Application of machine learning and deep learning methods for load prediction in institutional buildings

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Abstract

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Sahar Javadian

Worldwide, the building sector consumes a significant amount of energy in different stages such as construction and operation. Depending on the type of energy source used, buildings have a considerable impact on air pollution and greenhouse gas emissions. To reduce the amount of emissions from the building sector and manage energy consumption, many tools and incentives are used around the world. One of the most recent and successful approaches in this regard is the application of machine learning techniques in building engineering. The increasing availability of real-time data measured by sensors and building automation systems enable the owner and energy planner to analyze the collected information and explore the hidden useful knowledge and use it to answer specific questions such as which parts need retrofit, how much energy can be saved and what would be the cost. At the building level, machine learning has different applications, such as pattern extraction and load prediction. Amongst those, load analysis and energy demand prediction are of specific importance for the building energy managers, as it can lead to a more efficient operation schedule of energy systems in the building. The analysis of load profiles can give a good overview of the energy use and user behavior in the building. Detailed load analysis and understanding is an essential step before the predictive analysis.

In this study, electrical load data from three transformers installed in EV building, Concordia University and weather data collected from the weather station installed in EV building were used for load analysis and load prediction. EV building includes two main parts, which are Engineering

(ENCS) and visual arts departments (VA). The three transformers considered in this study measure heating, ventilation, and air conditioning (HVAC) load from a mechanical room (located in 17^{th} floor of the EV building) in addition to the plug and miscellaneous loads from ENCS and VA departments. In the load analysis part, the representative daily loads of these three transformers of the building are studied. The magnitude and trend of daily loads are extracted and discussed. The average load from 17^{th} floor's transformer is found to be 1,441 kW during office hours of weekdays in summer, whereas this load during office time in winter is 991 kW. Note that, this load does not include the gas consumption, used for meeting the heating load during the winter. Regarding the plug load from ENCS and VA department, the average load during office hours of weekdays in summer is 512 kW, and 453 kW, respectively. Moreover, the load reduction during the COVID19 pandemic is studied by comparing the two months (April and May) of 2019 and 2020 for all three transformers. There was a significant reduction of 42 % for the load of 17^{th} floor between April 2019 and April 2020 (weekdays), while 24% and 40% load reduction was observed for ENCS and VA transformers, respectively. Based on the results during COVID 19 period, we see that the existence of people in the building affects the load, but a great part of the load is related to the schedule and policy of the building. That is why there is a good potential to save energy just by changing the schedule and plans that systems are running based on.

The second part of the work deals with load prediction using regression analysis and long short-term memory (LSTM) model. The importance of input variables for load prediction is evaluated in the regression section. In linear regression, twenty scenarios are considered. Each scenario is a different combination of input features. It was found from the results that the best scenario is when all calendar and weather data are considered as input attributes. The best scenario in winter has R^2=0.29 and MAPE=24.46, while in summer, R^2=0.64 and MAPE=10.47. The results are confirmed with correlation analysis. For this case study, adding meteorological data did not improve prediction in winter significantly because in winter, gas is used for heating and the considered data does not reflect it, but in summer, weather variables were of great importance. Also, specific and unusual events in consumption could be detected with polynomial regression. Regarding load forecasting, LSTM is used as a deep learning model, which considers the sequential load data and predicts future load for different time horizons. Regarding the size of the dataset and LSTM parameters, the best performance was obtained for one-year ahead forecasting with R^2= 0.75, and MAPE= 10.97. Another result was that the type of load influences the performance of the LSTM model. Considering different load types, the plug and lighting loads from the ENCS and VA departments could be better predicted than the 17^{th} floor HVAC load, since HVAC load is affected by weather variables that are fluctuating and not easy to predict, but plug loads are more related to the schedule of building. The other influencing factor on prediction performance is the choice of train-set and test-set. The lowest R-squared belongs to the model that has the year 2019 as test-set. The results of this project could be useful for building facility managers to adapt and optimize the schedule of the energy systems and give recommendations to the users to improve energy efficiency.

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Chapter 1

Introduction

1.1 Background and Motivation

Globally, one of the biggest environmental concerns is global warming. After the industrial revolution, human activities have caused our planet to heat up. The rise of the earth's temperature leads to an increase in water level and more frequent climatic disasters. CO_2 and other pollutant gases, which are considered as the main cause of global warming, mainly originate from burning fossil fuels for the purpose of heating and electricity generation, transportation, and industrial activities.

Each country is responsible for greenhouse gas (GHG) emissions to an extent. In 2016, Canada was responsible for 1.5 % of global GHG emissions, whereas this value was 25.8 % for China in the same year [can, 2020c]. In Canada, 8.8 % of GHG emissions originate from electricity generation, while the building sector is responsible for 13% of emissions [can, 2020a]. Regarding the Paris agreement, Canada tries to cut off GHG emissions until 2050 [can, 2020d]. Several motivations, such as "low carbon economy fund " and the "climate action incentive fund", are set up to decrease GHG emissions in the building sector [can, 2020a]. In addition to incentives, energy-efficient plans have gained significant attention and could contribute to the reduction of GHG emissions. For the purpose of energy efficiency, it is important to manage energy usage and save it when possible. The use of electricity has been increased in recent years as occupant behavior has been changed. Considering this increase, the importance of energy-efficient actions becomes even more pronounced since it revers this increase and helps to save electricity for other parts that need electrification, such as electric cars.

Generally, electrical energy is being used in different sectors such as transportation, industry, residential and commercial sectors. Primary energy sources are petroleum, biomass, coal, and natural gas. As a secondary energy source, electricity is being produced from primary sources such as natural gas. It can also be generated from renewable sources such as solar, wind, or hydro. In Canada, 60 % of electricity originated from hydro energy sources in 2018 [can, 2020b]. In the building sector, electricity is mainly used for lighting, refrigeration, HVAC, computers, electrical equipment, and systems. Electricity consumption can be monitored in real-time in buildings equipped with smart tools. The installed sensors are measuring the real value of the load. These data help the building's facility managers to observe how the building is performing in terms of energy usage. The existence of a measured data-set enables us to apply machine learning techniques for different purposes. The usage of machine learning in the building sector is a very new topic. So far, it has been used in many fields such as the finance sector, the health industry, and image processing. One of the typical applications of machine learning is load forecasting.

1.2 load forecasting in buildings

Load forecasting has various applications for both utility companies and consumers. In the building sector, it is beneficial to know what the load in the future will be so that scheduling plans can be managed more effectively. Load forecasting also can be used to determine the optional size of renewable energy systems to be installed for future facilities. These advantages of load forecasting lead to more energy-efficient buildings that consume less energy and reduce carbon emissions. Load forecasting can be done in different time horizons: short-term, medium-term, and long-term forecasting. Each of them is suitable for a specific application. Short-term load forecasting (STLF) represents the prediction of load for the next thirty minutes to the next two weeks. Medium-term load forecasting (MTLF) represents a time horizon from two weeks to one year, and long-term load forecasting (LTLF) is for one to ten years' time span.

Short term load forecasting has various applications. It is used to confirm that power systems are performing properly. The other usage of STLF is to prevent issues arising from underestimating or overestimating demand and to properly schedule the generation level of power systems [Raza and Khosravi, 2015]. There are many techniques used for short-term load forecasting, such as linear regression, time series approaches, and machine learning models. Regarding machine learning methods, long short-term memory, artificial neural network, multi-layer perceptron, and support vector machine could be mentioned [Jacob et al., 2020].

Many studies applied medium-term load forecasting for the prediction of peak load. [Amjady and Keynia, 2008] aims to forecast the peak load for each day of next month. It can be implemented for better maintenance planning and fuel trade plans. [Bunnoon et al., 2009] applied MLR and ARIMA to predict the peak load of each month for a complete year.

In long-term load forecasting, the accuracy will be affected by many factors due to the various inputs of the model that change over a long-time horizon. For example, long term forecasting considers technology updates, population, and economic growth in the model. These input variables are uncertain, and this will affect the accuracy of LTLF [Fallah et al., 2019]. Regarding long term forecasting, utilities could benefit from the results when they want to expand the grid infrastructure and invest their money for future projects on a much bigger scale (city or country). One of the challenges in long-term load forecasting is the accuracy of prediction, which needs to be improved by upgrading the current predictive models or creating new ones [Khuntia et al., 2018].

There are different techniques for load prediction known as white-box, grey-box, and black-box models. Each one requires different tools and inputs. The white-box method refers to building simulation software such as EnergyPlus, which can model the energy usage of a building by taking physical details as the model input. They are not easy to implement and take significant time to run, but the accuracy is good comparing to grey-box models. Black box or data-driven methods require historical data gathered from sensors as their input. Excluding regression, the accuracy of data-driven models is high. The grey-box method is the combination of the black-box and white-box methods since it considers both historical and physical data in the model [Wei et al., 2018].

1.3 Objectives

The main objectives of the research are as follows:

1) Understanding the consumption pattern of the building. 2) Providing energy-related feedback to the facility manager based on load analysis. 3) Understanding the influence of weather variables on load. 4) Load forecasting for different time horizons and load types.

This thesis is organized as follows: In chapter 2, a review of previous literature about data mining methods for the prediction of energy consumption is provided. In chapter 3, the case study building (EV building) is introduced and described. Chapter 4 describes the methodology, which includes data preprocessing, load analysis, and prediction methods. Chapter 5 provides the result of the study, which is grouped into data analysis and prediction part. Finally, the conclusion is provided and discussed.

Chapter 2

Literature Review

Internet of Things (IoT) devices' deployment has made lots of opportunities for researchers from different fields, such as computer, electrical, and building engineering to access data. The information can be used for different purposes, such as data analysis and prediction of a specific variable. Load prediction and forecasting have been favorite research topics for many years. Various information is discussed in the literature, such as types of load, time horizon, input variables, time interval, type of building or system, scale, evaluation metrics, and forecasting tools. Some researchers tried to apply several machine learning methods and then compare them in terms of accuracy, other researchers tried to develop new methods that cover existing ones' problems, and some research focused on the importance of input variables. This part overviews the previous works done by researchers and discusses them from different perspectives such as input variables, time horizons, and used methods.

2.1 Data mining approaches for load prediction

Data mining is an approach to use the potential of data to answer real-world questions. There are five main steps in the data mining approach. The first critical step is to understand the data and the problem we try to solve. Then we need to preprocess the data, for example, removing missing values. The clean data is categorized into a training set and test set. After implementing a chosen model on the train set, we test the model performance with the test set. After verifying the performance, the model can be implemented, and knowledge can be extracted to answer a specific question. Data mining approaches are grouped into the descriptive and predictive analysis. Association and clustering methods belong to descriptive analysis, while regression and classification are predictive methods. Time series forecasting is a type of predictive approach. It has two types, which are data-driven and model-driven. The data-driven category includes moving average, and the model-driven section includes polynomial regression [Kotu and Deshpande, 2014].

[Fan et al., 2018] divided data mining (DM) methods into supervised and unsupervised groups. It gives an overview of unsupervised techniques such as clustering, association rule mining, motif discovery, and anomaly detection, used for different applications. For example, k-means algorithm is used for pattern recognition and even for load prediction in some of the cases. This paper refers to some of the challenges in the implementation of unsupervised data mining methods, which are privacy concerns, low quality of data, and the absence of knowledge that satisfies both building engineers and DM specialists. Regarding the application of data mining in the building sector, [Yu et al., 2016] reviewed data mining methods for building energy efficiency purposes. As mentioned in this paper, data mining approaches are divided into six groups: classification, clustering, association rule mining, regression analysis, summarization, and anomaly detection.

There are many studies that focused on understanding and predicting future load with data mining methods. [Wang et al., 2015] introduced a five-stage workflow of load profiling, which is data preprocessing, clustering, clustering assessment, customer grouping, and usages of load profiling. To cluster load curves, direct and indirect methods are introduced. In direct clustering, the clustering approaches like k-means are applied to the main data, whereas in the indirect method, the dimensionality of data is reduced before applying the main clustering approaches. As mentioned in this paper, one of the usages of load profiling is demand response, which is divided into groups of price-based and incentive-based plans. Load forecasting is the other utilization of load profiling. [Wang and Srinivasan, 2017] did a comprehensive review of the cases that used AI-based techniques for prediction purposes. Five perspectives are considered in this review paper. 1) The type of target value such as heating load, 2) building category such as commercial buildings, 3) time interval, 4) dependent features, and 5) predictive models (Artificial neural network or ANN, support vector machine or SVM, multiple linear regression or MLR, Ensemble models). It also estimates the pros and cons of each model. For instance, ensemble models are the most accurate compared to other models, but the implementation is hard, and the speed is low. MLR model is easy and fast to implement. [Wei et al., 2018] explored the application of different techniques and investigated the pros and cons of each. ANN is a proper choice in case of nonlinear problems, and it can be used in load forecasting. It has high accuracy and is robust against noises. But the choice of its parameters is a challenge, and the results may vary from one case to the other. Support vector regression (SVR) is a type of SVM model for regression. It is an accurate predictor, capable of capturing nonlinearity. However, the computational time is high comparing to other techniques. Decision tree is easy to implement but not suitable for time series and nonlinear problems. Clustering models, like k-means are mostly used for pattern identification.

[Deb et al., 2017] concentrated on forecasting of time series data and investigated nine methods used in load forecasting. These nine models are ANN, ARIMA, SVM, CBR, Fuzzy time series, grey prediction method, MA ES, KNN, and hybrid approaches. This research discusses the pros and cons of each model. For example, SVM can easily tackle local minima and nonlinear problems, but the choice of kernel function is the main difficulty in this model. This issue highlights the need for optimization methods to choose the best parameters. Hybrid methods have been discovered more in detail by considering twenty-nine sets of combinations. [Tso and Yau, 2007] tried to predict household energy consumption (kWh) in Hong Kong by applying a regression model, decision tree, and neural network. The study is divided into summer and winter analysis. As discussed in this paper, the effect of each parameter in energy consumption varies in winter and summer analysis. [Amasyali and El-Gohary, 2018] investigates data-driven techniques for the prediction of energy usage in the building sector. Some of the considered factors in this review paper are the building category, the amount of required data, and the evaluation metric. Based on the reviewed papers, fewer studies have been done for long-term horizons, and deep learning is a potential candidate in this field. The rest of this section overviews the papers from different perspectives, which are: Types of input data, different time horizons, specific methods such as artificial neural network, deep learning methods, and ensemble models.

2.1.1 Types of input variables

Depending on the purpose of the work and available data, type of input features varies in each paper. [Kwok et al., 2011] predicted the cooling load of a commercial building by ANN. Meteorological data, occupancy information, and system load are mentioned as inputs. The study evaluates the importance of each input data by defining three scenarios. The first one takes meteorological data as input. The second scenario considers meteorological and occupancy, and the third one considers all three input features. Based on the results, scenarios 2 and 3 report better performance, highlighting the significance of occupancy information in our predictive model.

For heating load prediction, [Yun et al., 2012] utilized meteorological data and occupancy information in the model. Meteorological data consists of dry bulb temperature, relative humidity, speed of the wind, and solar radiation. The result proved the significance of temperature for load prediction in summer and winter, apart from transition hours of the day. [Jetcheva et al., 2014] used temperature and historical load information as model input to forecast electrical load for the next day with a hybrid model. [Zhao et al., 2016] wants to predict how much energy (kWh) is being consumed by Variable refrigerant volume system. ANN, SVR, and ARIMA are the predictive models, and the type of day, type of time, and temperature are model inputs. [Pao, 2006] studies the effects of economic features in electrical energy usage. These features are national income, population, consumer price index, and gross domestic production. The study implemented linear and nonlinear methods and showed that population and national income are the two most influential variables.

Knowing which feature to select and implement has many advantages. It improves the speed, increases the performance efficiency, and prevents overfitting [Saleh et al., 2016]. Apart from feature selection, other methods such as Principal component analysis (PCA) can be applied to reduce the dimensionality of data-set. [Torkzadeh et al., 2014] First checked the Pearson correlation of variables, then applied PCA to get the secondary dataset and finally MLR was implemented for load forecasting. [Jinhu et al., 2010] implemented weighted support vector machine (WSVM) with PCA to predict cooling load and [Guo et al., 2004] applied PCA along with neural network (NN) model.

2.1.2 Forecasting time-span

Long term load forecasting

[Daneshi et al., 2008] utilized Fuzzy-ANN and regression techniques. ANN proved to be a better predictor because it can capture nonlinearity. As discussed in this study, some features such as energy price, weather variables, and population influence the results. [Agrawal et al., 2018] investigated LSTM-RNN method to do forecasting for the next five years. The main data-set covers twelve years and input variables are the records of hour, weekday, months, year, and the measured demand from the previous year. [Akdemir and Çetinkaya, 2012] applied an adaptive neural fuzzy inference method by taking peak load, population, and income as input features. The implementation of particle swarm optimization in forecasting of peak load is discussed in [AlRashidi and El-Naggar, 2010].

Short term load forecasting

Short-term load forecasting is a research goal in [Ryu et al., 2017]. In this research, Deep neural network (DNN) forecasts the load for the next 24 hours, and then the performance is evaluated, comparing shallow neural network, double seasonal Holt-Winters, and ARIMA. Based on the results, DNN reported less error.

Three predictive methods, including multilayer perceptron, multiple linear regression, and support vector regression, are investigated in [Massana et al., 2015]. In this research, the performance assessment was done based on MAPE. The other objective of this research was to study the importance of input variables. The input features considered in the models were meteorological information, calendar, occupancy, and indoor environment information. Each model was evaluated with different combinations of features. SVR with temperature and occupancy information reported the lowest MAPE 0.06%. [Dudek, 2015] implemented Random Forest. Comparing the performance of ARIMA and CART, Random Forest was a better predictor in this study.

Medium-term load forecasting

[Ghiassi et al., 2006] explained the dynamic artificial neural network to predict a power company's load for seasonal and yearly time horizons. The importance of meteorological data is discussed in this paper, and it was shown that the seasonal approach is more preferred than the yearly approach since weather features are less critical in the seasonal approach. Therefore, the number of required inputs will be reduced. The results also proved the proposed method's superiority compared to MLR, ARIMA, and a common neural network method. [Feilat and Bouzguenda, 2011] applied neural network (NN) and linear regression method to get the peak load of each month. Temperature, wind speed, and humidity are taken as meteorological features. In this study, NN method performed better than linear regression.

Regression method and ANN are implemented in [Samuel et al., 2017] to predict the medium-term load of institutional building. The ANN's accuracy was better than regression, but regression is a faster approach. [Pan and Lee, 2012] studied ANN and SVM. Based on the results, both methods were performing at almost the same level of accuracy. However, SVM was more powerful in detecting not normal records. Prediction of daily peak load is discussed in [Hutama et al., 2018]. The study applied SARIMAX and MLP. SARIMAX model reported a lower MAPE error. [Niu et al., 2008] tried to know the maximum daily load in each month by developing dynamic least squares support vector machines (DLS–SVM). Comparing with LS-SVM and SVM, DLS–SVM reported the lowest error for the medium-term horizon. In [Han et al., 2018], the load is forecasted for short and medium time horizon with deep learning models, which are time-dependent CNN (TD-CNN) and cycle-based long short term memory (C-LSTM) network.

2.1.3 Used methods

Multivariable linear regression-MLR

[Yildiz et al., 2017] evaluated data-driven algorithms such as ANN, SVR, and MLR. The dataset includes load and meteorological information. Considering regression, multicollinearity is detected with a correlation matrix and Variance inflation factor (VIF) approach. PCA was applied to drop this collinearity. Overall, the accuracy of MLR cannot be good as other ML algorithms, but it is always good to know which features affect the prediction more than others. This study is done on two scopes (single building and whole campus). As discussed in the paper, the bigger scale was more successful than the small scale. MLR is used in [Qiang et al., 2015] for the prediction of cooling load. Two office buildings are considered as the case study. MLR has low accuracy in comparison to other models, such as ANN. However, it is an easy and fast model to apply. Considering these benefits, this paper tries to compensate for low accuracy and increase it. The principal component analysis is one of the suggested techniques that upgrades MLR models by removing the multicollinearity between predictor features. Before applying PCA, correlation analysis is developed to observe the correlation of input features and target. Both Pearson and Spearman coefficients are used in this step, depending on a normal or not normal distribution of variables. [Fumo and Biswas, 2015] studies various categories of regression with the purpose of household energy usage prediction. The paper highlights the importance of regression as an easy and efficient model. If collinearity exists between inputs, PCA can be helpful in handling this issue.

There are two regression methods in the literature. Linear and nonlinear methods. Considering a library building as the case study, [Fan and Ding, 2019] implemented multiple nonlinear regression to estimate the value of the cooling load. [Anand et al., 2019] implemented Deep neural network and Multiple nonlinear regression (MNLR) to approximate a factor known as ”energy use per person” and compared the results of two models. Considering MAPE of the two models, DNN outperformed MNLR. Also, the potential for energy reduction in different parts of the building was explored in this paper.

The implementation of three regression methods (linear, polynomial, and exponential) was studied in [Nazih et al., 2011] for hourly load prediction of one-year time horizon. Comparing the performance of predictive models, linear and polynomial were at the almost same level. [Li and Huang, 2013] compared the performance of four techniques, which are ARMAX, MLR, ANN, and RC network. The goal is forecasting the cooling load of an office building for a short time horizon. The models take outside temperature, solar radiation, and temperature set-point as input features. In this study, MLR and ARIMAX were perfect predictors.

Artificial Neural Network

[Deb et al., 2016] investigated the usage of feedforward ANN method to estimate cooling load of university buildings. Four ANN methods are studied in [Nasr et al., 2002]. In this paper, the target value is electrical energy usage (GWh). Based on the results, multivariate ANN models outperformed univariate ANN methods.

The performance of ANN and EnergyPlus were compared in [Neto and Fiorelli, 2008]. In this study, ANN was performing slightly better than EnergyPlus. Based on the results from ANN, the outside temperature is a critical factor rather than humidity and solar radiation.

Deep learning

[Mocanu et al., 2016] reviewed the implementation of two deep learning models named, Conditional Restricted Boltzmann Machine (CRBM) and Factored Conditional Restricted Boltzmann Machine (FCRB) to estimate building-level energy consumption. It also compared the performance of these techniques with other machine learning approaches, such as ANN, RNN, and SVM. Overall, FCRMB showed better performance. This study showed that for a longer time span, deep learning models give less error. [Wang et al., 2019a] explained the application of deep learning techniques for renewable energy estimation, which are deep belief network (DBN), stack auto-encoder(SAE), deep recurrent neural network (DRNN).

Convolutional neural network (CNN)

[Tian et al., 2018] studied the performance of six machine learning methods on electricity load data-set. With more focus on CNN, LSTM, and CNN-LSTM (integrated methods), it was concluded that CNN-LSTM works better since it benefits from the advantages of each separate model, which are local trend and long-time dependencies. [Kim and Cho, 2019] investigates the application of the CNN-LSTM method for household energy usage forecasting. As mentioned in this paper, CNN is a common approach for image recognition, and RNN is powerful in speech recognition as well as natural language processing.

CNN-M-BDLSTM was introduced in [Ullah et al., 2019]. Comparing with other predictive models, it was working better. However, one result that could be achieved from this paper is that the integrated model is just slightly better than M-BDLSTM. This could indicate M-BDLSTM is good enough.

CNN-GRU model was the other deep learning method studied in [Sajjad et al., 2020]. The performance is compared with different algorithms such as SVR, CNN, XGBOOST, and MLR.

Regarding building load forecasting, eight structures of CNN are studied in [Amarasinghe et al., 2017]. Each structure represents a various choice of kernel size, pooling filter, and hidden layers. It was shown there is no significant difference between the performance of each type.

Long short-term memory (LSTM)

Artificial neural networks obtained lots of attention in load forecasting. Recurrent neural network or RNN is ANN's category, that is able to work with sequential data. Long-Short Term Memory or LSTM is one of the RNN models that eliminates the restrictions of normal RNN, which are vanishing and exploding gradients. Since LSTM can capture long-time dependencies, it is a proper candidate for time series prediction [Bouktif et al., 2018].

Implementation of LSTM for short-term load prediction is discussed in [Kong et al., 2017]. It is also compared with other models, which are conventional backpropagation neural network (BPNN), k-nearest neighbour, extreme learning machine (ELM), and sophisticated input selection scheme integrated with hybrid forecasting framework (IS-HF). For all of these models, different scenarios of having various time steps were proposed and the performance was evaluated in terms of average MAPE. LSTM showed superiority in this comparison. As mentioned in [Marino et al., 2016], load forecasting can be studied in an aggregate or building status. However, the later one is more difficult. This paper implemented two types of LSTM (standard LSTM and sequence to sequence LSTM) on two data sets (One minute and hourly interval). Based on the results, standard LSTM performed poorly on the one-minute dataset, but S2S LSTM outperformed on both mentioned datasets. [Chitalia et al., 2020] used nine predictive models, such as LSTM, BiLSTM, and CNN+LSTM. Five commercial buildings around the world are taken as a case study. The proposed LSTM architecture has two hidden layers with 20 and 10 neurons. The value of learning rate is 0.005, and the model runs over 400 epochs. For LSTM, Sigmoid is used as an activation function with Adam optimizer.

LSTM model was developed in [Wang et al., 2019b] for load prediction of next week. The performance was compared with multi-layer perceptron neural network (MLP), Random Forest (RF) as well as SVM models. The LSTM model has three hidden layers with 20, 5, and 20 neurons in each. The activation function is RELU, and the learning rate is 0.01. Calendar data such as hour, and meteorological data such as temperature, wind velocity, and humidity are considered as input variables in this study.

Nonlinear autoregressive models with exogenous inputs (NARX)

Nonlinear Autoregressive models with exogenous inputs or NARX is a predictive neural model for nonlinear and dynamical problems [Xie et al., 2009]. NARX is a proper candidate to capture long-term dependencies, and it is compared with conventional recurrent neural networks in that regard in [Lin et al., 1996].

Comparing the MAPE of other models such as conventional feedforward artificial neural network and bagged regression tree, NARX proved to be a better candidate for load prediction in [Abbas et al., 2018] where the load is being predicted considering time-dependent features such as day, hour and month as well as weather-related variables such as temperature. As discussed in [Koschwitz et al., 2018], NARX-RNN obtained better accuracy in comparison to SVM-based model. The goal of this study is to predict the heating and cooling load.

Tao's Vanilla benchmark

With the focus on short-term load prediction, Tao Hong developed Tao's benchmark model For the first time [Hong et al., 2010].

It is a forecasting approach, which is also implemented in [Sobhani et al., 2019] to know the future load. As mentioned in this paper, Tao's Vanilla benchmark method relates a weather variable (mostly temperature) to time dependant variables such as month, day, and hour. The output is the sum of different combinations of temperature and time features. This method has been used in [Hong et al., 2015], where the research question is what the proper choice of weather station for load forecasting.

Using the MLR approach, Tao's Vanilla Benchmark was applied in Competition 2012, where the goal was to estimate future and past missing load time series [Hong et al., 2014]. Some studies tried to beat the performance of this model. for instance, [Wang et al., 2016] proved that the suggested predictive model based on the recency effect is performing better than Tao's vanilla benchmark for aggregated level.

Ensemble models

[Fan et al., 2014] wants to predict energy usage and peak demand of next day. For this purpose, eight data mining approaches, including MLR, ARIMA, SVR, RF, MLP, boosting tree (BT), multivariate adaptive regression splines (MARS), and KNN were implemented, and the performance was compared to each other as well as to the ensemble method, which is the combination of single algorithms based on their performance weight. As the result illustrates, SVR and RF outperformed the other models. Therefore, their weight in the ensemble algorithm is higher. [Qiu et al., 2014] integrated deep belief network, (DBN) and SVR as a new ensemble deep model. [Li et al., 2017] developed a deep learning algorithm by integrating stacked autoencoders and extreme learning machine (SAE+ ELM). Considering other predictive models such as MLR and SVR, a performance comparison is done and the results proved the superiority of the deep learning technique. [Amjady and Keynia, 2008] investigated a model for maximum load prediction of each day in medium-time horizon, which is the integration of neural network (NN) and evolutionary algorithm (EA).

2.2 Understanding from literature

Data-driven approaches have two main categories, descriptive and predictive analysis. Descriptive analysis tries to extract useful knowledge in the form of rules such as rule mining, whereas in predictive analysis, the purpose is to predict future trends and values such as load forecasting. Many methods such as ANN, SVR, MLR, and ARIMA are used in the literature for prediction.

Prediction of daily or monthly peak demand or load profiles were two main predicted targets in the literature review. Regarding the prediction time horizon, short term load forecasting is mostly used in this field. Overall, the usage of each method is case dependent because building characteristics, running schedules, and type of available data are unique properties for each case. Individual building level load forecasting is more complicated than aggregation at bigger scales. Many studies have tried to compare predictive models' performance based on accuracy, error, and running time.

The comparison was either between individual models or individual and ensemble models. Many studies reviewed ensemble models. They are more challenging to implement and need more knowledge. They usually outperform unique models. However, in one case, the performance of individual models was close to the ensemble model.

Based on the literature, MLR is one of the most used models since they are easy to use and fast, but the low accuracy is one of these models' drawbacks. Some studies tried to increase accuracy by removing multicollinearity between input features. Another disadvantage of linear regression is that they are not capable of dealing with non-linearity. ANN is a proper model for nonlinear problems, but the choice of parameters is the main challenge. Deep learning methods are very new in the field of load forecasting in the building sector. CNN and LSTM are two mostly used deep methods. LSTM is a type of RNN, which can capture long time dependencies and eliminates the problem of vanishing gradient descent.

2.3 Existing gaps

Based on the literature review, the following research gaps were identified.

1) Studies focusing on comparing the prediction performance of LSTM on different time horizons and different types of loads (HVAC, appliances load) is scarce. 2) Prediction model performance assessment based on different train and test-sets are not discussed explicitly. 3) The usage of results from the analysis and prediction part is missing in the literature. A limited number of studies talked about what should be done after prediction and how the results could be useful. 4) Deep learning in load forecasting in building sector still has great potential to be discovered, especially for medium and long-term load prediction.

2.4 Contribution

Previous studies focused more on comparing different models. This thesis focuses on different perspectives. In addition to a comprehensive load analysis, this thesis investigated the application of machine learning method and deep learning approaches for different purposes. The regression models are used for load prediction based on historical data, where you can find the effect of weather information in four seasons. It is also used for unusual load detection. At the same time, LSTM is used for time series load forecasting. The performance of different time horizons are compared, and the importance of load type is discussed. This work also provides some recommendations to the facility manager to reduce energy consumption.

Chapter 3

Case study building description

3.1 EV building - Concordia university

Concordia university in Montreal has two campuses, named Sir George Williams (SGW) and Loyola Campus. The buildings of SGW campus are in downtown Montreal. The main buildings of SGW campus are EV building, GM building, MB building, LB building, FB building, and FG building. Among these main buildings, EV is taken as the case study in this project. This project studies EV building more in detail. As a university building, it has some specific characteristics some other universities may not have. This building is in one of the main intersections of the city (Saint-Catherine St and Guy St), exposed to a large population moving around and through the building. It has two parts of Engineering Computer science building and Art and Science. They are connected but have different heights and usage. Figure (3.1) shows the two towers of EV building. ENCS tower has 16 floors on the ground surface, which include offices, conference rooms, and also some mechanical and chemical laboratories located in the 12^{th} – 16^{th} floors. Each of three floors has a unique atrium. On the 17^{th} floor, there is a mechanical room, which is divided into five rooms plus one electrical room. There are two underground levels that have a connection to the metro station, underground restaurants and a tunnel connecting to the library building and Hall building. This means the roots of the building are attached to other spaces and buildings. The VA tower also has some offices and workshops. It has eleven floors above the ground, with one floor dedicated to a mechanical room in the 12^{th} floor. The gross floor area of EV building is 69,204 m². Most of the details in this section are provided by the facility manager of the EV building.

Figure 3.1: ENCS and VA department [web, 2008]

3.1.1 Energy systems of EV building

• Ventilation

EV building has a decentralized HVAC system. Air conditioning of both ENCS and VA is separate. Three fresh air handling units (FHU) 001, 002 and 003 are located on the 17^{th} floor's mechanical room. These FHUs are responsible for the air conditioning of the whole ENCS department and laboratories. Also, on each floor of ENCS, there are air handling units (AHUs) to distribute fresh air on each floor. In the VA department, FHU 004 and 005 are situated on the 12^{th} floor. Each level of the VA department also has AHUs. [Yu et al., 2012]

Generally, the ventilation of offices is 6 air change per hour. The ventilation of corridors is the same as offices.

• Heating

This heating demand is being provided by four boilers running on natural gas. Two condensing boilers and two conventional boilers. There is also an electrical boiler, which is sometimes running during the year. These five boilers are producing medium temperature water. This medium water is used for producing hot water at low temperature, heating mechanical room of the 17^{th} floor, and to heat domestic water. The low-temperature water is the combination of leaving and returning water of boilers, and it is used for the purposes like heating the entire pavilion, heating fresh air handling units 001-005, heating building Fan coil in mechanical rooms of each floor, heat the 12^{th} floor's mechanical room by fan coil and preheat domestic water. Also, a part of the heat is recovered from exhaust air with recuperation by glycol [Facility manager report].

• Cooling

The cooling load is being provided mainly with three chillers installed on 17^{th} floor. A part of the cooling load is also being provided by natural ventilation [Facility manager report].

3.2 Data Description

The data-set used in this study comes from two sources. 1) The sub-metered load of transformers of EV building. 2) The weather data from the weather station, installed at the rooftop of the EV building. Table (3.1) describes the data set for EV building. The original file contains more points. (13 points).

Table 3.1: EV dataset

	Points in data set	Name of attribute	Unit	Time resolution
EV dataset	Point_1	EV electric boiler	kW	15 minutes
	Point_3	17^{th} floor transformer	kW	15 minutes
	Point_4	ENCS transformer	kW	15 minutes
	Point_5	VA transformer	kW	15 minutes

Sub-metered data from EV building are as below:

1: 17^{th} floor transformer (Point_3):

17^{th} floor has one electrical room and five mechanical rooms, which are responsible for:

• Ventilation Room

• Producing hot water and cold water

• Dirty air evacuation

• Heat recovery

• Domestic water production

• Electrical generator

• Electrical boiler

• Heating equipment and cooling equipment

2: ENCS transformer (Point_4):

ENCS transformer measures the load, which includes:

• Lighting

• Plug loads

• Basement tenants

• VAV Fans for Floor level mechanical rooms

• Some lab equipment like wind tunnels

3: VA transformer (Point_5) is the same as ENCS transformer and reflects a similar category of loads.

4: The electrical boiler transformer (Point_1) is located at 17^{th} floor. Data is being measured individually but included in the load of 17^{th} floor.

There is a weather station located on the rooftop of EV building, which measures the meteorological data. Table (3.2) describes meteorological data measured by weather station.

Table 3.2: Weather data-set

	Features name	Unit	Time resolution
Weather dataset	Solar Radiation	W/m^2	hourly
	Humidity	$\%$	hourly
	Temperature	$^\circ c$	hourly
	Wind direction	Degrees from North	hourly
	Wind velocity	m/s	hourly

Chapter 4

Methodology

The methodology part is divided into three parts as data preprocessing, load analysis, and load prediction.

1:Data preprocessing:

Data-set mainly includes sub-metered load from transformers and weather information from the weather station. EV data-set is provided by the facility manager of EV building. After data prepossessing part, clean data is used for load analysis and load prediction.

2:Load analysis:

In the analysis part, first, the load from three transformers is analyzed. Weekday and weekend representative daily load profiles are studied for four seasons of 2019. The representative load profile of weekday is the average load of all weekdays in a specific season. Secondly, the reduction of load during COVID19 is studied. For this purpose, representative loads from April and May of 2020 are compared with the similar ones from 2019. Finally, the historical load from 2016 to 2019 are illustrated to understand the variation from one year to the other in terms of magnitude and trend.

3:Load prediction:

In the prediction part, three predictive models are applied- each with a different purpose. Linear regression is applied to know which weather variables are most important for load prediction. The correlation analysis is also done to confirm the results. Polynomial regression is applied to check the model performance on capturing unusual consumption. LSTM model is also used to forecast future load based on historical load data for different time horizons and on different load types.

Figure (4.1) shows the methodology used in this study.

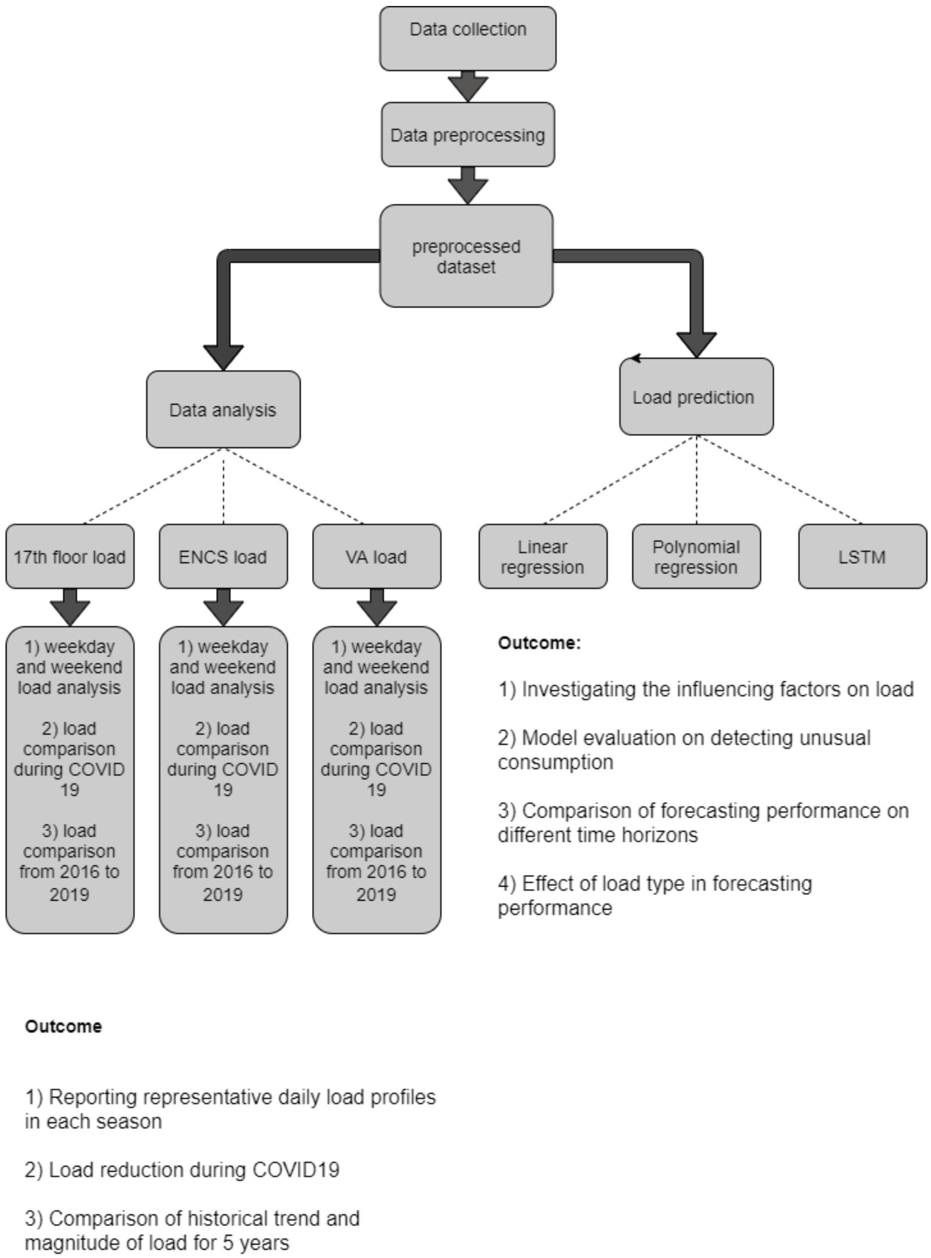


Figure 4.1: Thesis methodology

4.1 Data pre-processing

The most critical and time-consuming part of data analytic is data preprocessing. It is essential for model development and the accuracy of the results. For this project, EV data-set and weather data-set are preprocessed separately. The following steps are taken to have clean data.

Figure (4.2) shows the chronological steps taken in this part.

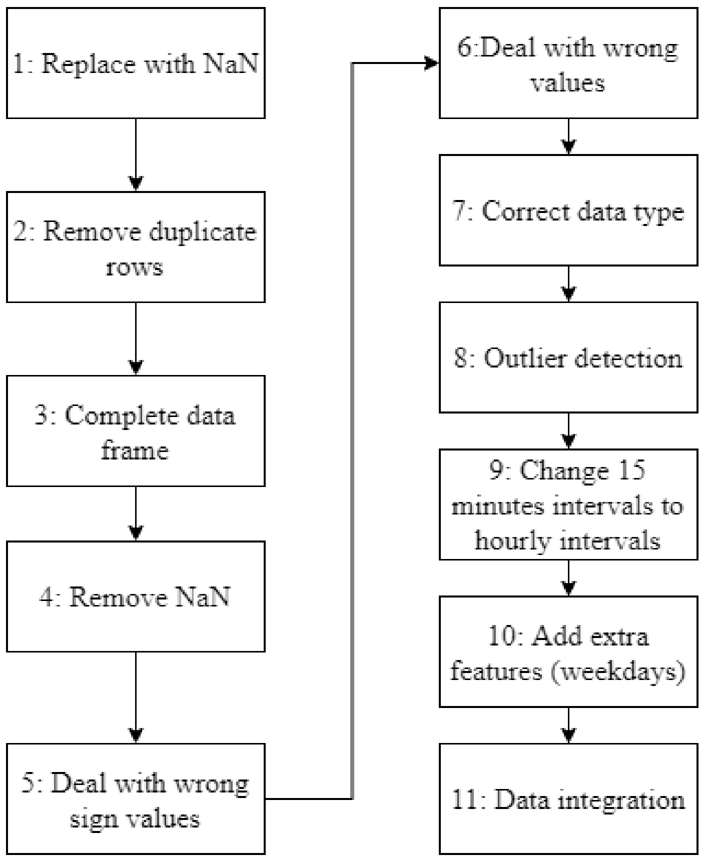


Figure 4.2: Data preprocessing steps

These steps are :

1: Replacing strings with NaN values: There is a lot of text inside numeric columns. These values should be detected and replaced with NaN, as they were missing values. Most of these strings were reported as ’Data Loss’.

2: Remove duplicate Time indexes: It is not possible to have two time indexes, such as 2016-06-12 1:30 AM. Each date and time index occurs once in our data set. So, in case of duplicate occurrence of the same date and time, one of them will be completely removed.

3: Complete data frame: A complete data frame means the one with 365 days and 24 hours in each. In the original data-set, some days or even some hours of a day do not exist. In this step, these missing rows will be detected and added again. When you create a complete data-frame index, those missing values will appear, but there are no values for them, so they will be filled with NaN.

4: Removing NaN: Now the data set is complete with all days and hours in place. There is no string except NaN. We should deal with NaN values. A strategy is defined in this project as: if a day consists of more than two hours of continuous missing values, the whole day is removed from the data-frame. Otherwise, they will be filled with linear interpolation.

5: Wrong sign values: Some features can not accept negative values. Such as solar radiation and load data. In the case of the occurrence of wrong sign values, they were replaced by zero or NaN. Point 1 from the EV data-set is reporting the load for the electric boiler. It is not working all the time. Most of the time, it is off, and the values are zero. There were some negative values that could not be true in the real world. They mostly were occurring between zero values. Therefore, all of them were replaced by zero. Negative values for solar radiation were replaced by 0 since they were reading error. Those days with all zero values for 24 hours were deleted from the data-set since, even in cold winter days, we can have a small amount of solar radiation for some hours. Other columns also were inspected against wrong sign values and replaced with NaN.

6: Wrong values: for weather files, some values were 100.1 %, which is not correct, and they were replaced by 100 %.

7: Correct data type: All numeric values (load and weather data) need to be converted to float.

8: Outlier detection: The outliers are detected visually first with box plots in Python. It is essential to decide whether you need to keep the outlier or remove them. In other words, are they error or abnormality? The outliers are checked in this chapter. It should be checked if an outlier happens for several hours or not. If they happen for continuous hours, they are not errors.

9: Change the intervals to hourly: The EV data-set is in 15 minutes time intervals and needs to be converted to hourly ones. However, the weather data-set is reported hourly. So, no need to change them.

10: Adding weekday and weekend information: Electrical usage of the building is different on weekdays and weekends. Adding this information to the data set helps to improve the accuracy of the predictive model.

11: Data integration: After cleaning the EV data-set and weather data-set, they are integrated into a single data frame.

12: Special Notes in data preprocessing and considered points.

A: 2016 is a leap year. To be able to match data with other years, 29^{th} of February 2016 is deleted from the main file 2016.

B: There were two temperature columns with an almost similar range in the weather file. Temperature is being measured with two sensors to ensure if one sensor has a problem, the other one will work. BAS system considers the average of two temperatures [EV-, 2015]. Therefore in this study, the average of two columns is taken as the temperature value.

C: In our data-set, 2017 is not complete.

D: Outliers were detected with Box plots and then treated in the main file.

E: The seasons in Canada are mentioned as follows:

Table 4.1: Seasons in Canada

Winter	December	January	February
Spring	March	April	May
Summer	Jun	July	August
Autumn	September	October	November

F: Office hours and non-office hours are defined as: Office Time: 8 AM -6.59 PM and Non-Office Time: 7 PM – 7:59 PM

4.2 Load analysis

The load is studied to extract the typical daily loads in four seasons. The typical load means the average load. For example, the typical weekday load in summer is the average of all weekday loads in summer. Comparison of the load curves for two months of 2019 and 2020 is also done to see how much reduction happened during COVID 19.

4.3 Load prediction

In this project, the used machine learning methods are discussed. Linear regression is used for load prediction and to evaluate the importance of input variables. Polynomial regression is used to check the unusual energy consumption, and a deep learning model known as LSTM is applied for the purpose of load forecasting and to discover the effect of different time horizons and different load types. This part gives information about the used methods, their architecture, and selection of parameters, as well as evaluation metrics, which are R^2, MAPE, and MSE.

4.3.1 Measure of performance

The performance of models is evaluated based on MAPE and R^2.

R-squared or the coefficient of determination indicates the model goodness of fit on real data.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

y_i = Actual value

$\hat{y}_i$= Predicted value

$\bar{y}$=Average of actual sample values

n= Number of data records

MAPE or mean absolute percentage error indicates how well the model predicts.

$$\frac{1}{n} * \sum \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

MSE or mean squared error :

$$MSE = \frac{1}{n} * \sum(y_i - \hat{y}_i)^2$$

4.3.2 Linear regression

Linear regression is used for seasonal load prediction and to extract the most important affecting features on load in Summer, Winter, and complete year. The seasonal load is predicted based on seasonal data from all four years of data. For example, the summer load is predicted using the summer months from all four years of historical data. In linear regression, 20 % of the data-set is considered as a test set randomly. Finally, the prediction is done on the complete data set without separating the seasons.

Linear regression is divided into two sections:

1: Seasonal load prediction.

2: load prediction (without separating seasons)

The formula of linear regression is as follows:

$$\hat{y}_i = \beta_0 + \beta_1 * x_{i1} + \beta_2 * x_{i2} + ...\beta_j * x_{ij} + \varepsilon$$

β_0 is intercept, x_i is input variable, ε is error or residual and j is number of features.

Linear regression is also used to answer the question: what are the most important factors in summer, winter, and complete year. To answer this question, this project applies linear regression on twenty different combinations of features and then compares the improvements of R-squared to extract how much each variable has been contributing to load prediction. The results are confirmed with correlation analysis. Figure (4.3) shows the general overview of regression models used in this project.

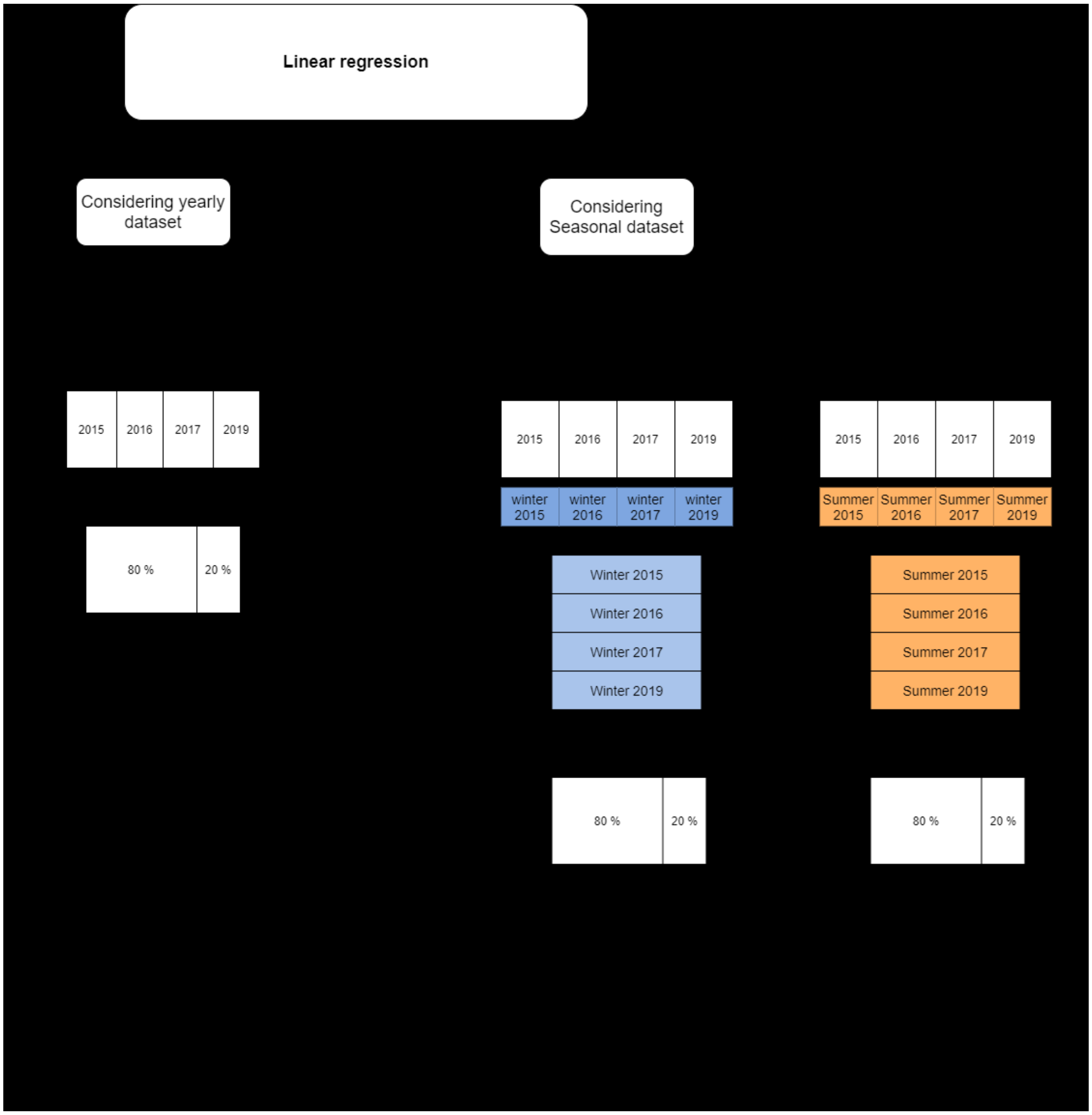


Figure 4.3: Workflow of linear regression

The performance of linear regression is evaluated based on twenty scenarios. Each scenario considers a different combination of features. Table (4.2) shows these scenarios. Calendar data includes hour, day of the week, day of the month, month, and year.

Table 4.2: Different combination of calendar data with weather data

	Calendar data	Solar Radiation	Temperature	Relative humidity	Wind direction	Wind velocity
S1	*	*				
S2	*		*			
S3	*			*		
S4	*				*	
S5	*					*
S6	*	*	*			
S7	*	*		*		
S8	*	*			*	
S9	*	*				*
S10	*		*	*		
S11	*		*		*	
S12	*		*			*
S13	*			*	*	
S14	*			*		*
S15	*				*	*
S16	*	*	*	*		
S17	*	*	*		*	
S18	*	*	*			*
S19	*	*	*	*	*	*
S20	*					

4.3.3 Polynomial

Polynomial regression is one of the regression models that can fit the curves of load better than linear regression since linear regression just fits a straight line. Polynomial regression is used for load prediction considering the yearly data-set. It is also used to evaluate how unusual consumption can be captured. The formula of polynomial regression can be represented as:

$$\hat{y}_i = \beta_0 + \beta_1 * x_{i1} + \beta_2 * x_{i2}^2 + \beta_3 * x_{i3}^3 + ...\beta * x_{ij}^j$$

4.3.4 LSTM

Recurrent Neural Networks is a deep learning model which has loops in their structure [web, 2015]. Figure (4.4) shows a regular RNN which is unfolded.

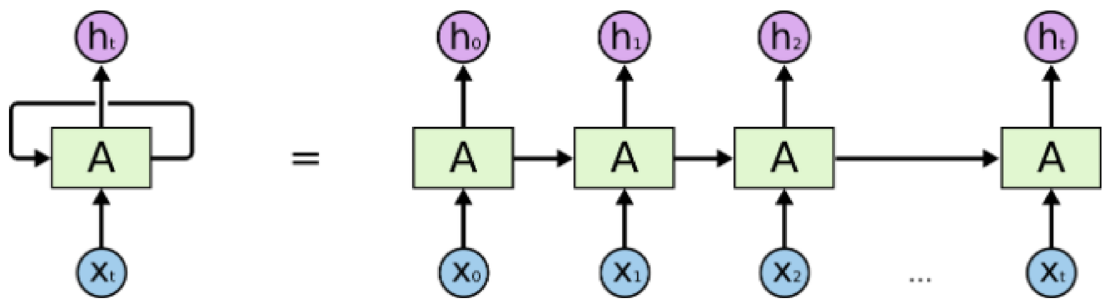


Figure 4.4: Simple RNN network[web, 2015]

Long Short Term Memory networks or (LSTM) is a category of RNN that eliminates the drawback of main RNN models, which is vanishing gradient. It is also powerful in capturing the long time dependencies compared to RNN. Figure (4.5) shows the general architecture in one unfolded LSTM cell. Each cell has four neural network layers, which are σ, σ, tanh, and σ. The straight line above the cell determines the status of the cell, which is fed by the outputs of the neural network layers inside of the cell. The first sigmoid layer takes h_{t-1} and X_t as inputs, and the output is a positive value less than one, that indicates which part of the information is not required. [web, 2015]

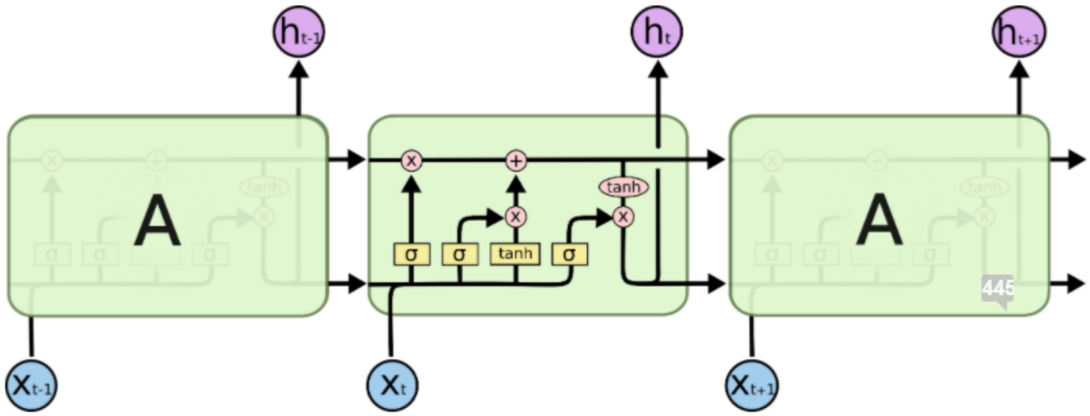


Figure 4.5: Simple LSTM architecture[web, 2015]

$$f_t = sigma(W_f.[h_{t-1}, x_t] + b_f)$$

The second and third neural network layers are responsible for updating the cell status. The outputs are i_t and C_t, respectively. The state of the cell will be changed from C_{t-1} to C_t. The formulas are as below: [web, 2015]

$$i_t = sigma(W_i.[h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = tanh(W_c.[h_{t-1}, x_t] + b_c)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Besides cell status, we need to have an output. The last neural network layer contributes to reporting h_t, which is the output of the cell. The formulas are as below: [web, 2015]

$$o_t = sigma(W_o[h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * tanh(C_t)$$

The problem of load forecasting is a time series regression. LSTM works well with time series as it considers the sequential order of data. In this project, Bidirectional LSTM is chosen as the

LSTM model. Bidirectional LSTM is a model that looks to both directions of the future and past [web, 2020].

Description of LSTM model used in this study

The data-set used for LSTM consists of four years (2015-2016-2017-2019). 2018 is removed since the trend is different from other years, and the reason is the out of order electrical boiler in that year. This was unplanned maintenance, meaning that it is not what usually happens every three or four years. Removing 2018 from the main data set yields 32,496 data points (number of rows). In this project, two hidden layers with one dropout layer are chosen as the main structure of the LSTM network. Each hidden layer is a bidirectional LSMT layer with 50 neurons, and the activation function is 'relu'. The shuffle is set to "False" since we are working with time series and the order of values matters. Table (4.3) illustrates the structure and parameters used in the model. It should be mentioned that all of the parameters in the table are tested to choose the best value that gives us a higher R^2 score.

Table 4.3: LSTM parameters

LSTM model	
Number of hidden layers	2
Neurons in each layer	50
Timesteps	24
Learning rate	0.0001
Activation function	relu
loss	MSE
optimizer	adam
epoch	30
Validation split	0.25
Batch size	64
shuffle	False

LSTM architecture and parameters

The data-set used for LSTM is time-series load data as input. Based on the window size, the model predicts the load of a specific hour based on 24 previous hours. For LSTM, years 2015 to 2017 is considered as train set, and 2019 (the recent year) is considered as the test-set. The parameters are obtained by testing different values to see which one gives the best performance in terms of R-squared. Table (4.4) illustrates the various scenarios tested for hyperparameter tuning. The results are based on trying different scenarios and it can be improved with a better choice of parameters. Also, for future studies, more automatic approaches to detect parameters with specific algorithms is suggested.

Table 4.4: Parameter tuning

Activation function	Learning rate	epoch	batch size	R-squared
relu	0.01	30	64	0.73
relu	0.001	30	64	0.75
relu	0.0001	30	64	0.75
softmax	0.0001	30	64	0.01
sigmoid	0.0001	30	64	-0.45
relu	0.0001	50	64	0.74
relu	0.0001	30	128	0.73
relu	0.0001	10	64	0.72
relu	0.0001	40	64	0.74

Overfitting in LSTM

Overfitting in LSTM is considered by putting dropout rate, which is =0.25. On the other hand, different selections of test and train-set are discussed as cross-validation. Each time one year is taken as the test set and the rest as a train set. Finally, the average accuracy and error of all four scenarios are considered to report the average performance of LSTM.

In this project, most work is done with Python in the Jupyter notebook environment. Python is a simple and practical programming language with many libraries that make it a proper candidate for machine learning projects. [web, 2019] and [Brownlee, 2018] were two websites that were helpful in model development for LSTM.

Chapter 5

Results

This chapter discusses the results from load analysis and load prediction parts. It also suggests recommendations to save energy in the building.

5.1 Load analysis

In this section, first, the results from outlier detection are discussed, then Concordia university is compared with other universities in terms of energy consumption per area, and finally, the results from load profile analysis and load comparison from 2015 to 2019 are illustrated.

5.1.1 Outlier detection

In this study, outliers were detected visually by investigating the box plots. The box plot of each variable for all years of both data sets is illustrated and checked.
Here, the outliers of each transformer for the year 2016 is shown below:

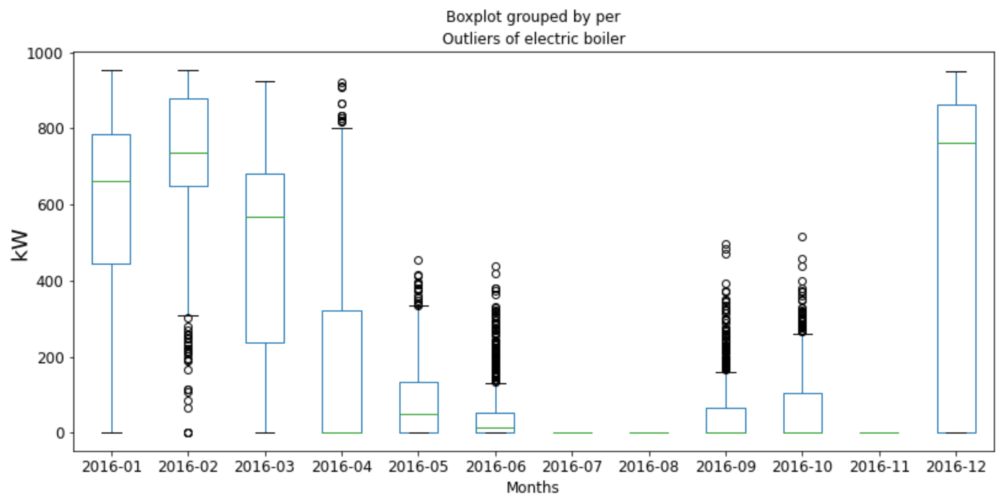


Figure 5.1: Outliers of electric boiler - 2016

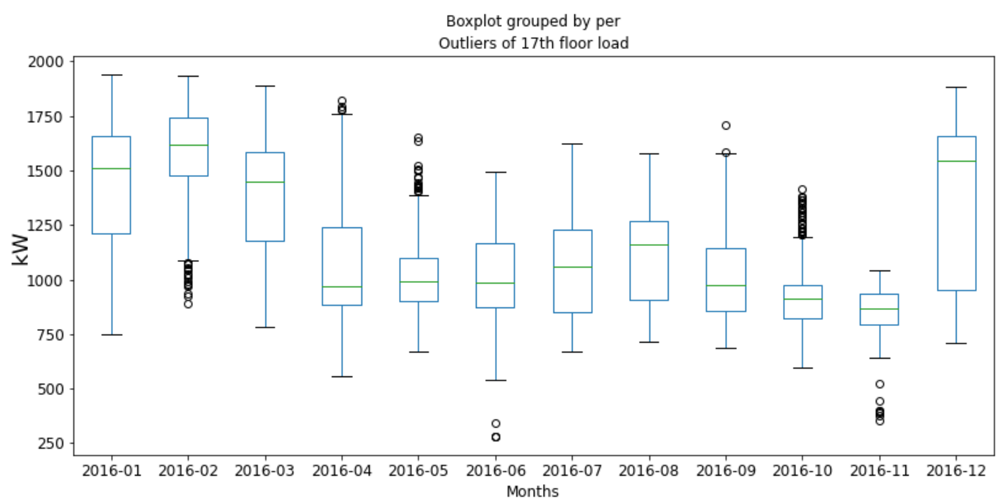


Figure 5.2: Outliers of 17^{th} floor load - 2016

The outliers in 2016-06 are happening for continuous hours, so there is no need to remove them because they are not errors.

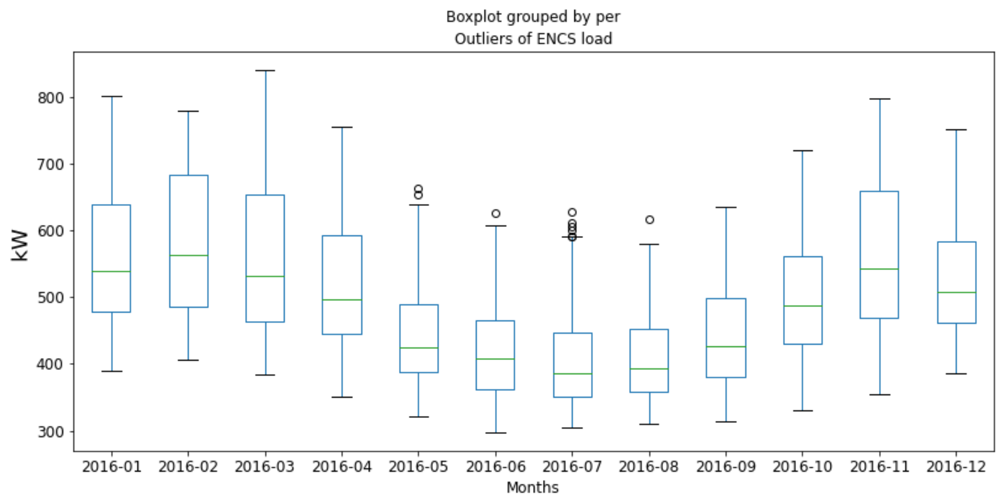


Figure 5.3: Outliers of ENCS load - 2016

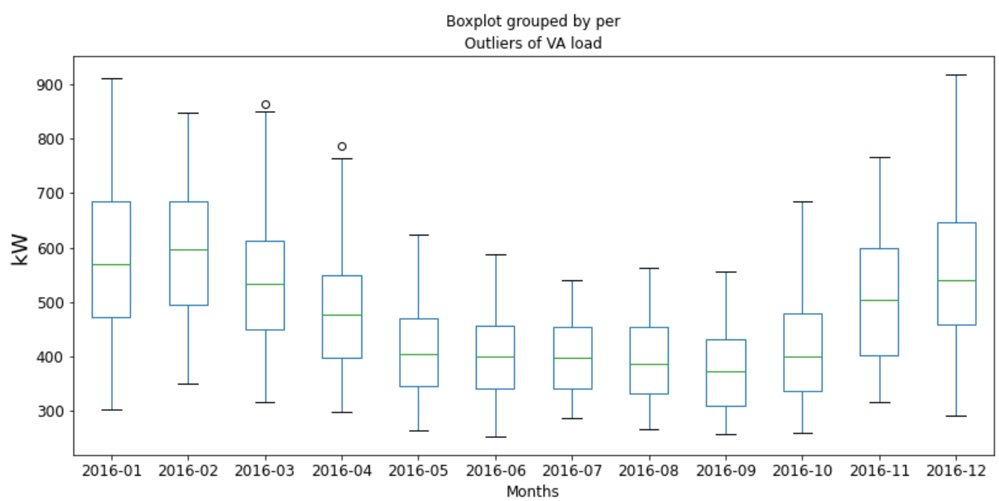


Figure 5.4: Outliers of VA load - 2016

Sometimes the Outliers are error and need to be treated. For example, in Figure 5.5, the outlier is happening in 2019-10. This outlier is replaced with the correct value of 100 % for relative humidity and 14.75 degrees for temperature with linear interpolation.

Figure (5.6) shows these outliers in the main excel file.

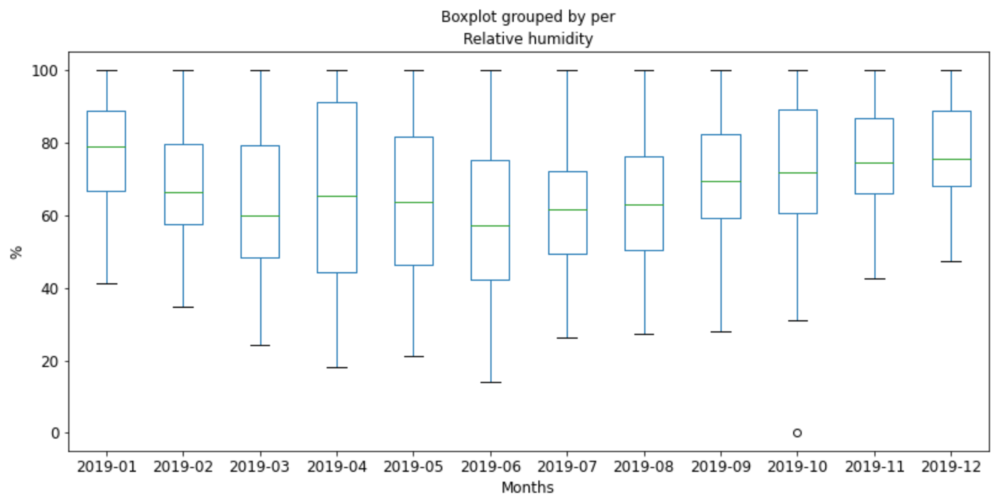


Figure 5.5: Outliers of Relative humidity - 2019

2019-10-31	10:00:00	124.7	100.1	12	172	1.66
2019-10-31	11:00:00	110.6	100.1	13	257	1.56
2019-10-31	12:00:00	97.7	100.1	13.7	173	0.89
2019-10-31	13:00:00	85.8	100.1	14.7	139	0.43
2019-10-31	14:00:00	19.9	100.1	14.7	180	1.63
2019-10-31	15:00:00	12.8	0	-39.9	234	1.46
2019-10-31	16:00:00	7.2	100.1	14.8	186	0.84
2019-10-31	17:00:00	0.7	100.1	15.1	196	2.44
2019-10-31	18:00:00	-0.5	100.1	15.1	160	1.93
2019-10-31	19:00:00	-0.4	100.1	15.6	63	1.54
2019-10-31	20:00:00	-0.4	100.1	11.7	53	7.26
2019-10-31	21:00:00	-0.5	100.1	9.7	67	5.65
2019-10-31	22:00:00	-0.5	100.1	8.3	51	11.83
2019-10-31	23:00:00	-0.4	100.1	7.8	53	9.01

Figure 5.6: Outlier in excel file

5.1.2 Comparison of energy consumption with other universities

It is always good to know what is the status of an institutional building in terms of energy consumption in comparison with other universities. Figure (5.7) compares the total energy consumption per area of several universities. The results of [Ma et al., 2015] is compared with Concordia university in almost the same time.

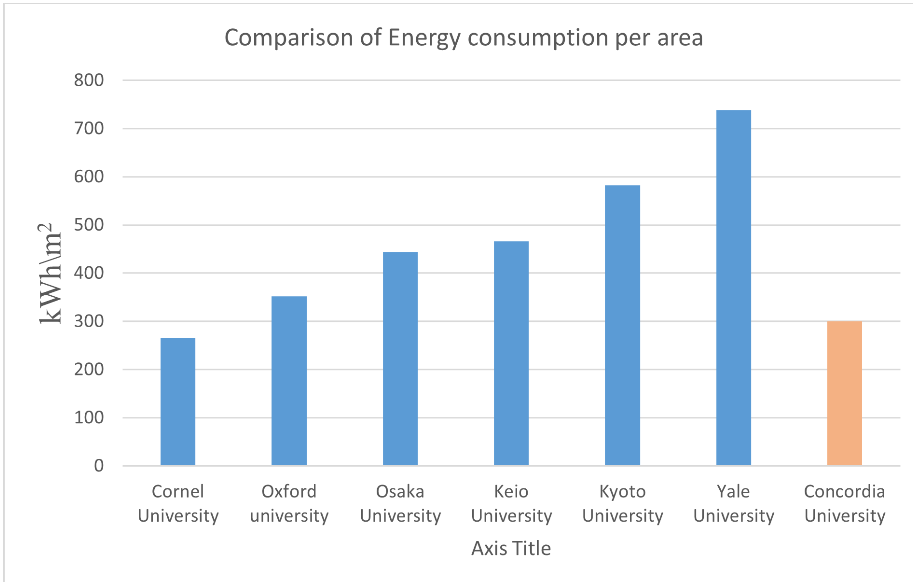


Figure 5.7: Compariosn of total energy consumption per area

As this graph shows, the energy consumption per area for Concordia university is almost the same as Cornel university but significantly lower than Yale University. Overall, these universities consume more energy compared to Concordia university. The energy consumption per area of Yale university is around 59% higher than Concordia and the value for Concordia university is around 11% higher from Cornel university [Ma et al., 2015].

Based on the average energy consumption of european universities mentioned in [Droutsa et al., 2020], which is 254.0 kWh/m2 [51.3–567.2], Concordia has higher energy consumption per area.

5.1.3 Analysis of load profiles

In this part, the representative weekday and weekend load profiles for each season of 2019 is illustrated. The average load is studied for office hours and non-office hours. The load of three transformers is studied in this project. Transformer 1 reports ENCS load, Transformer 2 is reporting VA load, and transformer 3 is assigned to the load from 17^{th} floor.

Transformer3 - 17^{th} floor

A comparison of representative weekday and weekend load profiles in different seasons is done for 17^{th} floor transformer.

Figures 5.8 and 5.9 illustrate the representative weekday and weekend loads in four seasons of 2019. In the 17^{th} floor load, the reduction from office hours to non-office hours in weekdays is 11.1%, 13.4 %, 15.8 %, and 15 % for winter, spring, summer, and Autumn, respectively. This percentage of reduction from office time to non-office time decreases for weekends.

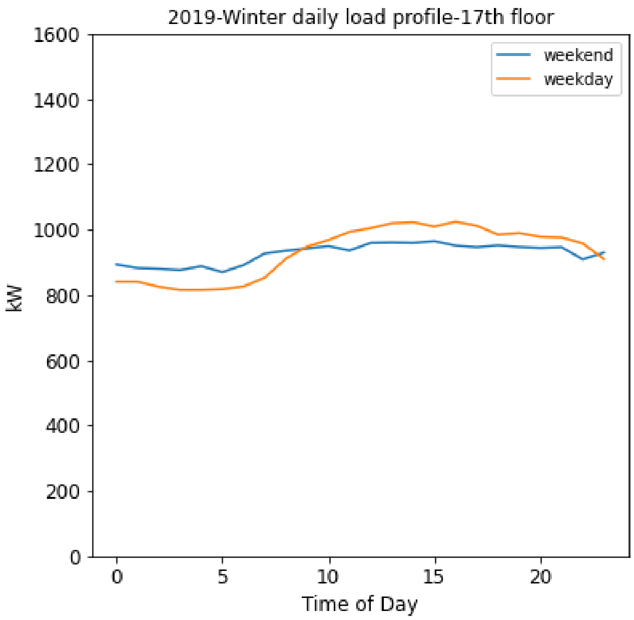
In winter, the difference between weekdays and weekends is so negligible compared to summer. This is due to the gas contribution of heating, as the graphs do not show it. Also, in winter, the load for weekends during the night is slightly higher than for weekday nights. The reason is the off-peak electrical boiler that is running during the night-time in winter.

In summer, the difference between weekdays and weekends for office hours is higher than in other months. This could be due to the schedule on which the building is used.

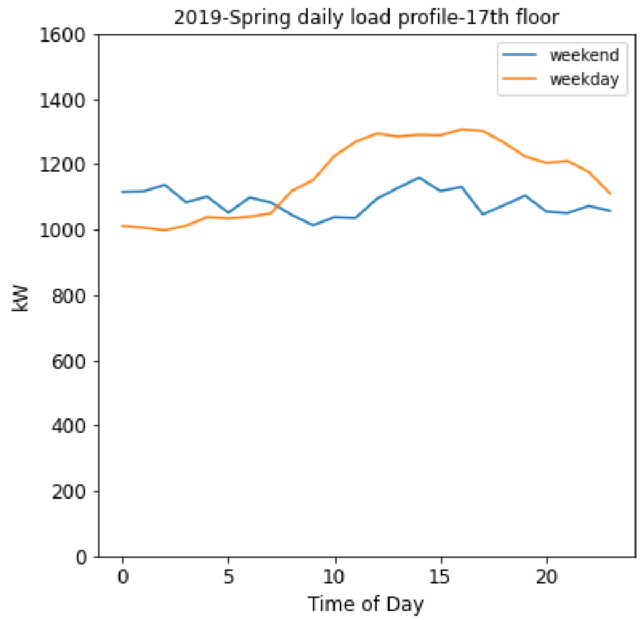
Table (5.1) shows the average load from 17^{th} floor during office and non-office hours for weekdays and weekends.

Table 5.1: Representative daily loads-17^{th} floor load

seasons	Average load (kW)	Office	Non-Office	Reduction
Winter	Weekday	991	881	11.1 %
	Weekend	951	907	4.6 %
Spring	Weekday	1254	1086	13.4 %
	Weekend	1080	1087	-0.6 %
Summer	Weekday	1441	1213	15.8 %
	Weekend	1241	1121	9.7 %
Autumn	Weekday	1387	1179	15 %
	Weekend	1164	1114	4.3 %

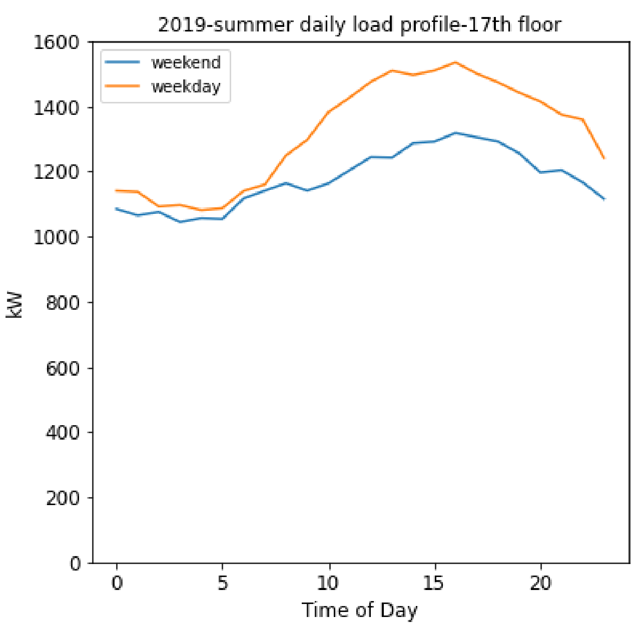


(a) 2019-Winter daily load profile-17th floor

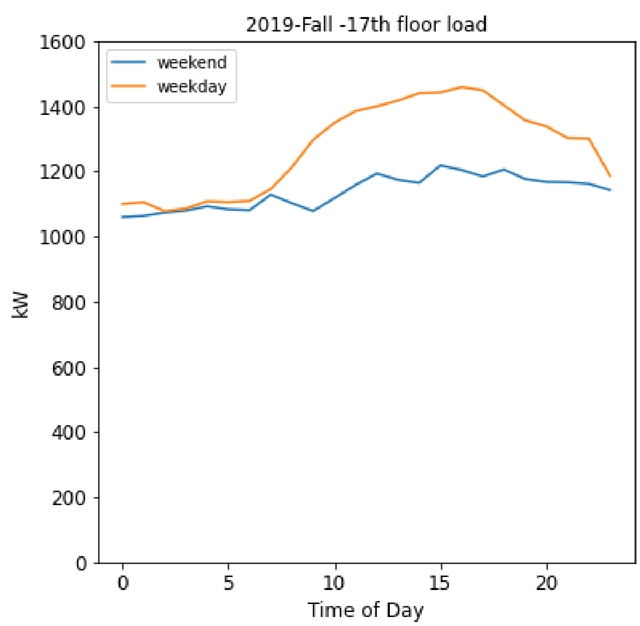


(b) 2019-Spring daily load profile-17th floor

Figure 5.8: Winter Spring -17$^{th} floor$ daily load



(a) 2019-Summer daily load profile-17th floor



(b) 2019-Autumn daily load profile-17th floor

Figure 5.9: Summer Autumn -17$^{th} floor$ daily load profile

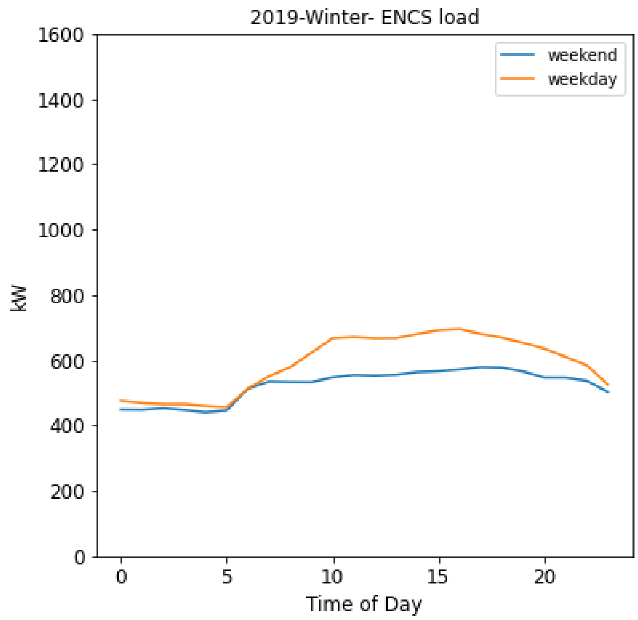
Transformer 1 - ENCS

Figure (5.10) and (5.11) show daily ENCS load profiles for weekday and weekend in four seasons. According to the figures, during the night, the load of ENCS is similar until around 5 AM, when there is an increase in the load both for weekday and weekend until around 7 AM. The reason for this increase is the transition from night-time unoccupied mode to daytime unoccupied mode. After that, occupants are coming to the building, and the graph reflects this behaviour.

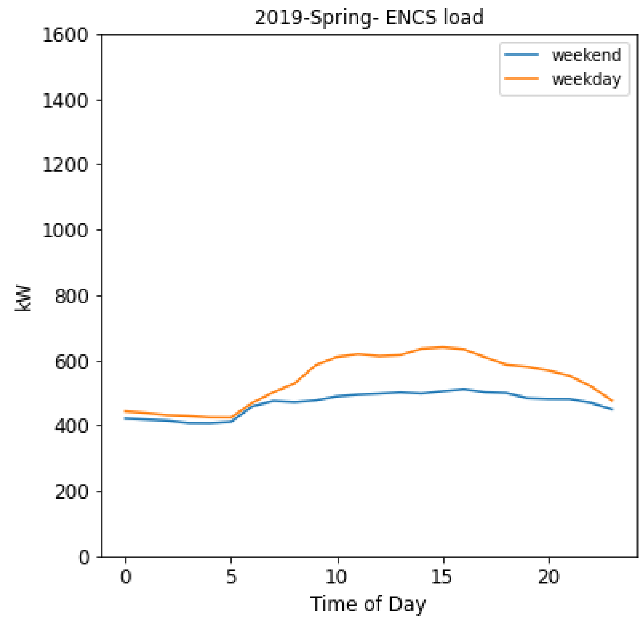
Table (5.2) shows the average ENCS load during office time and non-office time on weekdays and weekends.

Table 5.2: Representative daily loads -ENCS

Seasons	Average load (kW)	Office	Non-Office	Reduction
Winter	Weekday	663	528	20.4 %
	Weekend	558	495	11.3 %
Spring	Weekday	607	482	20.6 %
	Weekend	496	445	10.3 %
Summer	Weekday	512	411	19.7 %
	Weekend	445	404	9.2 %
Autumn	Weekday	616	472	23.4 %
	Weekend	494	438	11.3 %

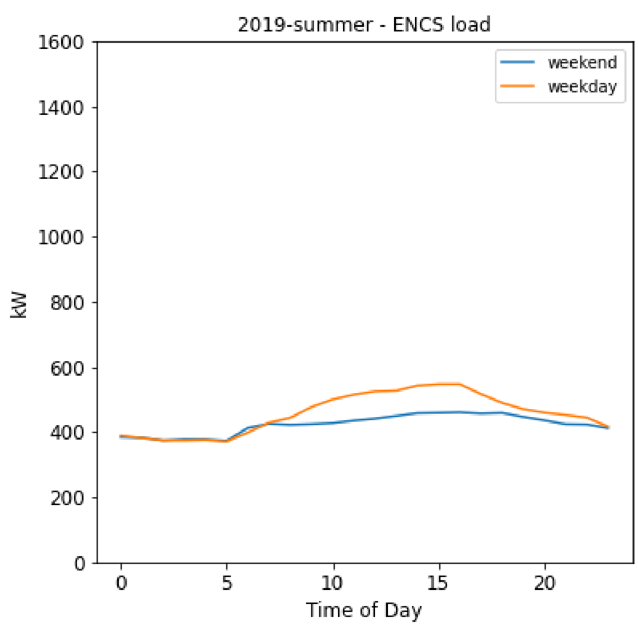


(a) 2019-Winter daily load profile-ENCS

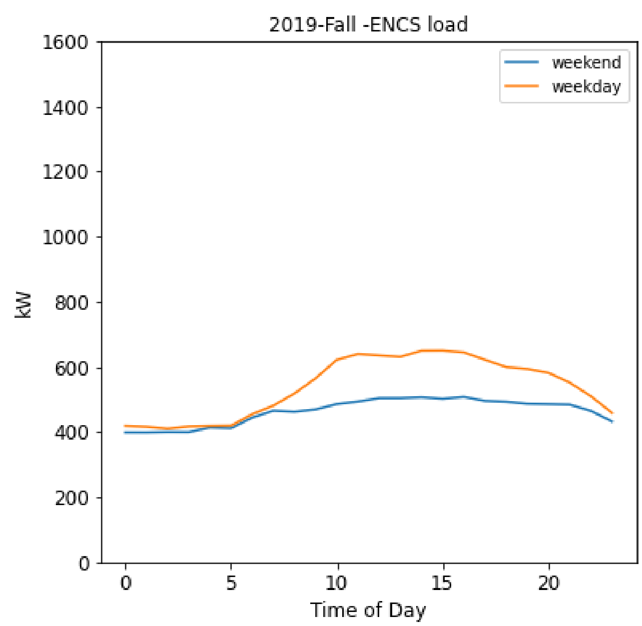


(b) 2019- Spring daily load profile-ENCS

Figure 5.10: Winter Spring - daily load profile- ENCS



(a) 2019- Summer daily load profile -ENCS



(b) 2019- Autumn daily load profile-ENCS

Figure 5.11: Summer Autumn daily load profile -ENCS

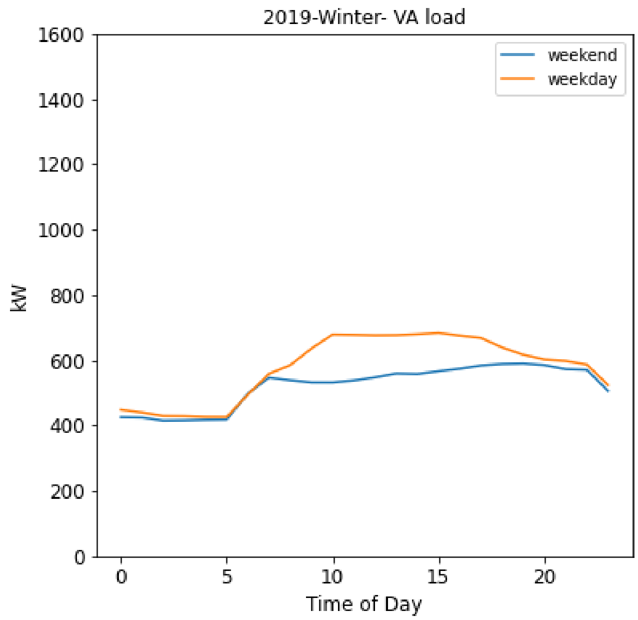
ENCS load in summer is low. The reason is that fewer students go to university in the summer months. Therefore there will be a reduction in plug loads in the summer.

Transformer 2 -VA

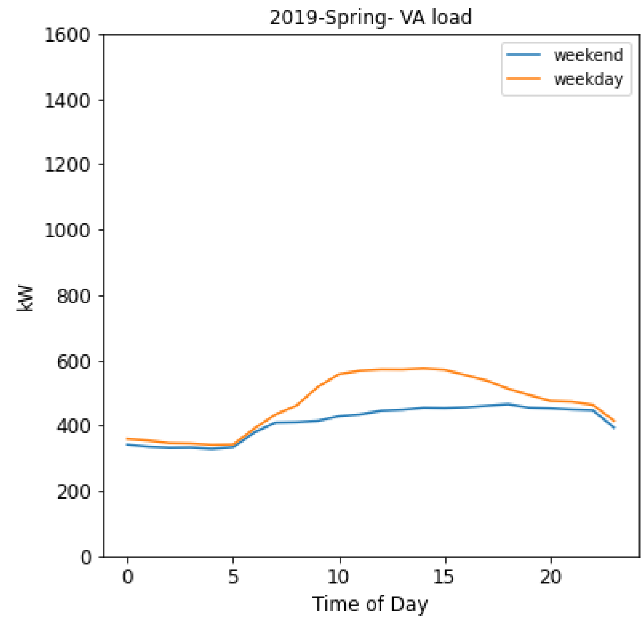
The patterns are very similar to ENCS load except for the last hours of the day, reflecting the difference between the behaviour of engineering students and VA students. Comparing to ENCS load, engineering students tend to stay more in the building at night. Table (5.3) explains the average VA load during office time and non-office time on weekdays and weekends.

Table 5.3: Representative daily loads - VA

Seasons	Average load (kW)	Office	Non-Office	Reduction
Winter	Weekday	662	507	23.4 %
	Weekend	557	492	11.7 %
Spring	Weekday	545	403	26.1 %
	Weekend	443	384	13.3 %
Summer	Weekday	453	333	26.5 %
	Weekend	365	316	13.4 %
Autumn	Weekday	537	375	30.2 %
	Weekend	412	356	13.6 %

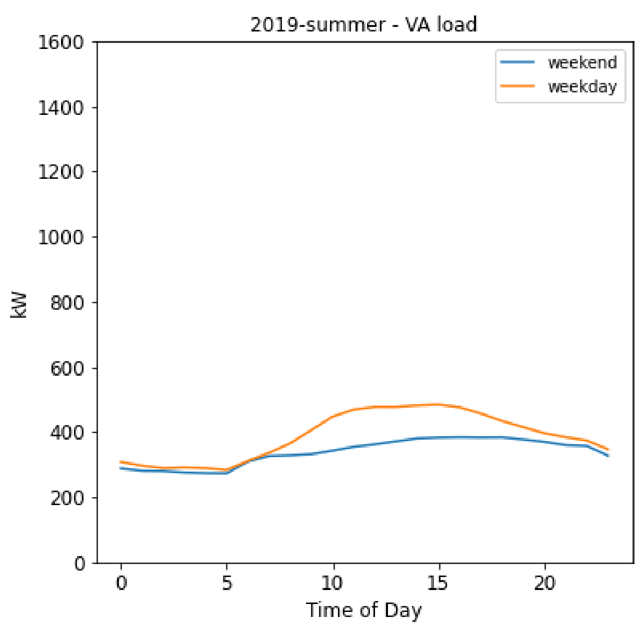


(a) 2019-Winter daily load profile -VA

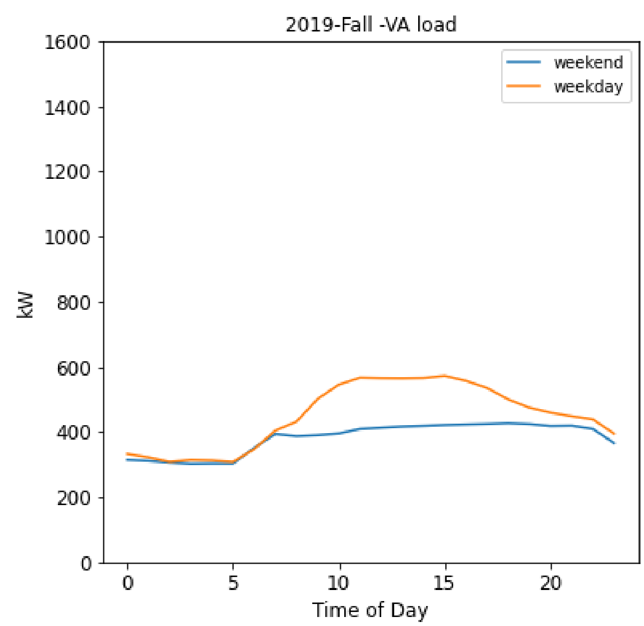


(b) 2019-Spring daily load profile -VA

Figure 5.12: Winter Spring daily load profile -VA



(a) 2019- Summer daily load profile -VA



(b) 2019-Autumn daily load profile- VA

Figure 5.13: Summer Autumn daily load profile -VA

5.1.4 Load comparison from 2015 to 2019

In this part, yearly load of 17^{th} floor, ENCS, and VA department is illustrated for different years (2015, 2016, 2017, 2018, 2019).

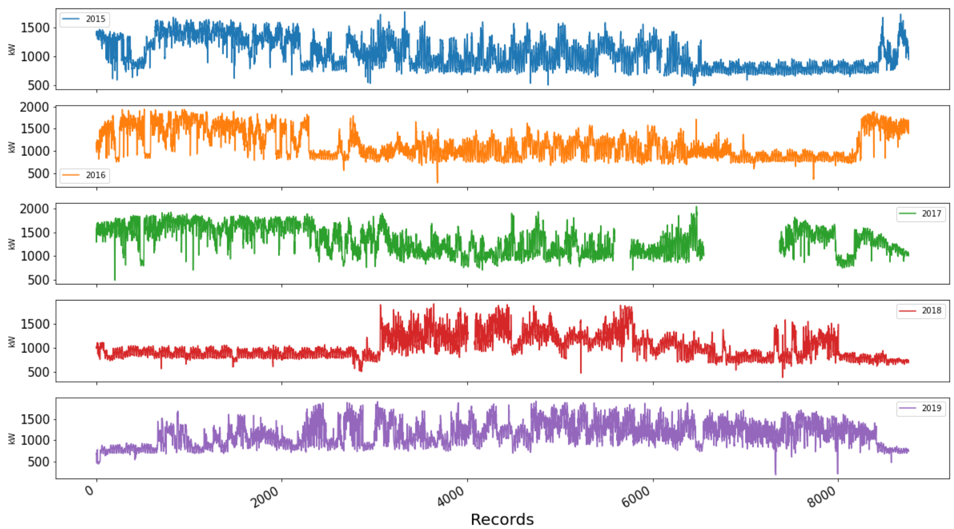


Figure 5.14: Electrical load of 17^{th} floor of EV from 2015 to 2019

As Figure (5.14) shows the magnitude and trend of 17^{th} floor load is different from one year to the other. This difference is pronounced for the first few months of 2018.

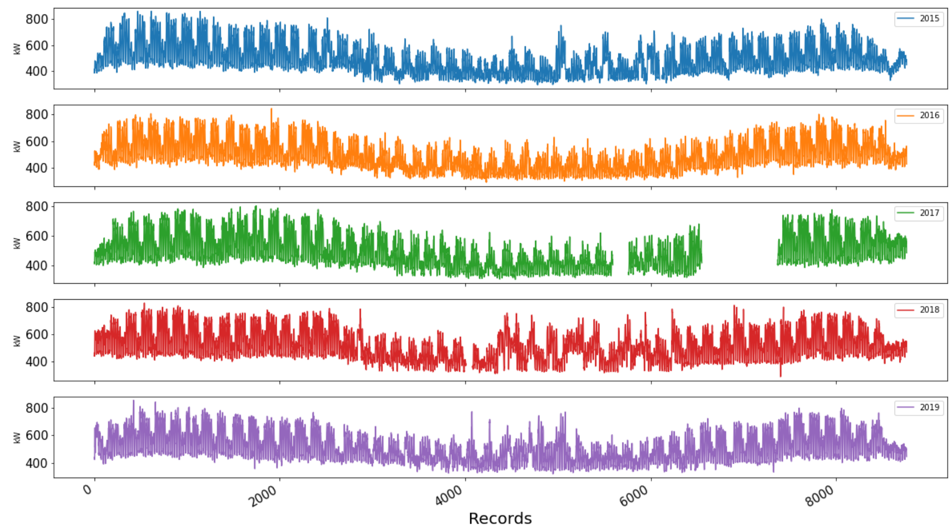


Figure 5.15: Electrical load of ENCS department from 2015 to 2019

The load for ENCS is almost the same throughout the years. It shows higher values during cold months than summer since in summer, daylight is available for more hours, and the need for lighting reduces compared to other months. Another reason is that fewer students go to university in the summer months. Therefore there will be a reduction in plug loads in the summer.

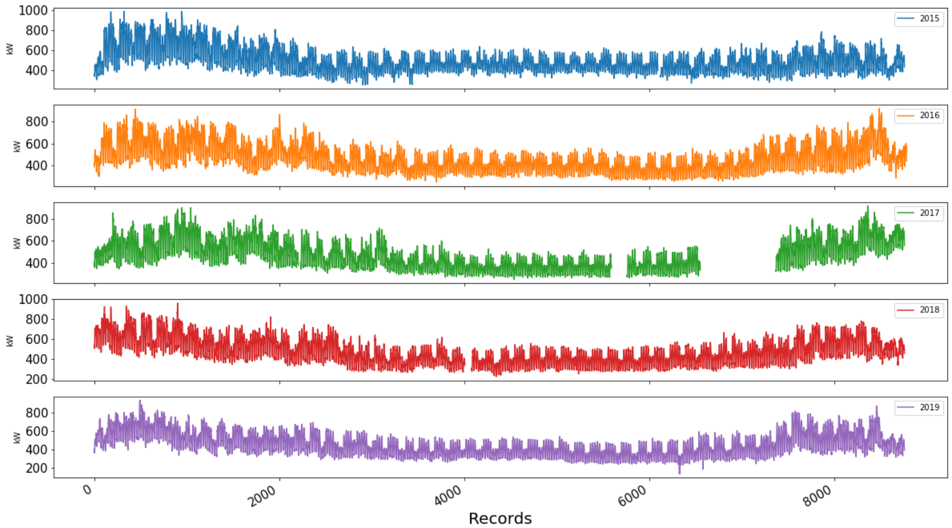


Figure 5.16: Electrical load of VA department from 2015 to 2019

Figure (5.16) shows the almost same pattern for different years. However, it is somehow different from the ENCS load since VA department experiences a low load for more months.

5.1.5 load profiles during COVID19 period

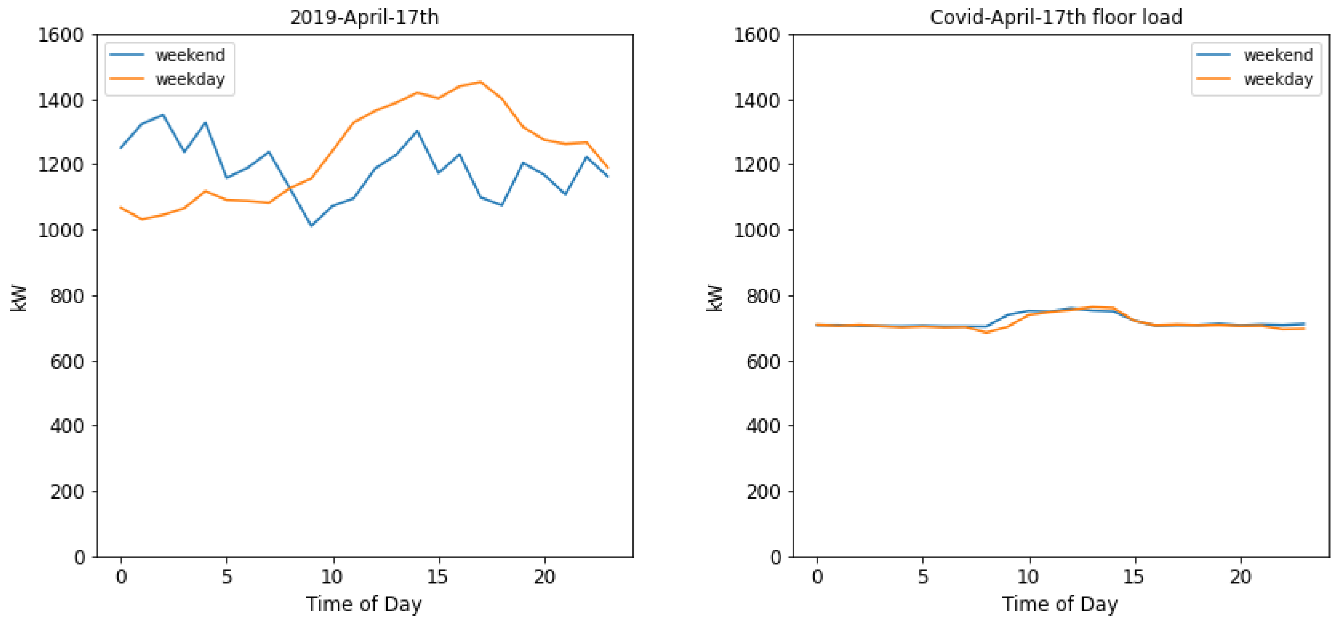
April and May of the year 2020 were two months of lockdown due to COVID 19. During this time, the university was closed to the students and the majority of the employees. In this section, the comparison of load profile for COVID 19 time and a similar time from 2019 is made to see how much reduction the load had when almost no one was at the university. The comparison is done for all three transformers.

17_{th} floor load during COVID 19

Comparing April and May 2019 with April and May 2020, we see a reduction of 42 % and 32 % for weekdays. This reduction is due to unoccupied spaces that eliminate the need for ventilation. A lot of offices and spaces in EV have sensors that detect the presence of people. So, when there is no one at the building, the need for ventilation decreases. The baseload of the 17th floor during COVID 19 (May 2020) is 724 kW for weekdays and 724 kW for weekends. Although there is almost no one at the building, this baseload is high. University must maintain the minimum load. One of the reasons for this minimum load is the labs of EV building, which should be kept at a regular exchange rate of ventilation. The laboratories' air exchange rate is 9 air change per hour for occupied status and 6 air change per hour for unoccupied status in the day time, and 3 air change per hour for unoccupied status during nights and weekends [facility manager reports]. Table (5.4) compares the average load of weekdays and weekends for two months of 2019 and 2020.

Table 5.4: Comparison of average weekday and weekend 17^{th} floor load in 2019 and 2020

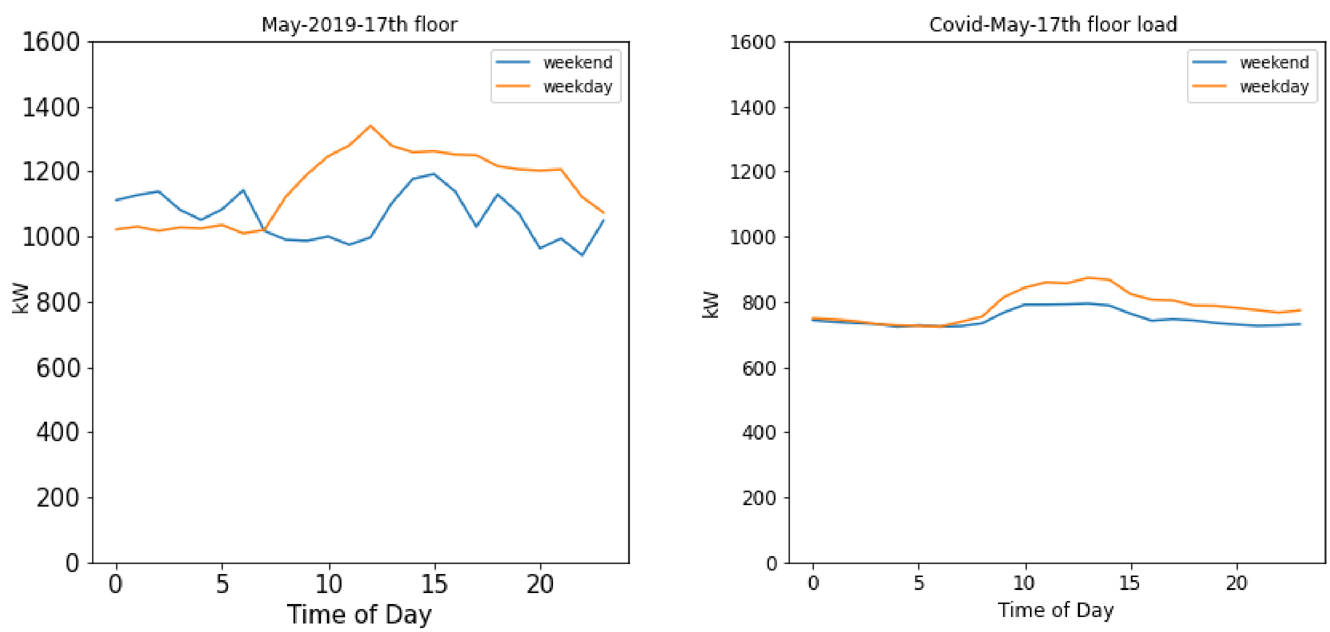
	April 2019-Average load		April 2020-Average load	
17th floor load	weekday	1234 kW	weekday	714 kW
	weekend	1189 kW	weekend	718 kW
	May 2019-Average load		May 2020-Average load	
	weekday	1154 kW	weekday	786 kW
	weekend	1062 kW	weekend	748 kW



(a) April-2019-17th floor.

(b) Covid-April-17th floor load.

Figure 5.17: Comparison of 17th floor load in April 2019 and April 2020



(a)

(b)

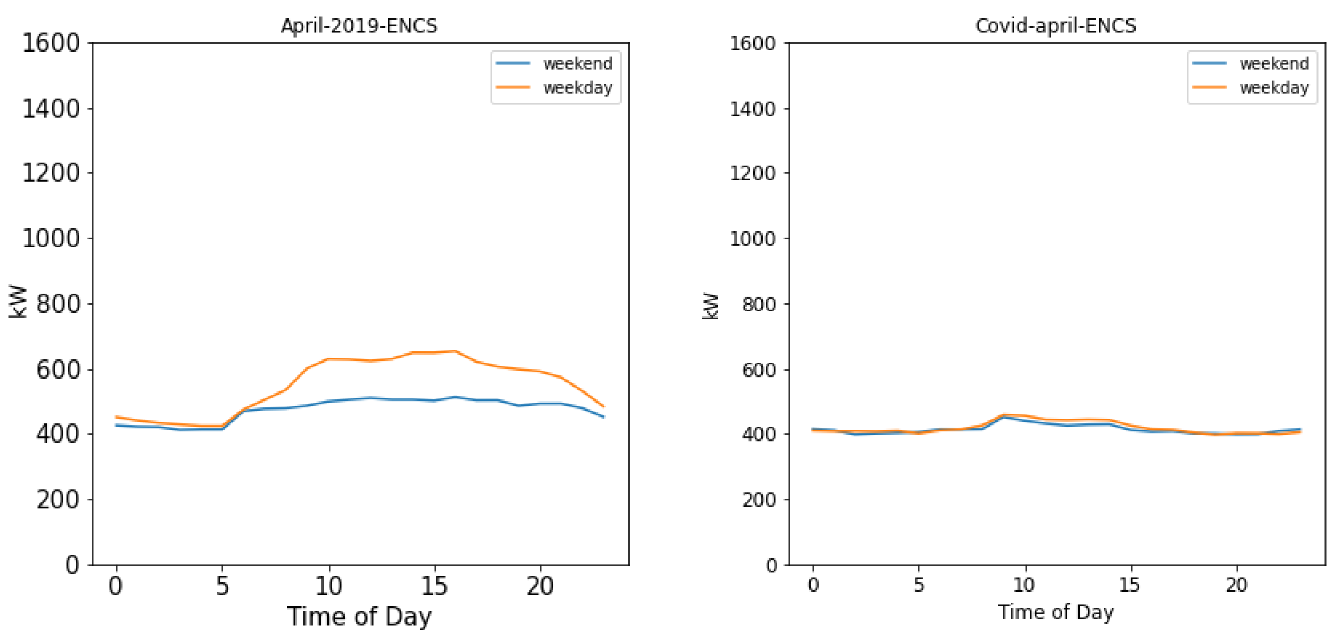
Figure 5.18: Comparison of 17th floor load in May 2019 and May 2020

ENCS load during COVID 19

As figure (5.19) and (5.20) show, for ENCS load, the reduction of load due to COVID19 is significantly less. Especially when compared to the 17^{th} load reduction. The baseload for ENCS, even when there is no one at the building, has some reasons. For example, one-third of the lighting should be kept. Also, a lot of computers are still on, and some tenants are not completely closed.

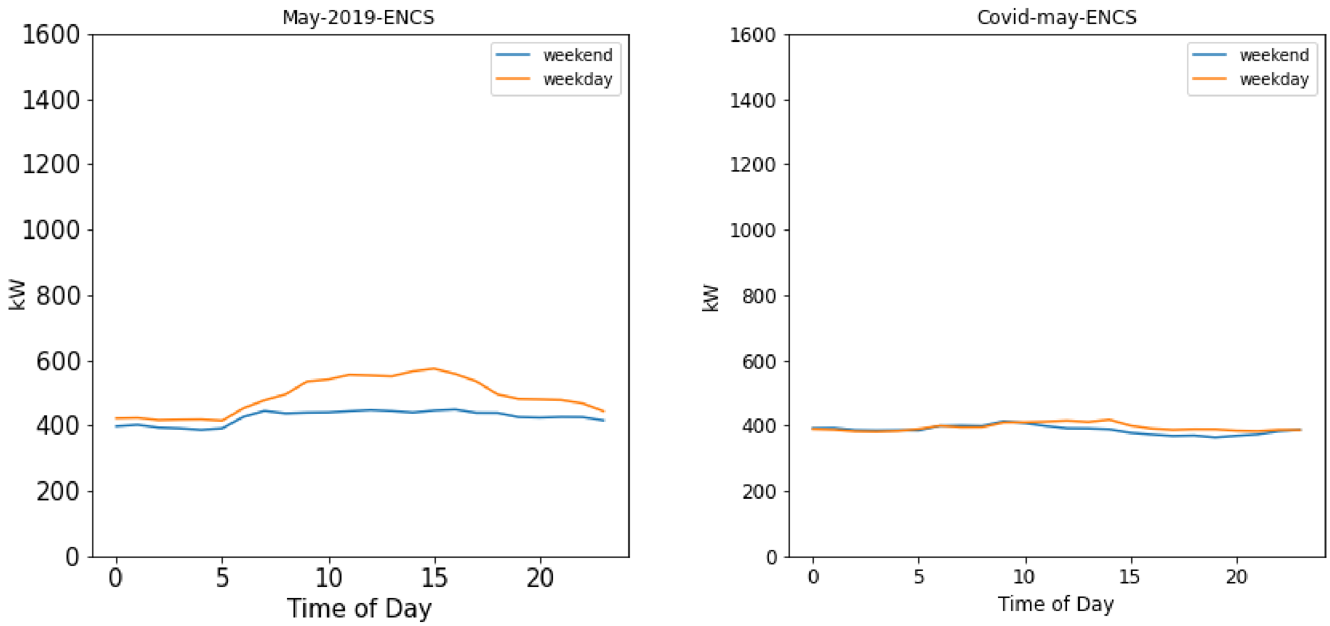
Table 5.5: Comparison of average weekday and weekend ENCS load in 2019 and 2020

<table>
<tr><td></td><td colspan="2">April 2019-Average load</td><td colspan="2">April 2020-Average load</td></tr>
<tr><td rowspan="5">ENCS load</td><td>weekday</td><td>549 kW</td><td>weekday</td><td>418 kW</td></tr>
<tr><td>weekend</td><td>473 kW</td><td>weekend</td><td>414 kW</td></tr>
<tr><td colspan="2">May 2019-Average load</td><td colspan="2">May 2020-Average load</td></tr>
<tr><td>weekday</td><td>490 kW</td><td>weekday</td><td>395 kW</td></tr>
<tr><td>weekend</td><td>426 kW</td><td>weekend</td><td>387 kW</td></tr>
</table>



(a) (b)

Figure 5.19: Comparison of ENCS load in April 2019 and April 2020



(a)

(b)

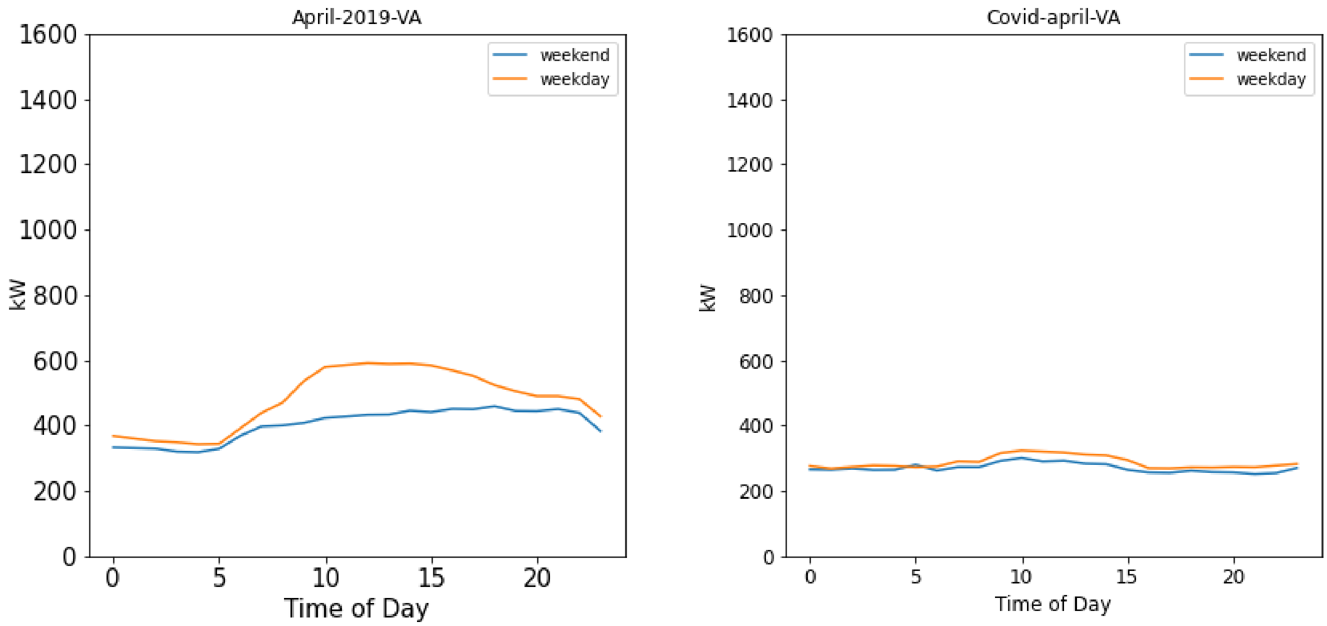
Figure 5.20: Comparison of ENCS load in May 2019 and May 2020

VA load during COVID 19

The load of VA department is also compared in this analysis. Figure 5.21 and 5.22 show the average load for two months of 2019 and 2020.

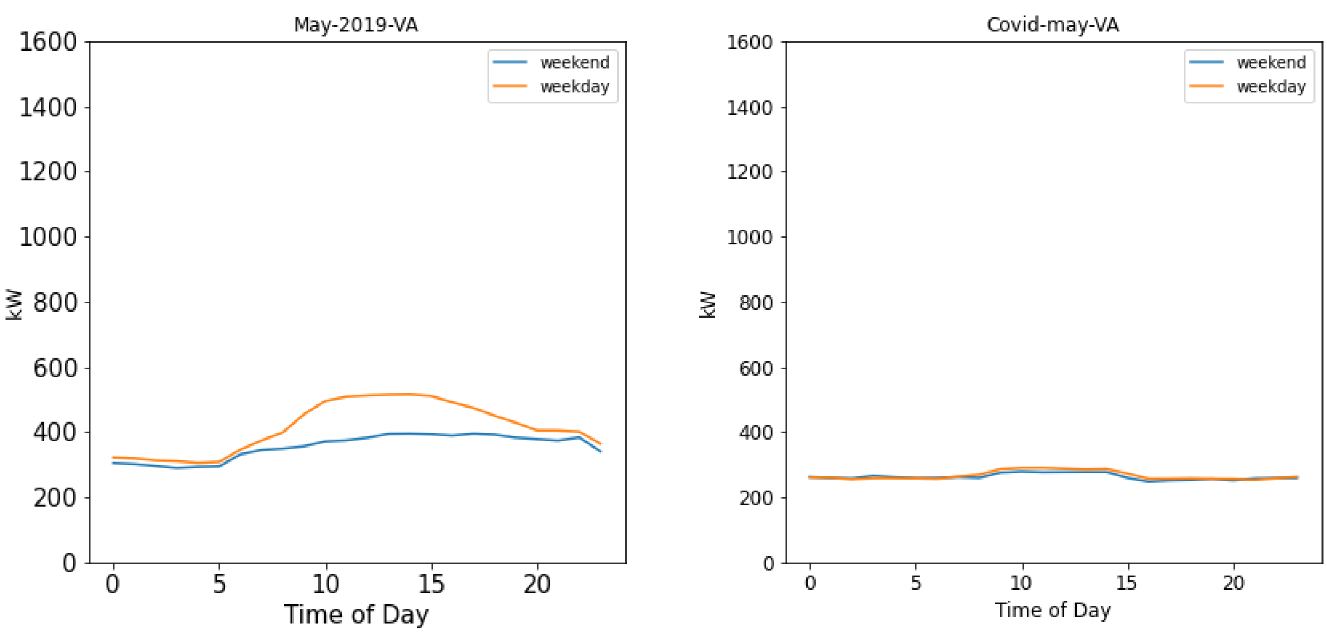
Table 5.6: Comparison of average weekday and weekend VA load in 2019 and 2020

<table>
<tr><td></td><td colspan="2">April 2019-Average load</td><td colspan="2">April 2020-Average load</td></tr>
<tr><td rowspan="5">VA load</td><td>weekday</td><td>480 kW</td><td>weekday</td><td>287 kW</td></tr>
<tr><td>weekend</td><td>403 kW</td><td>weekend</td><td>271 kW</td></tr>
<tr><td colspan="2">May 2019- load</td><td colspan="2">May 2020- load</td></tr>
<tr><td>weekday</td><td>414 kW</td><td>weekday</td><td>267 kW</td></tr>
<tr><td>weekend</td><td>355 kW</td><td>weekend</td><td>263 kW</td></tr>
</table>



(a) (b)

Figure 5.21: Comparison of VA load in April 2019 and April 2020



(a) (b)

Figure 5.22: Comparison of VA load in May 2019 and May 2020

5.2 Load prediction

In this part, Linear regression, Polynomial regression, and LSTM model are used for load prediction.

5.2.1 Load prediction with Linear regression

Linear regression - Considering yearly dataset

In this part, linear regression is used for load prediction without separating the seasons. (complete years of data set is considered). This is done to evaluate the importance of each variable in load prediction without separating the seasons. The performance of linear regression is tested on 20 scenarios. Table (5.7) shows the R^2 and error obtained from each scenario.

Table 5.7: Linear regression scenarios- without separating seasons - The whole year

Linear – whole year	R^2	MAPE
S1	0.18	22.08
S2	0.18	22.2
S3	0.16	22.33
S4	0.17	22.31
S5	0.16	22.34
S6	0.21	21.8
S7	0.18	22.03
S8	0.18	22.06
S9	0.18	22.08
S10	0.18	22.2
S11	0.18	22.15
S12	0.18	22.21
S13	0.17	22.31
S14	0.16	22.34
S15	0.16	22.31
S16	0.21	21.78
S17	0.21	21.76
S18	0.2	21.81
S19	0.21	21.75
S20	0.16	22.33

Figure (5.23) illustrates the improvements in R-squared for different scenarios. As it shows, solar radiation, temperature, and wind direction are contributing to increase of R-squared by 0.02 and less.

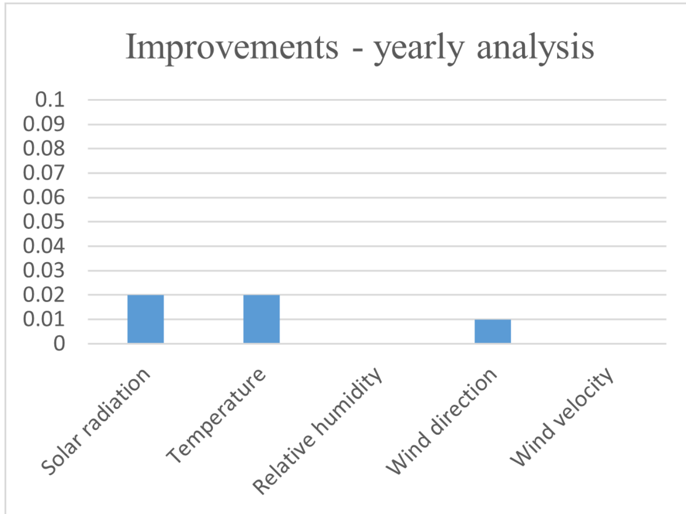


Figure 5.23: Improvement of accuracy - yearly

Seasonal load prediction

Linear regression is used to evaluate the importance of each meteorological variable in winter and summer.

Winter load prediction:

The winter months of four years of data-set is extracted as a new data-set for winter (January, February, and December). The new data set is used in linear regression.

Table (5.8) illustrates twenty scenarios in winter. As it shows, the best scenario is S19, which is the model that considers all calendar data and weather features with R^2= 0.29. However, there is no big difference between the accuracy of other scenarios in winter. Just considering calendar data will give R^2= 0.27, so one can conclude, calendar data is enough for load prediction with linear regression in winter. Figure (5.24) shows the improvement of R^2 by adding weather information to our model in winter. Solar radiation, temperature, and relative humidity increased R-squared by 0.01 in winter.

Table 5.8: Linear regression-scenarios-Winter load

Linear regression scenario-Winter load	R^2	MAPE
S1	0.28	24.52
S2	0.28	24.62
S3	0.28	24.64
S4	0.27	24.68
S5	0.27	24.63
S6	0.29	24.5
S7	0.28	24.51
S8	0.28	24.51
S9	0.29	24.47
S10	0.28	24.61
S11	0.28	24.62
S12	0.28	24.58
S13	0.28	24.64
S14	0.28	24.59
S15	0.27	24.63
S16	0.29	24.5
S17	0.29	24.5
S18	0.29	24.46
S19	0.29	24.46
S20	0.27	24.68

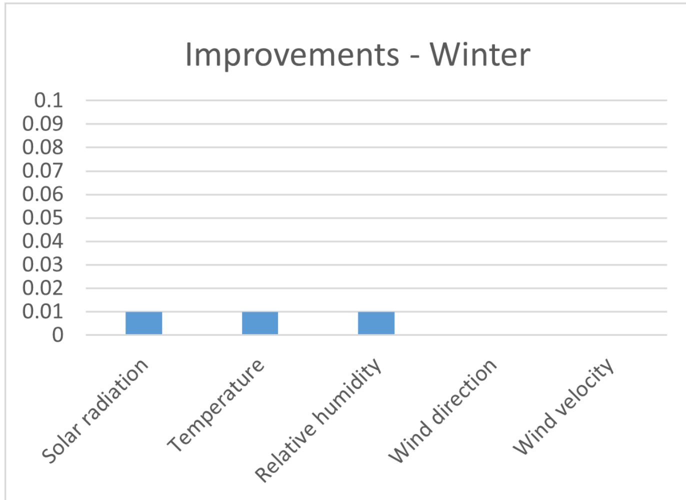


Figure 5.24: Improvement of accuracy in winter

Figure (5.25) illustrates the actual and predicted load (17^{th} floor load) for December 2018. In the figure, the predicted load includes both scenarios (S19 and S20). The year 2018 was extracted from the main data-set since the trend and magnitude of the load was completely different from other years. The reason was the electrical boiler, which was not working. The model has not seen 2018 before, and now, when it predicts the load for December 2018, it illustrates how different the load was.

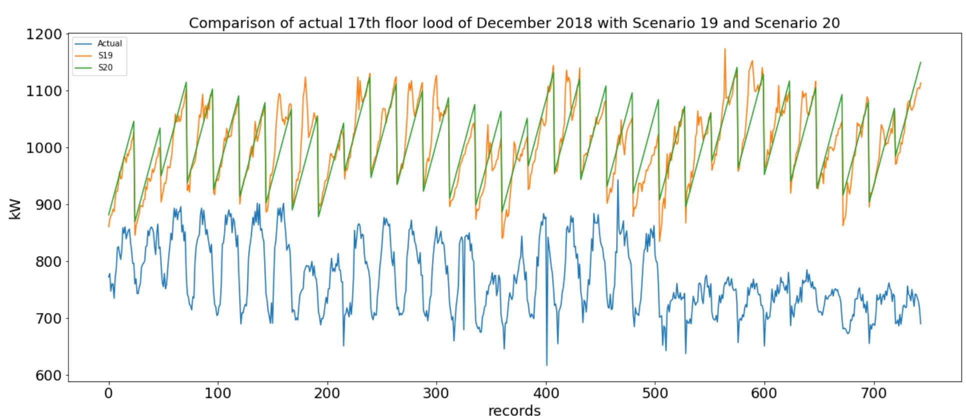


Figure 5.25: December 2018 - Actual load vs predicted (S19-S20)

Summer load prediction:

For summer analysis, the summer months (June, July, and August) of the main data set are extracted and used as a new data-set. Table (5.9) shows the performance of the predictive model for each scenario. As it shows, the best scenario is S19 and S16. Regarding the result of Table (5.9), there is considerable variation between each scenario's R-squared, starting from 0.39 to 0.64.
Just considering calendar data will give R^2=0.39. This value increases to 0.57 when just temperature is added to the model predictors, which highlights the important role of temperature in summer load prediction for 17^{th} floor .
Figure (5.26) explains the improvement of R^2 by considering individual weather variables in our model. In summer, temperature and solar radiation contribute to 18% and 8% improvement.

Table 5.9: Linear regression scenarios – Summer load prediction

Linear regression scenarios – Summer load	R^2	MAPE
S1	0.47	12.74
S2	0.57	11.36
S3	0.39	13.58
S4	0.4	13.48
S5	0.39	13.59
S6	0.59	10.94
S7	0.47	12.74
S8	0.48	12.67
S9	0.47	12.74
S10	0.59	11.14
S11	0.57	11.37
S12	0.57	11.35
S13	0.41	13.46
S14	0.39	13.57
S15	0.4	13.48
S16	0.64	10.46
S17	0.59	10.94
S18	0.59	10.94
S19	0.64	10.47
S20	0.39	13.59

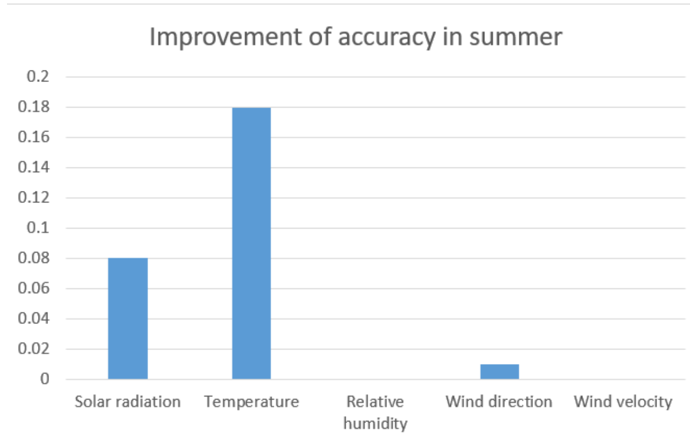


Figure 5.26: Improvement of accuracy in summer load prediction

Figure (5.27) shows the prediction and actual summer load of the 17^{th} floor in July 2018. Comparing to figure (5.25), where the winter load of 2018 is predicted, we see that the model is doing well in predicting the summer load of 2018. This indicates that the model performs well in the prediction of summer load in that year. However, for winter load prediction in 2018, the actual load and predicted had a significant difference. In fact, this difference in winter prediction refers to the not working boiler during cold months.

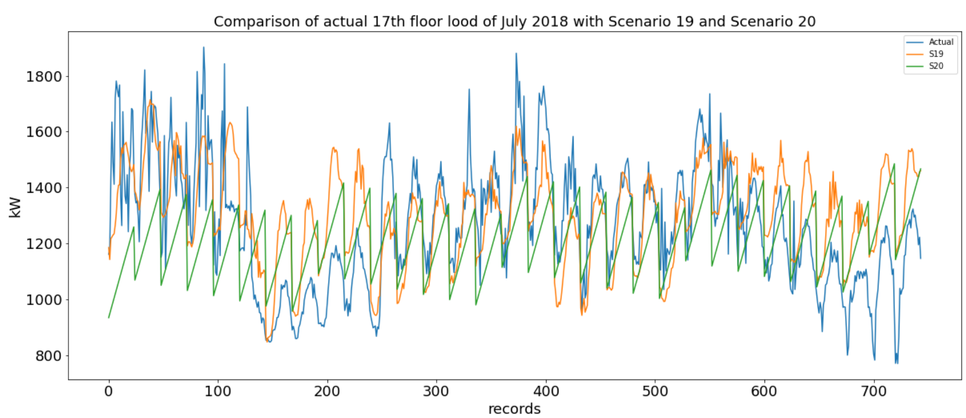


Figure 5.27: Summer2018-Actual load vs predicted (S19-S20)

Correlation analysis

Correlation analysis is done to understand the importance of the input variables on load. There are two concepts: positive correlation and strong correlation. The positive correlation is when input increases, the output increases as well. However, the correlation may be negative when the output increases while the input variable decrease. A strong correlation has a greater magnitude. Here we consider both concepts and confirm that the results obtained by linear regression match (for summer, winter and complete year) the strongest correlations, not the positive.

Table (5.10) illustrates the correlation analysis results and compares with the result from linear regression.

Table 5.10: Important factors from Correlation analysis and linear regression

	Positive Correlation	Strongest correlation	Linear regression
Summer	Temperature- Solar radiation	Temperature- Solar radiation	Temperature- Solar radiation
Winter	Solar radiation-wind velocity	Solar radiation- Relative humidity- Temperature	Solar radiation- relative humidity- Temperature
Complete year	Solar radiation-wind velocity	Temperature- Solar radiation	Temperature- Solar radiation
Autumn	Solar radiation-wind direction	Solar radiation-Relative humidity	-
Spring	Solar radiation-wind velocity	Temperature-Solar radiation	-

Based on the results from this part, for all seasons, solar radiation and temperature are the most significant factors. In winter, relative humidity is also important.

5.2.2 Polynomial regression

Polynomial regression is also trained on the whole data set. The year 2018 is never seen before, and polynomial regression tries to predict it.

Scenario 19 or S19 is the one that considers all-weather and calendar variables. Scenario 20 is the one that considers calendar data. Figure (5.28) compares the actual load in 2018 and predicted load in the same year with two scenarios: scenario 19 and scenario 20.

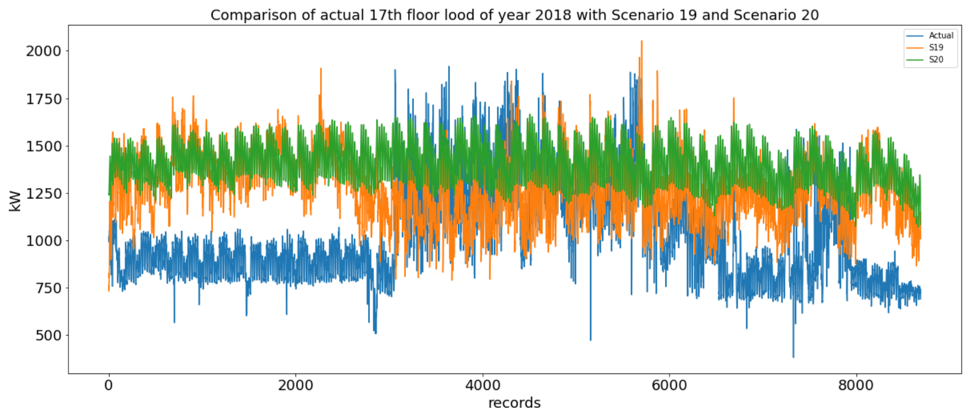


Figure 5.28: Actual load and predicted load with polynomial regression - year 2018

As this figure (5.28) shows, S19 could better predict the load comparing S20. Both of them could not match the actual load in the first few months of the year (cold months). The reason is not working electrical boiler during this time. In the data analysis part, it was shown that 2018 is different from other years. Both trend and magnitude was different. So it was excluded from the main data-set from the first step. Now feeding this year to polynomial regression, it is shown that the model captures this unusual consumption since there is a gap between the actual and predicted load in the first months of 2018.

5.2.3 LSTM

LSTM is used for load forecasting as it is capable of capturing long time dependencies. The train set contains 2015, 2016, 2017, and the test set includes 2019. LSTM forecasts the load of 17^{th} floor for different time horizons (different test-set size), and its performance is compared with the other two transformers' load.

17^{th} floor load forecasting

Different train and test-set

Overfitting in LSTM is considered by putting a dropout rate, which is 0.25. On the other hand, different selections of test and train-set are discussed as cross-validation. Each time one year is taken as the test set and the rest as a train set. Finally, the average accuracy and error of all four scenarios are considered to report the average performance of LSTM.

Table 5.11: Variouse test-sets

Test sets	R-squared	MAPE	MSE
2015	0.92	5.18	5801.03
2016	0.91	5.9	9328.21
2017	0.88	5.56	10287.42
2019	0.75	10.97	19812.66

As the table (5.11) shows, the R-squared is the lowest when 2019 is taken as test-set. The average R-squared for all four scenarios is 0.86.

Different time horizons

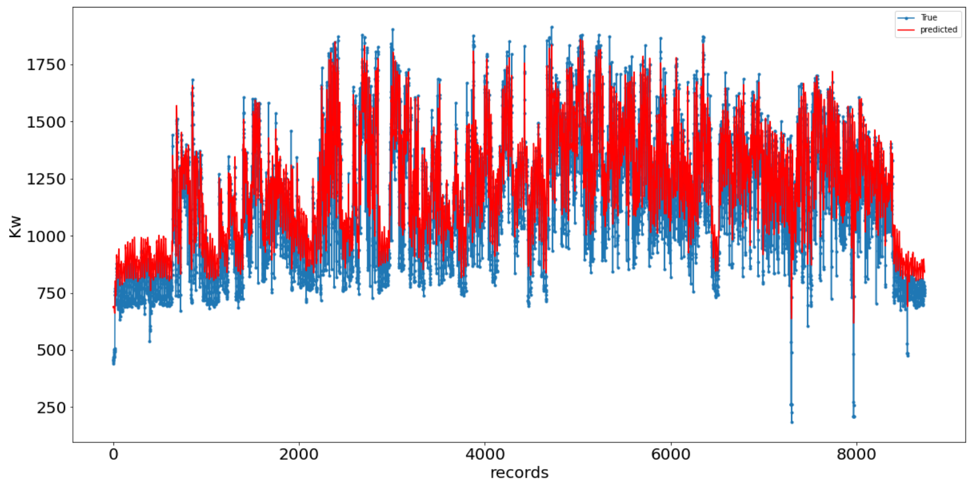
The model's performance on different time spans depends on the model structure and the size of the train set. Here different scenarios of time horizons (different test set size) with fixed LSTM model (fix structure and train set size) are discussed. LSTM forecasts different time horizons starting from one year ahead to the next day. In fact, the model is being trained over the years 2015, 2016, 2017 and tested over different time horizons, mentioned in Table (5.12).

Table 5.12: Comparison of different time horizons

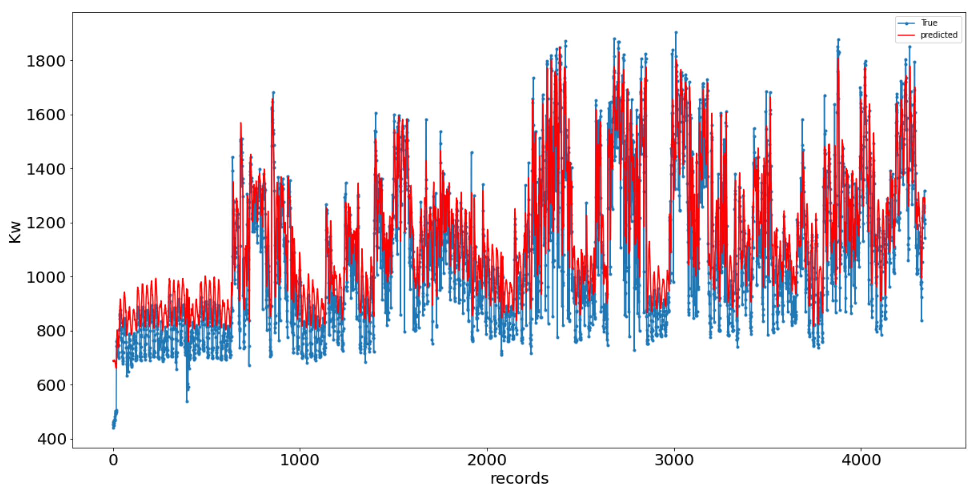
Time horizons	R^2	MAPE	mse
Full year	0.75	10.97	19812.66
1 month ahead	0.53	13.5	13094.16
6 month ahead	0.74	11.66	20210.15
2 week ahead	-0.35	14.33	11903.26
1 week ahead	-0.12	15.76	13277.7
1 day ahead	-1.64	35.64	34503.49

As shown in this table, LSTM performs best when one year ahead is being predicted. The performance decreases as the time horizon shrinks to one month ahead. For a shorter time horizon (two weeks and less), the model is not performing well and can not fit the data. The reason is the unusual load for that specific period.

Figure (5.29), (5.30), and (5.31) illustrate the actual and predicted load for different time horizons.

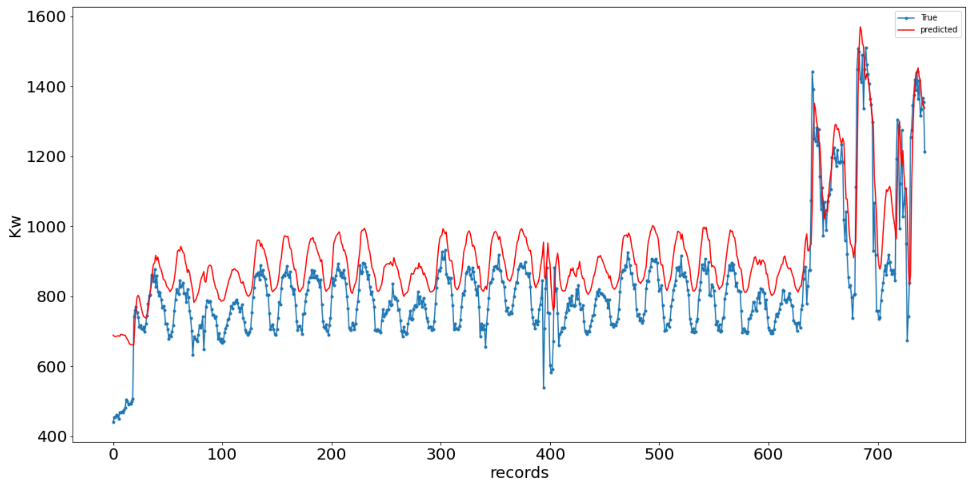


(a) Actual vs predicted load for full year 2019

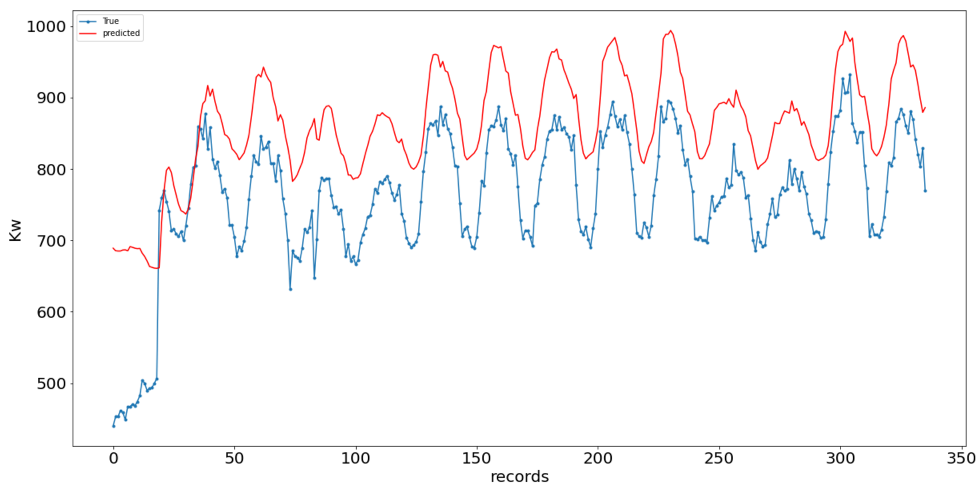


(b) Actual vs predicted load for the first six months of 2019

Figure 5.29: Comparison of load forecasting for different time horizons

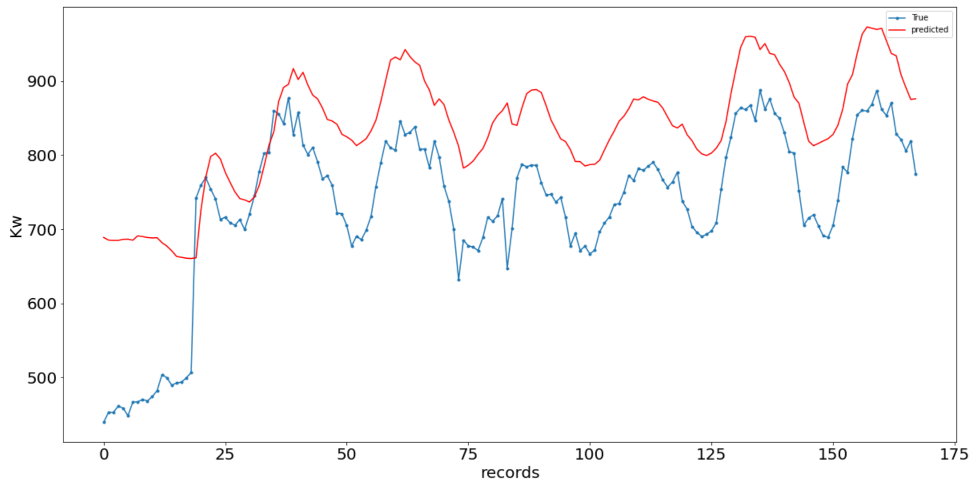


(a) Actual vs predicted load for first months of 2019

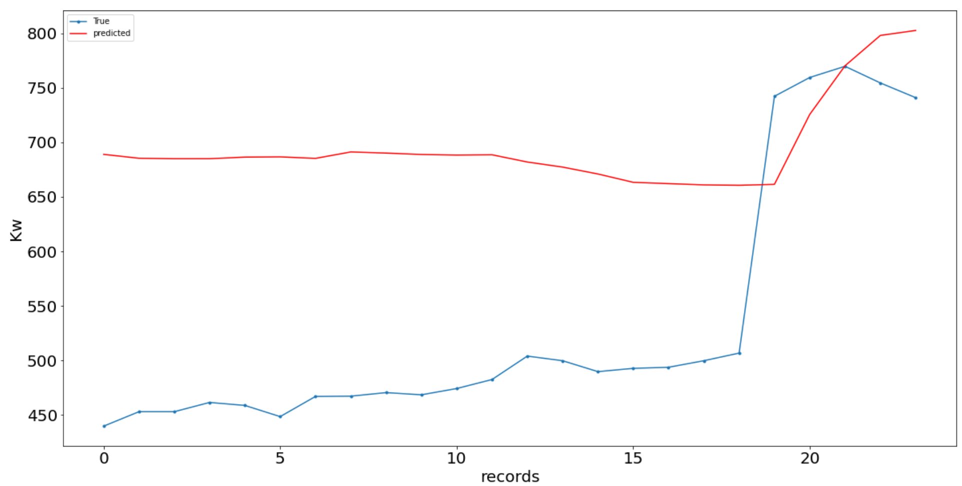


(b) Actual vs predicted load for the first two weeks of 2019

Figure 5.30: Comparison of load forecasting for different time horizons



(a) Actual vs predicted load for the first week of 2019



(b) Actual vs predicted load for the first day of 2019

Figure 5.31: Comparison of load forecasting for different time horizons

ENCS load forecasting

The load of ENCS department is being forecasted with LSTM. Figure (5.32) shows the actual load and predicted load of the test set (year 2019).

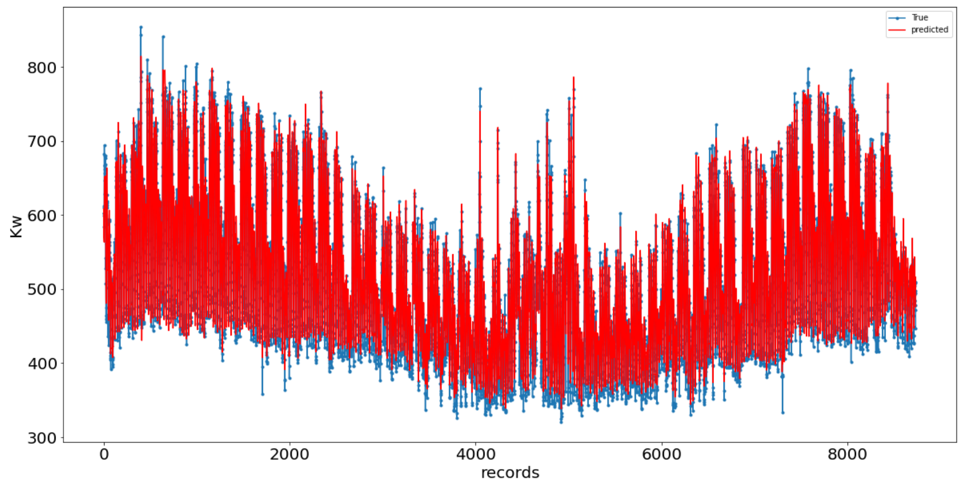


Figure 5.32: Actual vs predicted ENCS load- 2019

VA load forecasting

The load of VA department is being forecasted with LSTM. Figure (5.33) shows the actual load and predicted load of test-set (year 2019).

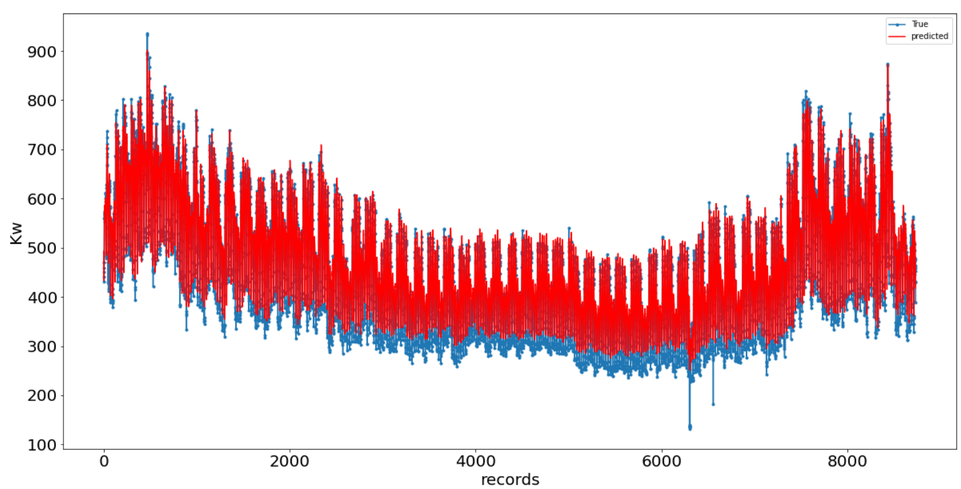


Figure 5.33: Actual vs predicted VA load - 2019

Comparison of LSTM performance for different load types

Load forecasting is done for three transformers, 17^{th} floor, ENCS, and VA. The accuracy and error in each case are illustrated as follows:

Load types	R^2	MAPE	mse
ENCS	0.92	4.35	818.3
VA	0.93	6.87	1146.4
17^{th} floor load	0.75	10.97	19812.66

According to the above table, LSTM had better performance for ENCS and VA department. The reason is the load type. ENCS and VA represent plug load, which depends on schedule and occupancy. In contrast, the 17^{th} floor load mainly includes the HVAC load, mostly dependent on weather and variant parameters.

5.3 Recommendations

The recommendations are:

1) Pre-cool the building specially in summer during the night with natural ventilation to reduce the temperature of building so that during the day less energy will be consumed to cool the building. 2) There is a shift in load from 5 AM to around 7 AM in plug loads both for weekday and weekend. We can change the schedule of weekends and prevent that shift in weekends so the general base load will be less. 3) By having more sub-metering we will know how much each system (such as lightning, computers and so on) are responsible for the load.

Implementation of data preprocessing load forecasting in the urban energy modelling workflow:

This project aims to observe the building's performance, discover potentials to save energy, and know the load's influencing factors. A better understanding of the current energy consumption pattern is crucial for future load forecasting. The forecasts could be applied for decision-making strategies related to retrofitting the building and load shaving. Apart from the benefits of load forecasting for the facility manager of Concordia university, the methods can be generalized and integrated into a bigger picture. Load forecasting with machine learning is case dependent and may vary from one building to the other. Therefore, a single building's methods and results cannot be useful for other buildings in the same category. However, two services can be integrated to enrich the urban energy modelling workflow. The first one is to integrate Python code for data cleaning as a united block, which takes dirty data and cleans it. A similar approach could be implemented to the load forecasting part. Based on the chosen algorithms, one can make the complete procedure to clean, analyze, and forecast the data.

Chapter 6

Conclusion

Energy efficiency and energy savings in buildings are the major focus of different disciplines around the world. The professionals in each sector try to reduce energy consumption as much as possible. Efficient and reduced usage of energy in a building means less CO_2 emissions and has an economic benefit for both consumers and producers. This study tries to use machine learning tools to provide better approaches for energy usage reduction by detailed data analysis and predicting the building energy demand. In this research, a Concordia university building is taken as a case study. Electrical load and weather data collected for the years between 2015 to 2019 was used. Data quality is very important for a good machine learning model. Several steps are followed in the data preprocessing part, which include: dealing with missing, duplicate, wrong sign values, correcting type of data, outlier detection, aggregating 15-min values to hourly intervals, adding extra features, and data integration. After transforming the raw dataset to a dataset with high quality, load analysis is performed. Based on the analysis, the load from the 17^{th} floor is lower in winter. In winter, the weekday load during office hours is 991 kW, while this value is 1,441 kW in summer because the heating demand in EV building is majorly met through gas, and the load does not show the gas contribution for heating. Overall, the load from 17^{th} floor is significantly higher than two other transformer's load that represent plug loads. In autumn, the average weekday load during office time is 1387 kW for 17^{th} floor, while the load for ENCS and VA are 616 kW and 537 kW, respectively. ENCS and VA load show almost similar energy consumption patterns and magnitude except for the evening hours of the day, which shows a different behavioral pattern of engineering students compared to visual art students. An analysis is also done during the COVID 19 pandemic. Comparing April and May 2019 with April and May 2020, the load from 17^{th} floor during weekdays, reduced 42 % and 32 %, respectively. This reduction is due to the unoccupied status of spaces in the building. This is not considered a huge reduction when almost no one is at the building. In fact, there are chemical and mechanical laboratories in the building that need a specific ventilation rate and are responsible for a part of the baseload during this time. The load reduction during COVID19 period was even less for ENCS and VA load. Based on the results during COVID 19 period, there is a good potential to save energy by changing the running schedule of systems.

For load prediction, LSTM and two regression models (linear regression and polynomial regression) were implemented. Linear regression is a statistical model that takes different input variables and predict the output. Here the importance of each input variable is discussed. For linear regression, three scenarios are discussed in this thesis to evaluate the effects of weather variables in different times. The first one does load prediction without separating seasons, while the two other scenarios are based on seasons (winter and summer). For the complete-year prediction, solar radiation, temperature, and wind direction improved R-squared of prediction by around 2%, 2%, 1% and each.

For winter load prediction, solar radiation, temperature, and relative humidity contribute to 1% improvements each, which is not significant. The importance of weather variables in summer is more pronounced. Temperature contributes to 18% of R-squared improvement. Solar radiation improves the R-squared by 8%, and wind direction contributes to just 1% of improvement. Comparing winter and summer results, weather variables are not affecting the load of 17^{th} floor in winter. This is not a general result, and it is applicable just for this case study since at Concordia, the heating demand in winter is being achieved majorly by natural gas rather than electricity and the load in winter does not show the gas contribution. That is why the effect of weather variables is not obvious in winter load prediction.

The best result for all three cases was from scenario 19 (S19), which considers all weather variables as well as calendar data. The performance of S19 is compared with S20 (one with just calendar data) in figure (5.25). As it is shown, the variation of load during the day is considered by S19, whereas S20 is just a straight line from baseload to peak load. Comparing the results from correlation analysis, The affecting factors from linear regression are in line with the strongest correlations, not positive correlations.

Polynomial regression is also a statistical model that tries to fit the curve line between measured records. The regression model could capture unusual consumption in the first months of 2018. The year 2018 was extracted from the main dataset since it had a different trend and magnitude for 17^{th} floor load, and then it was given to the model to check if it captures this difference, Figure (5.28).

For developing the LSTM model, three years of old historical load data (2015, 2016, and 2017) were used as the training data set and predicts the load on the test set (2019). This is for next year's load forecasting, and other time horizons, including six months, one month, two weeks, one week, and one day are studied with this LSTM model. It was shown that as the time horizon reduces, the R-squared of the model decreases. For shorter time horizons, such as one day ahead, the accuracy becomes negative. This is due to the unusual load in that time.

Comparing the model performance in forecasting the load from all three transformers, ENCS and VA load had better accuracy and lower error compared to 17^{th} -floor load. This indicates how accurately different load types could be forecasted. Regarding LSTM, load type, prediction time horizon and the choice of train-set affect the performance of the model.

Overall, this thesis tried to answer essential questions that can help the facility manager of Concordia University. Based on the results from linear regression, where different scenarios were compared, it was concluded that the 17^{th} load, which is mainly HVAC, is influenced by external weather factors. For example, in summer, the temperature was the most important meteorological feature that improved R-squared by 18 %. This means the HVAC load is not completely based on schedule, so some recommendations could be given in this stage, such as pre-cooling the building during the night in summer. Some changes in the schedule of running systems can also help to save energy, for example, there is a shift in load from 5 AM to around 7 AM in plug loads both for weekday and weekend. We can change the schedule of weekends and prevent that shift in weekends so the general baseload will be less. It is also suggested to install more sub-metering since By having more sub-metering, we will know how much each system, such as lightning, and computers is responsible for the load.

As the summary, non-trivial findings could be mentioned as follows:

1) Based on the results during COVID 19 period, we see that the existence of people in the building affects the load, but a great part of load is related to the schedule and policy of the building. There is a great potential to save energy just by changing the schedule and plans that systems are running based on. 2) The influencing factors from linear regression parts match the strongest correlations, not positive correlations. 3) Load type, prediction time horizon and the choice of train-set affect the performance of LSTM.

For future studies, the suggested tasks to be done are as follows:

1) The weather variables could be added to LSTM model. 2) The performance of LSTM model can be improved by implementing optimization algorithms to find the best parameters. 3) LSTM model will be compared with other predictive models such as CNN and CNN-LSTM models, NARX, and Tao's vanilla benchmark. 4) All parts of data preparation, load prediction, and load forecasting is going to be used as different simulation blocks integrated into the CERC urban energy modelling platform. Also, a 3D Model of EV building was prepared that will be used as input for simulation models that will be enriched with other inputs to simulate load, and the results will be compared with real data to check how well the simulation models are working and what are the required inputs for simulation. This part is under development and is considered for future studies.

Bibliography

[web, 2008] (2008). Engineering, computer science and visual arts integrated complex. https://imtl.org/montreal/building/Concordia-engenring.php.

[web, 2015] (2015). Understanding lstm networks. http://colah.github.io/posts/2015-08-Understanding-LSTMs/.

[EV-, 2015] (2015). Weather information in support of smart buildings management activities.

[web, 2019] (2019). Time series prediction with lstms using tensorflow 2 and keras in python. https://www.youtube.com/watch?v=xaIA83x5Icg.

[web, 2020] (2020). Bidirectional long short-term memory (bi-lstm). http://primo.ai/index.php?title=Bidirectional_Long_Short-Term_Memory_(BI-LSTM).

[can, 2020a] (2020a). Canada's actions to reduce emissions. https://www.canada.ca/en/services/environment/weather/climatechange/climate-plan/reduce-emissions.html#shr-pg0.

[can, 2020b] (2020b). Electricity facts. https://www.nrcan.gc.ca/science-data/data-analysis/energy-data-analysis/energy-facts/electricity-facts/20068.

[can, 2020c] (2020c). Global greenhouse gas emissions. https://www.canada.ca/en/environment-climate-change/services/environmental-indicators/global-greenhouse-gas-emissions.html.

[can, 2020d] (2020d). United nations framework convention on climate change. `https://www.canada.ca/en/environment-climate-change/corporate/international-affairs/partnerships-organizations/united-nations-framework-climate-change.html`.

[Abbas et al., 2018] Abbas, F., Feng, D., Habib, S., Rahman, U., Rasool, A., and Yan, Z. (2018). Short term residential load forecasting: An improved optimal nonlinear auto regressive (narx) method with exponential weight decay function. *Electronics*, 7(12):432.

[Agrawal et al., 2018] Agrawal, R. K., Muchahary, F., and Tripathi, M. M. (2018). Long term load forecasting with hourly predictions based on long-short-term-memory networks. In *2018 IEEE Texas Power and Energy Conference (TPEC)*, pages 1–6. IEEE.

[Akdemir and Çetinkaya, 2012] Akdemir, B. and Çetinkaya, N. (2012). Long-term load forecasting based on adaptive neural fuzzy inference system using real energy data. *Energy Procedia*, 14:794–799.

[AlRashidi and El-Naggar, 2010] AlRashidi, M. and El-Naggar, K. (2010). Long term electric load forecasting based on particle swarm optimization. *Applied Energy*, 87(1):320–326.

[Amarasinghe et al., 2017] Amarasinghe, K., Marino, D. L., and Manic, M. (2017). Deep neural networks for energy load forecasting. In *2017 IEEE 26th International Symposium on Industrial Electronics (ISIE)*, pages 1483–1488. IEEE.

[Amasyali and El-Gohary, 2018] Amasyali, K. and El-Gohary, N. M. (2018). A review of data-driven building energy consumption prediction studies. *Renewable and Sustainable Energy Reviews*, 81:1192–1205.

[Amjady and Keynia, 2008] Amjady, N. and Keynia, F. (2008). Mid-term load forecasting of power systems by a new prediction method. *Energy Conversion and Management*, 49(10):2678–2687.

[Anand et al., 2019] Anand, P., Cheong, D., Sekhar, C., Santamouris, M., and Kondepudi, S. (2019). Energy saving estimation for plug and lighting load using occupancy analysis. *Renewable Energy*, 143:1143–1161.

[Bouktif et al., 2018] Bouktif, S., Fiaz, A., Ouni, A., and Serhani, M. A. (2018). Optimal deep learning lstm model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches. *Energies*, 11(7):1636.

[Brownlee, 2018] Brownlee, J. (2018). How to develop lstm models for time series forecasting. `https://machinelearningmastery.com/how-to-develop-lstm-models-for-time-series-forecasting/`.

[Bunnoon et al., 2009] Bunnoon, P., Chalermyanont, K., and Limsakul, C. (2009). Mid term load forecasting of the country using statistical methodology: case study in thailand. In *2009 International conference on signal processing systems*, pages 924–928. IEEE.

[Chitalia et al., 2020] Chitalia, G., Pipattanasomporn, M., Garg, V., and Rahman, S. (2020). Robust short-term electrical load forecasting framework for commercial buildings using deep recurrent neural networks. *Applied Energy*, 278:115410.

[Daneshi et al., 2008] Daneshi, H., Shahidehpour, M., and Choobbari, A. L. (2008). Long-term load forecasting in electricity market. In *2008 IEEE International Conference on Electro/Information Technology*, pages 395–400. IEEE.

[Deb et al., 2016] Deb, C., Eang, L. S., Yang, J., and Santamouris, M. (2016). Forecasting diurnal cooling energy load for institutional buildings using artificial neural networks. *Energy and Buildings*, 121:284–297.

[Deb et al., 2017] Deb, C., Zhang, F., Yang, J., Lee, S. E., and Shah, K. W. (2017). A review on time series forecasting techniques for building energy consumption. *Renewable and Sustainable Energy Reviews*, 74:902–924.

[Droutsa et al., 2020] Droutsa, K. G., Balaras, C. A., Lykoudis, S., Kontoyiannidis, S., Dascalaki, E. G., and Argiriou, A. A. (2020). Baselines for energy use and carbon emission intensities in hellenic nonresidential buildings. *Energies*, 13(8):2100.

[Dudek, 2015] Dudek, G. (2015). Short-term load forecasting using random forests. In *Intelligent Systems' 2014*, pages 821–828. Springer.

[Fallah et al., 2019] Fallah, S. N., Ganjkhani, M., Shamshirband, S., and Chau, K.-w. (2019). Computational intelligence on short-term load forecasting: A methodological overview. *Energies*, 12(3):393.

[Fan and Ding, 2019] Fan, C. and Ding, Y. (2019). Cooling load prediction and optimal operation of hvac systems using a multiple nonlinear regression model. *Energy and Buildings*, 197:7–17.

[Fan et al., 2018] Fan, C., Xiao, F., Li, Z., and Wang, J. (2018). Unsupervised data analytics in mining big building operational data for energy efficiency enhancement: A review. *Energy and Buildings*, 159:296–308.

[Fan et al., 2014] Fan, C., Xiao, F., and Wang, S. (2014). Development of prediction models for next-day building energy consumption and peak power demand using data mining techniques. *Applied Energy*, 127:1–10.

[Feilat and Bouzguenda, 2011] Feilat, E. and Bouzguenda, M. (2011). Medium-term load forecasting using neural network approach. In *2011 IEEE PES Conference on Innovative Smart Grid Technologies-Middle East*, pages 1–5. IEEE.

[Fumo and Biswas, 2015] Fumo, N. and Biswas, M. R. (2015). Regression analysis for prediction of residential energy consumption. *Renewable and sustainable energy reviews*, 47:332–343.

[Ghiassi et al., 2006] Ghiassi, M., Zimbra, D. K., and Saidane, H. (2006). Medium term system load forecasting with a dynamic artificial neural network model. *Electric power systems research*, 76(5):302–316.

[Guo et al., 2004] Guo, X.-C., Chen, Z.-Y., Ge, H.-W., and Liang, Y.-C. (2004). Short-term load forecasting using neural network with principal component analysis. In *Proceedings of 2004 International Conference on Machine Learning and Cybernetics (IEEE Cat. No. 04EX826)*, volume 6, pages 3365–3369. IEEE.

[Han et al., 2018] Han, L., Peng, Y., Li, Y., Yong, B., Zhou, Q., and Shu, L. (2018). Enhanced deep networks for short-term and medium-term load forecasting. *IEEE Access*, 7:4045–4055.

[Hong et al., 2010] Hong, T. et al. (2010). Short term electric load forecasting.

[Hong et al., 2014] Hong, T., Pinson, P., and Fan, S. (2014). Global energy forecasting competition 2012.

[Hong et al., 2015] Hong, T., Wang, P., and White, L. (2015). Weather station selection for electric load forecasting. *International Journal of Forecasting*, 31(2):286–295.

[Hutama et al., 2018] Hutama, A. H., Akbar, S., and Candra, M. Z. C. (2018). Medium term power load forecasting for java and bali power system using artificial neural network and sarimax. In *2018 5th International Conference on Data and Software Engineering (ICoDSE)*, pages 1–6. IEEE.

[Jacob et al., 2020] Jacob, M., Neves, C., and Vukadinović Greetham, D. (2020). *Short Term Load Forecasting*, pages 15–37. Springer International Publishing, Cham.

[Jetcheva et al., 2014] Jetcheva, J. G., Majidpour, M., and Chen, W.-P. (2014). Neural network model ensembles for building-level electricity load forecasts. *Energy and Buildings*, 84:214–223.

[Jinhu et al., 2010] Jinhu, L., Xuemei, L., Lixing, D., and Liangzhong, J. (2010). Applying principal component analysis and weighted support vector machine in building cooling load forecasting. In *2010 International Conference on Computer and Communication Technologies in Agriculture Engineering*, volume 1, pages 434–437. IEEE.

[Khuntia et al., 2018] Khuntia, S. R., Rueda, J. L., and Van der Meijden, M. A. (2018). Long-term electricity load forecasting considering volatility using multiplicative error model. *Energies*, 11(12):3308.

[Kim and Cho, 2019] Kim, T.-Y. and Cho, S.-B. (2019). Predicting residential energy consumption using cnn-lstm neural networks. *Energy*, 182:72–81.

[Kong et al., 2017] Kong, W., Dong, Z. Y., Jia, Y., Hill, D. J., Xu, Y., and Zhang, Y. (2017). Short-term residential load forecasting based on lstm recurrent neural network. *IEEE Transactions on Smart Grid*, 10(1):841–851.

[Koschwitz et al., 2018] Koschwitz, D., Frisch, J., and Van Treeck, C. (2018). Data-driven heating and cooling load predictions for non-residential buildings based on support vector machine regression and narx recurrent neural network: A comparative study on district scale. *Energy*, 165:134–142.

[Kotu and Deshpande, 2014] Kotu, V. and Deshpande, B. (2014). *Predictive analytics and data mining: concepts and practice with rapidminer*. Morgan Kaufmann.

[Kwok et al., 2011] Kwok, S. S., Yuen, R. K., and Lee, E. W. (2011). An intelligent approach to assessing the effect of building occupancy on building cooling load prediction. *Building and Environment*, 46(8):1681–1690.

[Li et al., 2017] Li, C., Ding, Z., Zhao, D., Yi, J., and Zhang, G. (2017). Building energy consumption prediction: An extreme deep learning approach. *Energies*, 10(10):1525.

[Li and Huang, 2013] Li, Z. and Huang, G. (2013). Re-evaluation of building cooling load prediction models for use in humid subtropical area. *Energy and Buildings*, 62:442–449.

[Lin et al., 1996] Lin, T., Horne, B. G., Tino, P., and Giles, C. L. (1996). Learning long-term dependencies in narx recurrent neural networks. *IEEE Transactions on Neural Networks*, 7(6):1329–1338.

[Ma et al., 2015] Ma, Y., Lu, M., and Weng, J. (2015). Energy consumption status and characteristics analysis of university campus buildings. In *5th International Conference on Civil Engineering and Transportation*. Atlantis Press.

[Marino et al., 2016] Marino, D. L., Amarasinghe, K., and Manic, M. (2016). Building energy load forecasting using deep neural networks. In *IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society*, pages 7046–7051. IEEE.

[Massana et al., 2015] Massana, J., Pous, C., Burgas, L., Melendez, J., and Colomer, J. (2015). Short-term load forecasting in a non-residential building contrasting models and attributes. *Energy and Buildings*, 92:322–330.

[Mocanu et al., 2016] Mocanu, E., Nguyen, P. H., Gibescu, M., and Kling, W. L. (2016). Deep learning for estimating building energy consumption. *Sustainable Energy, Grids and Networks*, 6:91–99.

[Nasr et al., 2002] Nasr, G., Badr, E., and Younes, M. (2002). Neural networks in forecasting electrical energy consumption: univariate and multivariate approaches. *International Journal of Energy Research*, 26(1):67–78.

[Nazih et al., 2011] Nazih, A.-S., Fawwaz, E., and Osama M, A. (2011). Medium-term electric load forecasting using multivariable linear and non-linear regression. *Smart Grid and Renewable Energy*, 2011.

[Neto and Fiorelli, 2008] Neto, A. H. and Fiorelli, F. A. S. (2008). Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption. *Energy and buildings*, 40(12):2169–2176.

[Niu et al., 2008] Niu, D.-x., Li, W., Cheng, L.-M., and Gu, X.-H. (2008). Mid-term load forecasting based on dynamic least squares svms. In *2008 International Conference on Machine Learning and Cybernetics*, volume 2, pages 800–804. IEEE.

[Pan and Lee, 2012] Pan, X. and Lee, B. (2012). A comparison of support vector machines and artificial neural networks for mid-term load forecasting. In *2012 IEEE International conference on industrial technology*, pages 95–101. IEEE.

[Pao, 2006] Pao, H.-T. (2006). Comparing linear and nonlinear forecasts for taiwan's electricity consumption. *Energy*, 31(12):2129–2141.

[Qiang et al., 2015] Qiang, G., Zhe, T., Yan, D., and Neng, Z. (2015). An improved office building cooling load prediction model based on multivariable linear regression. *Energy and Buildings*, 107:445–455.

[Qiu et al., 2014] Qiu, X., Zhang, L., Ren, Y., Suganthan, P. N., and Amaratunga, G. (2014). Ensemble deep learning for regression and time series forecasting. In *2014 IEEE symposium on computational intelligence in ensemble learning (CIEL)*, pages 1–6. IEEE.

[Raza and Khosravi, 2015] Raza, M. Q. and Khosravi, A. (2015). A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. *Renewable and Sustainable Energy Reviews*, 50:1352–1372.

[Ryu et al., 2017] Ryu, S., Noh, J., and Kim, H. (2017). Deep neural network based demand side short term load forecasting. *Energies*, 10(1):3.

[Sajjad et al., 2020] Sajjad, M., Khan, Z. A., Ullah, A., Hussain, T., Ullah, W., Lee, M. Y., and Baik, S. W. (2020). A novel cnn-gru-based hybrid approach for short-term residential load forecasting. *IEEE Access*, 8:143759–143768.

[Saleh et al., 2016] Saleh, A. I., Rabie, A. H., and Abo-Al-Ez, K. M. (2016). A data mining based load forecasting strategy for smart electrical grids. *Advanced Engineering Informatics*, 30(3):422–448.

[Samuel et al., 2017] Samuel, I. A., Adetiba, E., Odigwe, I. A., and Felly-Njoku, F. C. (2017). A comparative study of regression analysis and artificial neural network methods for medium-term load forecasting. *Indian Journal of Science and Technology*, 10(10).

[Sobhani et al., 2019] Sobhani, M., Campbell, A., Sangamwar, S., Li, C., and Hong, T. (2019). Combining weather stations for electric load forecasting. *Energies*, 12(8):1510.

[Tian et al., 2018] Tian, C., Ma, J., Zhang, C., and Zhan, P. (2018). A deep neural network model for short-term load forecast based on long short-term memory network and convolutional neural network. *Energies*, 11(12):3493.

[Torkzadeh et al., 2014] Torkzadeh, R., Mirzaei, A., Mirjalili, M. M., Anaraki, A. S., Sehhati, M. R., and Behdad, F. (2014). Medium term load forecasting in distribution systems based on multi linear regression & principal component analysis: A novel approach. In *2014 19th Conference on Electrical Power Distribution Networks (EPDC)*, pages 66–70. IEEE.

[Tso and Yau, 2007] Tso, G. K. and Yau, K. K. (2007). Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks. *Energy*, 32(9):1761–1768.

[Ullah et al., 2019] Ullah, F. U. M., Ullah, A., Haq, I. U., Rho, S., and Baik, S. W. (2019). Short-term prediction of residential power energy consumption via cnn and multi-layer bi-directional lstm networks. *IEEE Access*, 8:123369–123380.

[Wang et al., 2019a] Wang, H., Lei, Z., Zhang, X., Zhou, B., and Peng, J. (2019a). A review of deep learning for renewable energy forecasting. *Energy Conversion and Management*, 198:111799.

[Wang et al., 2016] Wang, P., Liu, B., and Hong, T. (2016). Electric load forecasting with recency effect: A big data approach. *International Journal of Forecasting*, 32(3):585–597.

[Wang et al., 2019b] Wang, X., Fang, F., Zhang, X., Liu, Y., Wei, L., and Shi, Y. (2019b). Lstm-based short-term load forecasting for building electricity consumption. In *2019 IEEE 28th International Symposium on Industrial Electronics (ISIE)*, pages 1418–1423. IEEE.

[Wang et al., 2015] Wang, Y., Chen, Q., Kang, C., Zhang, M., Wang, K., and Zhao, Y. (2015). Load profiling and its application to demand response: A review. *Tsinghua Science and Technology*, 20(2):117–129.

[Wang and Srinivasan, 2017] Wang, Z. and Srinivasan, R. S. (2017). A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models. *Renewable and Sustainable Energy Reviews*, 75:796–808.

[Wei et al., 2018] Wei, Y., Zhang, X., Shi, Y., Xia, L., Pan, S., Wu, J., Han, M., and Zhao, X. (2018). A review of data-driven approaches for prediction and classification of building energy consumption. *Renewable and Sustainable Energy Reviews*, 82:1027–1047.

[Xie et al., 2009] Xie, H., Tang, H., and Liao, Y.-H. (2009). Time series prediction based on narx neural networks: An advanced approach. In *2009 International conference on machine learning and cybernetics*, volume 3, pages 1275–1279. IEEE.

[Yildiz et al., 2017] Yildiz, B., Bilbao, J. I., and Sproul, A. B. (2017). A review and analysis of regression and machine learning models on commercial building electricity load forecasting. *Renewable and Sustainable Energy Reviews*, 73:1104–1122.

[Yu et al., 2016] Yu, Z. J., Haghighat, F., and Fung, B. C. (2016). Advances and challenges in building engineering and data mining applications for energy-efficient communities. *Sustainable Cities and Society*, 25:33–38.

[Yu et al., 2012] Yu, Z. J., Haghighat, F., Fung, B. C., and Zhou, L. (2012). A novel methodology for knowledge discovery through mining associations between building operational data. *Energy and Buildings*, 47:430–440.

[Yun et al., 2012] Yun, K., Luck, R., Mago, P. J., and Cho, H. (2012). Building hourly thermal load prediction using an indexed arx model. *Energy and Buildings*, 54:225–233.

[Zhao et al., 2016] Zhao, D., Zhong, M., Zhang, X., and Su, X. (2016). Energy consumption predicting model of vrv (variable refrigerant volume) system in office buildings based on data mining. *Energy*, 102:660–668.