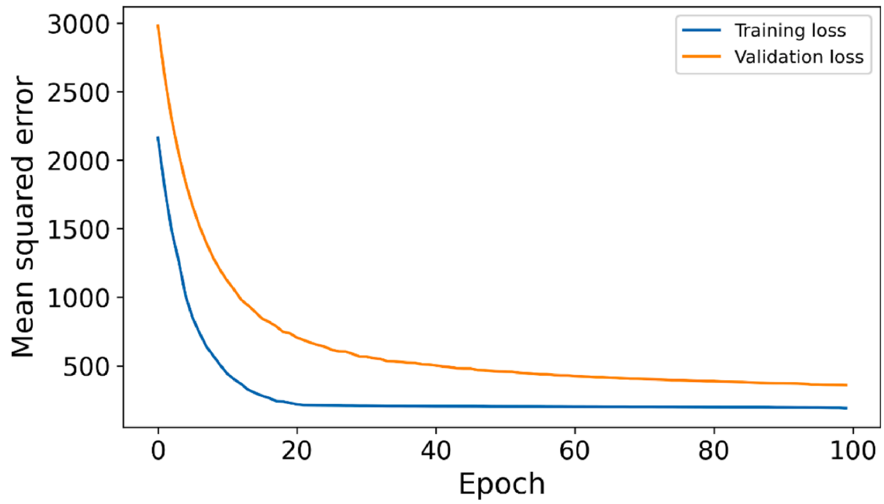

Fig. A1. Training and Validation Loss of the HistGB Model for August 2021.

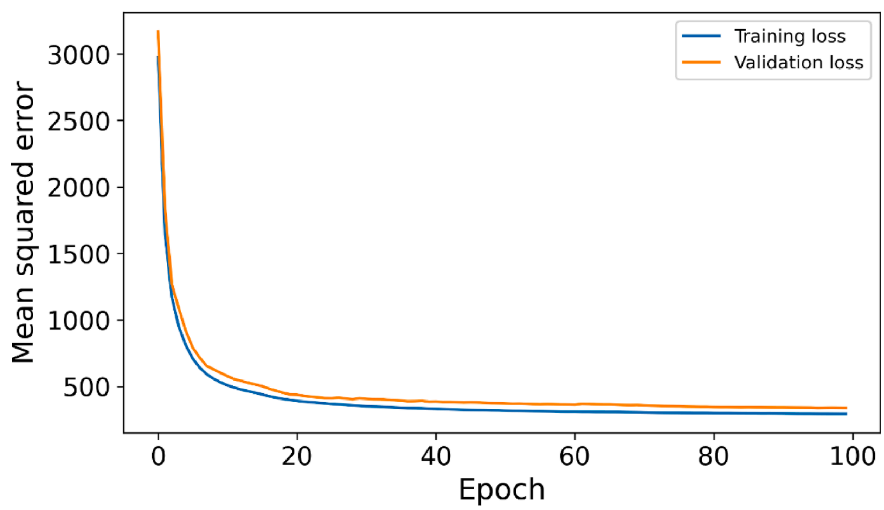

Fig. A2. Training and Validation Loss of the RF Model for August 2021.

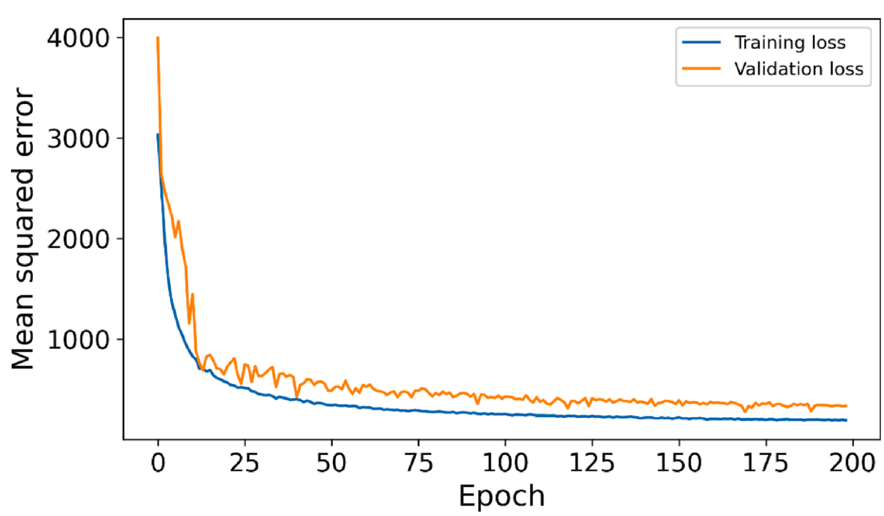

Fig. A3. Training and Validation Loss of the DNN Model for August 2021.

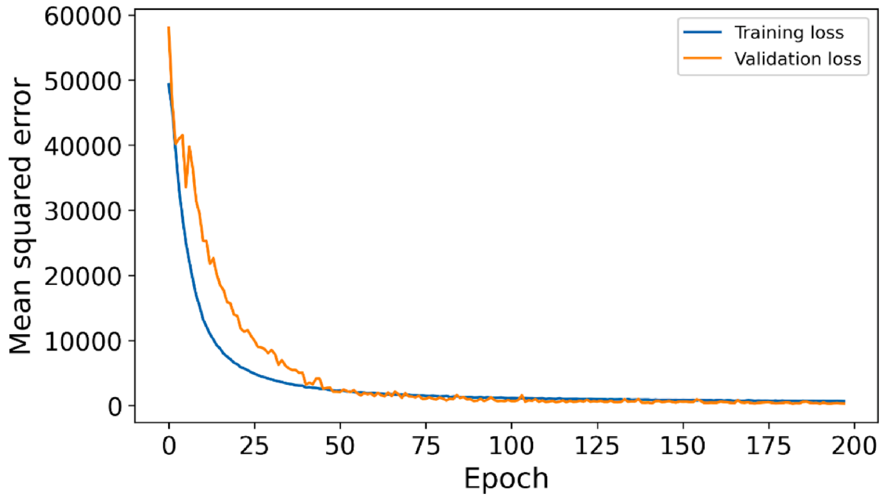

Fig. A4. Training and Validation Loss of the LSTM Model for August 2021.

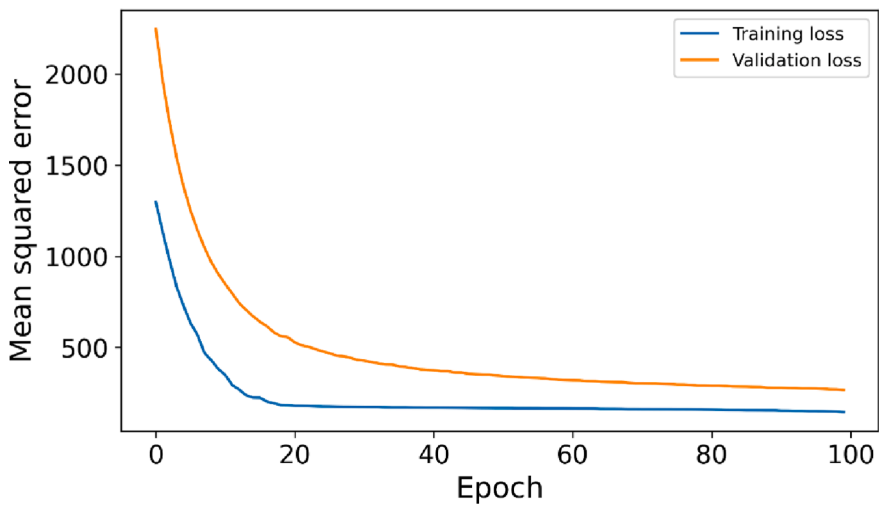

Fig. A5. Training and Validation Loss of the HistGB Model for September 2021.

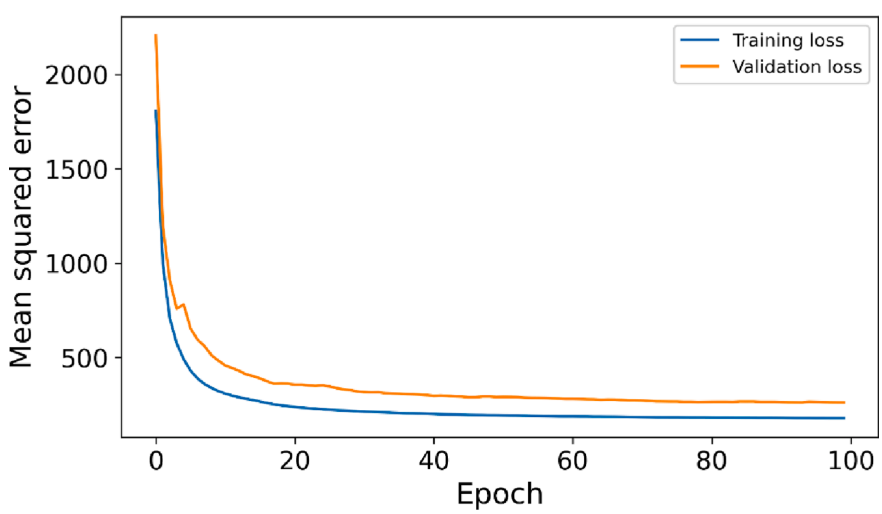

Fig. A6. Training and Validation Loss of the RF Model for September 2021.

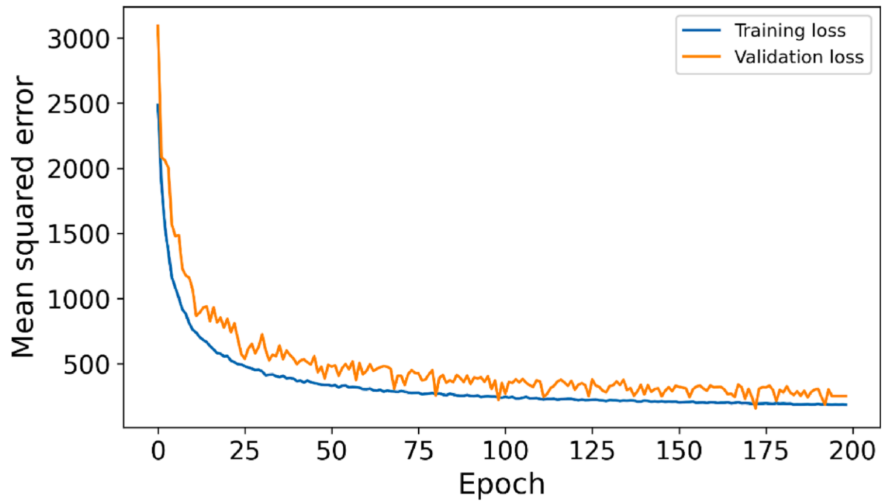

Fig. A7. Training and Validation Loss of the DNN Model for September 2021.

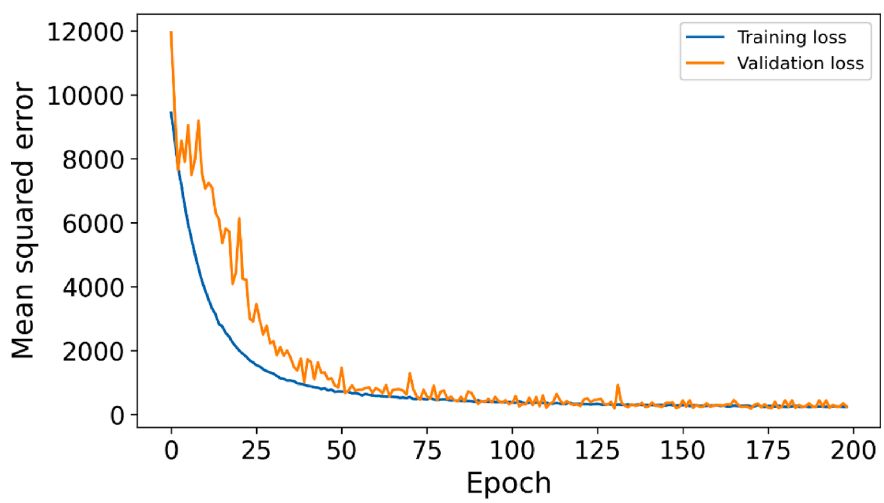

Fig. A8. Training and Validation Loss of the LSTM Model for September 2021.

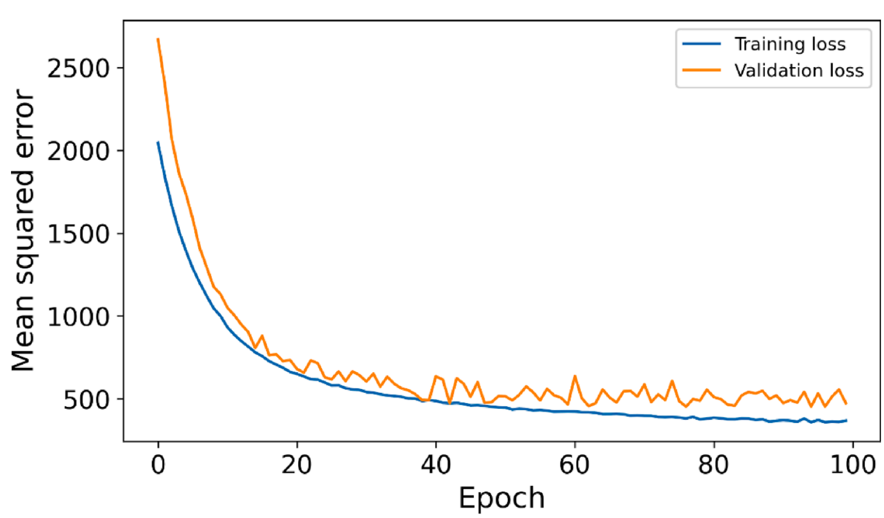

Fig. A9. Training and Validation Loss of the HistGB Model for October 2021.

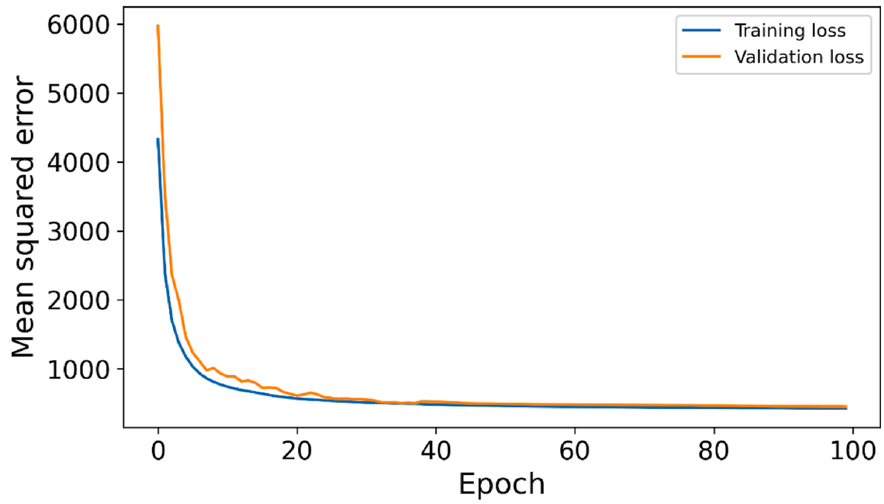

Fig. A10. Training and Validation Loss of the RF Model for October 2021.

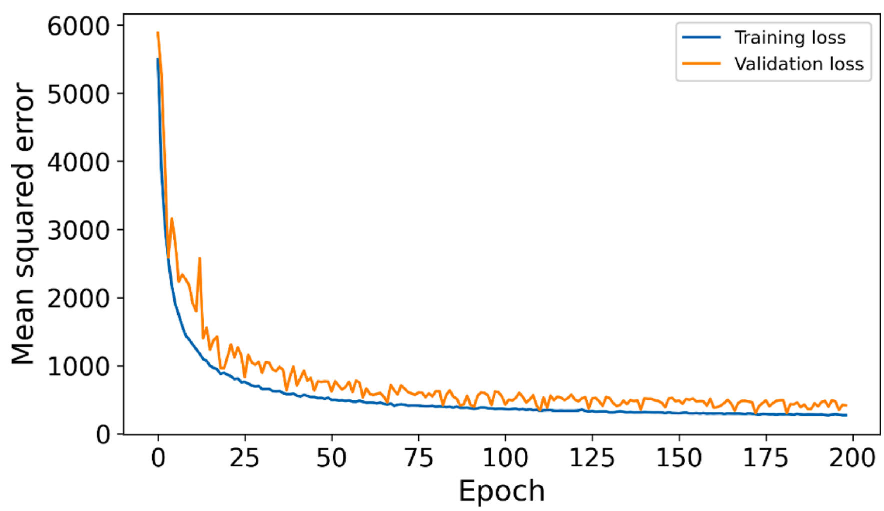

Fig. A11. Training and Validation Loss of the DNN Model for October 2021.

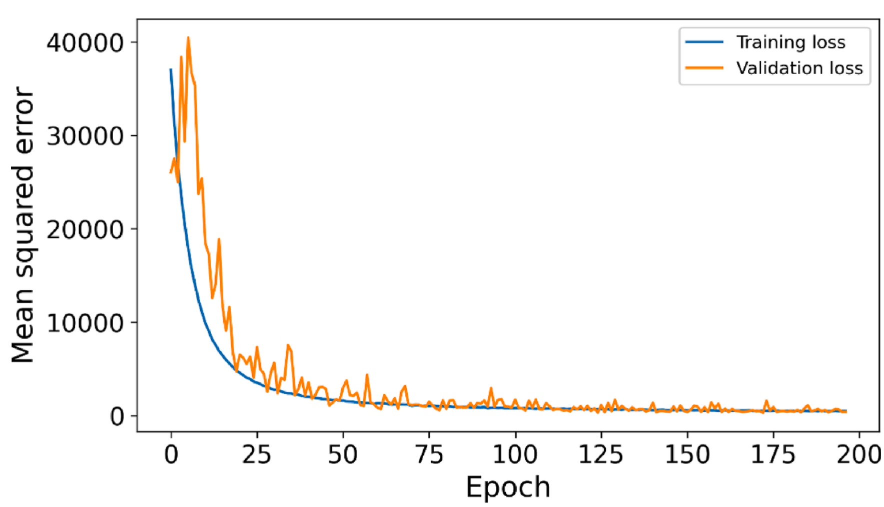

Fig. A12. Training and Validation Loss of the LSTM Model for October 2021.

Table B1
Recorded Peak Demand Reduction and Savings for Conventional Method.

Start Date	End Date	Invoice Month	Effective $/kW	Demand by the Utility Company (kW)	Demand Charges	Total Energy Cost	Peak Demand Reduction (kW)	Peak Demand Reduction (%)	Total Savings
8/9/2021	9/8/2021	August	21.89	146	$3,199	$5,372.60	15	9.3 %	$328.35
9/9/2021	10/7/2021	September	22.04	143	$3,154	$4,982.26	4.8	3.2 %	$105.79
10/7/2021	11/5/2021	October	17.5	149	$2,607	$4,714.23	14.5	8.9 %	$253.75

Data availability

The data that has been used is confidential.

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Appendix A

The training and validation loss of the four models are visualized, as shown in Figs. A.1 to A.4 for August, Figs. A.5 to A.8 for September, and Figs. A.9 to A.12 for October 2021.

Appendix B

The reported demand, demand charges, energy cost, peak demand reduction, and total savings of the conventional method for billing periods of August, September, and October 2021 are shown in Table B.1.

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