

Impacts of COVID-19 on Ontario's Electricity Market

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

The COVID-19 outbreak has not only threatened global health but has also significantly affected the energy sector. Most countries around the world have faced sudden changes in the electricity load as a result of the strict measures that have been taken by mid-March 2020 to limit the spread of the disease. In order to investigate the patterns of changes in the electricity sector and to predict future load, machine learning (ML) techniques, such as descriptive data analytics, clustering, and forecasting methods, have been used widely in practice. This research, in particular, studies the impacts of the pandemic on Ontario's electricity market by investigating changes in the electricity demand and prices. It further provides insights into incorporating ML methods for electricity load forecast and prescribes enhanced solutions for the pricing of electricity by assessing Ontario's Market Renewal pricing system during COVID-19.

The analysis of demand and price changes due to the pandemic is presented through a comprehensive study of Ontario's hourly electricity demand and hourly electricity prices (HOEP) considering annual, monthly, and daily granularity. Furthermore, the impact of the pandemic on load forecasting is investigated using a short-term Feed Forward Neural Network (FFNN) model, as in such rare events, load forecasting becomes more challenging and less accurate, causing high risks in the electricity system operation. Finally, the potential efficiency of Ontario's Market Renewal during COVID-19 is assessed through a comparative analysis between Ontario's current electricity market and New York's electricity market, which has a comparable electricity system with respect to load and supply of electricity. In order to conduct this study, Ontario's hourly electricity demand and price data, as well as the hourly weather data are used.

Our data-driven analysis shows that although the electricity demand dropped by 12% during the beginning of the pandemic in March, it started unexpectedly rising by the end of May 2020 to levels that exceeded the electricity demand in 2019. A similar pattern is observed for Ontario's HOEP. The load forecast model performance is evaluated using the mean absolute percentage error (MAPE) during three distinct periods: pre-pandemic, beginning of the pandemic, and during the pandemic to illustrate how the sudden changes in the early stage of COVID-19 have affected the load forecast compared to other periods. The results of the forecast model show an overall MAPE of: 3.21%, 13.86%, and 4.23%, respective to the periods identified. Expectedly, the performance of the model during the pandemic is significantly affected. However, the model is still considered plausible, as a MAPE index between 10%

and 20% is classified as good forecast accuracy. Finally, through the comparative analysis between the current Ontario's uniformed price market and New York's locational marginal price (LMP) based market, it is observed that Ontario's current pricing system is less efficient and that consumers' welfare could increase with an LMP pricing system, which will be part of the proposed Ontario's Market Renewal.

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Acronyms

AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Auto-Regressive Integrated Moving Average
CMSC	Congestion Management Settlement Credits
DAM	Day Ahead Market
FFNN	Feed-Forward Neural Network
GHG	Greenhouse Gas
HOEP	Hourly Ontario Energy Price
ICI	Industrial Conservation Initiative
IEA	International Energy Agency
IESO	Independent Electricity System Operator
LDCs	Local Distribution Companies
LMPs	Locational Marginal Prices
MAPE	Mean Absolute Percentage Error
MCPs	Market Clearing Prices
ML	Machine Learning
MLR	Multiple Linear Regression
MRP	Market Renewal Program
MW	Megawatt
NYISO	New York Independent System Operator
OEB	Ontario Energy Board
ReLU	Rectified Linear Unit
RESs	Renewable Energy Sources

RPP	Regulated Price Plan
RTM	Real Time Market
TOU	Time of Use
WHO	World Health Organization

Chapter 1

Introduction

At the beginning of the year 2020, countries around the world faced the spread of the novel Coronavirus, which was first discovered in Wuhan, China on December 31, 2019. On January 30, 2020 the Coronavirus disease was declared to be a concerning public health emergency by the World Health Organization (WHO) [1]. The number of COVID-19 confirmed cases started to spike in Ontario in March 2020, exceeding 170,000 cases by the end of the year 2020 [2]. To restrict the spread of the disease, the government took drastic measures, such as social distancing, business closures, and travelling suspensions. Consequently, the resulted regulations, not only changed citizens' everyday life, but also impacted energy providers who faced sudden changes in electricity demand patterns.

The report by International Energy Agency (IEA) estimated a decrease of the global energy demand by 6% in 2020, which is the largest percentage drop in 70 years as shown in Figure 1 [3]. As declared by Ontario's independent electricity system operator (IESO), in April 2020, the overall electricity demand reduced by almost 12% in Ontario, in March and April 2020. Although the system operator faced an overall decrease in demand, during this period, the residential electricity consumption increased by around 14%, as the consequences of the lockdown and working from home mandates [4].

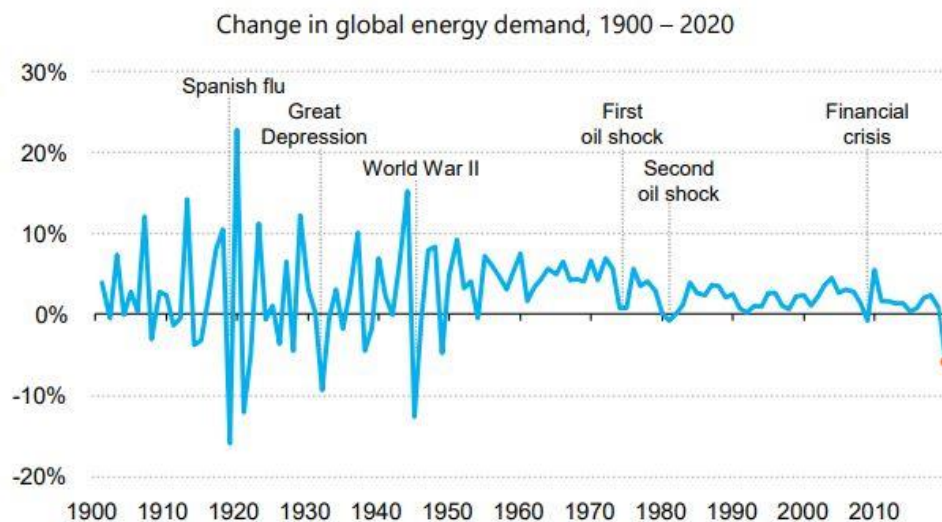


Figure 1: IEA Global energy demand 1990-2020 [3]

1.1 Motivation

Due to COVID-19, the electricity sector faced some sudden changes, such as an initial drop in the overall load, shift of the peak demand, changes in the energy-related emissions, and increased uncertainty in demand patterns and forecast. Those changes presented threatening challenges to the energy stakeholders and policymakers. Therefore, understanding the effects of the pandemic on the electricity consumption, generation and forecasting is vital in order to improve the resiliency of the grid.

Researchers started investigating the early stage of COVID-19 effects on the electricity sector in different countries, like Canada [5] [6] [7], United States [8], and India [9]. However, there is not much research covering the long-term impacts of such sudden events on the electricity demand to utilize lessons learned and to prepare the system for future events. A province like Ontario has experienced a wide range of changes in the electricity demand patterns during 2020. The early stage of COVID-19 started when an emergency state was declared on March 17th, followed by a non-essential businesses closure restriction on the 25th. Since then, electricity demand was significantly decreased by around 12% by the end of April 2020. On the other hand, due to initiation of work from home mandates, the residential electricity consumption increased by 14% between the hours 11:00 am to 7:00 pm accompanied by a delayed morning and evening peak shifts [4]. However, by the beginning of the Summer 2020, this trend was changed despite the continuing existence of pandemic and related governmental and provincial mandates.

This research provides researchers, energy stakeholders, and policymakers with an extensive understanding of the pandemic implications on the hourly electricity demand and prices, as well as the load forecasting in the province of Ontario. Moreover, it presents a comparison between Ontario and New York's electricity demand and price implications, taking New York's market as a benchmark for Ontario's market renewal plan. This comparison aims to investigate how a locational marginal price based market would react during COVID-19 against a uniform price market.

1.2 Literature Review

This section provides a brief outline of some of the literature relevant to this research. After the spread of COVID-19, many researchers were interested in investigating the impacts of the pandemic related restrictions on the energy sector. Hence, some papers [10], [11], [6] and [7] are looked at to get an overview of how researchers analyzed those impacts on different aspects of the electricity market.

Furthermore, since machine learning (ML) algorithms have been widely used in the different power system applications, those methods are studied by several papers, some of which are reviewed in this section [12]- [15]. One aspect of ML techniques in the energy sector is the load forecasting applications, which plays an important role in the operations of electricity markets. As the proposed research relies on a neural network (NN) model to show the impact of COVID-19 on the electricity load forecast during pandemic, some ML-based load forecasting models related literature are reviewed to decide on the most adequate method to follow [16]- [19].

1.2.1 Impacts of COVID-19 on Electricity Systems

Significant number of publications discuss the implications of the early stage of the pandemic on different aspects of the electricity sector, such as electricity demand, supply, prices, or GHG emissions, whether globally or locally. This section investigates some of those literature [10]- [11], and [6]- [7].

For example, in [10], the authors aim to provide an overview of the global challenges of COVID-19 outbreak on electricity demand and consumption and present novel ideas on energy-related lessons and emerging opportunities by capturing energy main trends. They also analyze the extra energy demand, assess the environmental and economic impacts, and discuss the energy demand recovery. The authors have summarized the energy challenges and opportunities in this paper as shown in Figure 2.

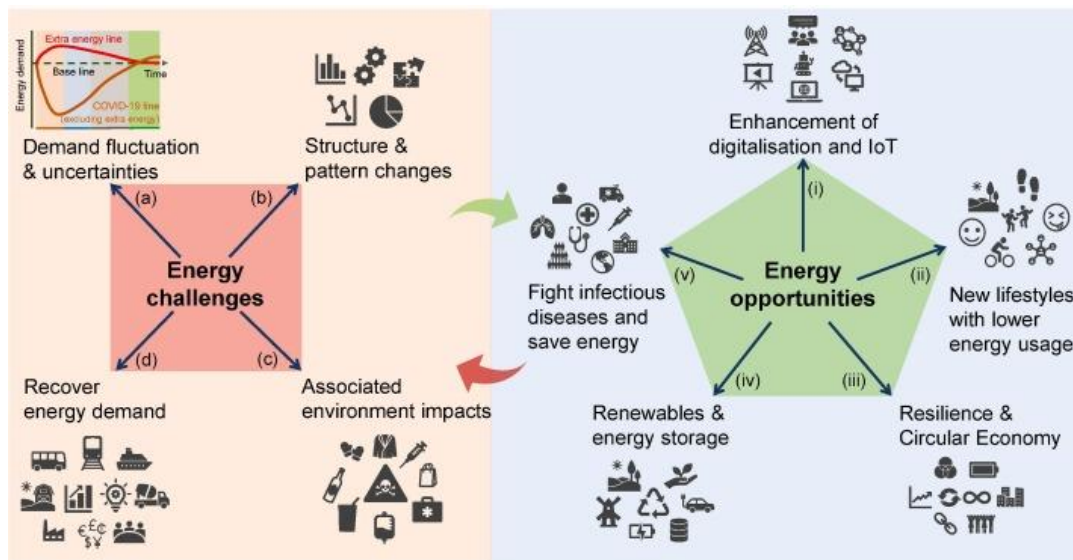


Figure 2: Summarised challenges and opportunities in the energy industry related to COVID-19 [10]

In [11], authors discuss the impacts of COVID-19 on the electricity demand and supply, challenges faced by the power system, impacts on prices and investments, as well as emission reduction. The

researchers looked at 4 different countries: Italy, Japan, the U.S., and Brazil and compared their 2020 load profile to those of 2018 and 2019 from January to May. They showed that the total electricity load and prices decreased, whereas the residential consumption increased for most countries. The total load witnessed an opposite trend in Japan where the total load stayed similar in all years. The authors concluded that this behaviour relates to different governmental measures and the lockdown policy in Japan. The authors conclude that the increased uncertainty in load forecast requires more accurate load forecasting and system flexibility reserve.

In [6] and [7], the authors focus on the implications on the province of Ontario's energy consumption. Both papers discussed the impacts on the electricity demand and supply, as well as the emissions reduction. In [6], researchers included how the transportation, economy, social norms, and technology were affected. The paper studies the interconnection between the smart city concept and the cities energy resiliency and health infrastructures. While in reference [7], the authors added the human and environmental related pandemic impacts to their research. The energy use related results presented a 10-12% decrease in Ontario's energy use which resulted in greenhouse gas emissions reduction.

1.2.2 Applications of Machine Learning in Power System

Lately, machine learning techniques have been gaining greater advantages due to their accuracy, scalability, and generalization capabilities, compared to traditional computational methods. Therefore, they have been widely applied in diverse fields and specializations, one of which is the power system. Some of the ML applications in the power system field include load, price, and renewable power prediction, power system blackouts, security assessment, demand response programs, and power flow optimization [12]. There are several literature studying the application of appropriate ML techniques to solve several issues in the field of power grid operation and management, as will be discussed in this section [12]- [15].

In [12], authors present a literature survey of ML applications in the power system field, while providing an evaluation of the main advantages and drawbacks of different techniques. They also discuss how the transition to smart grids and the increasing intervention of distributed and intermittent power generation by Renewable Energy Sources (RESs) needs more advanced prediction models in the decision-making process. The study presented in this paper indicates that supervised machine learning, based on classification algorithms are used more than other methods for engineering problems. It also concludes that the application of machine learning in the field of electrical engineering simplifies the complex problems and guarantees more accurate and reliable results.

The authors in reference [13] provide a systematic review of artificial intelligence (AI) and machine learning (ML) approaches to energy demand response (DR) applications. As the tasks related to DR become more complex, needing large amount of data and real-time decisions, AI and ML techniques are increasingly implemented to enable DR. Based on reviewing over 160 papers, 40 companies and commercial initiatives, as well as 21 projects related to AI/ML techniques in DR applications, the authors conclude which AI/ML methods proved to work best for the DR problem. Their review showed that some AI techniques are more commonly used for specific tasks than others. For example, supervised learning techniques, such as artificial neural network (ANN) are widely used for short-term load and price forecasting, whereas unsupervised learning are mostly used for DR customers clustering tasks, and aggregators schedule DR participants activation and plan their compensations or penalties. They also discuss the advantages and disadvantages of the reviewed techniques for various DR problems and point out the need for additional research initiatives to provide more accurate AI/ML models and solutions in this area.

In [14], the authors present an example of Optimal Power Flow problem (OPF) using ML techniques, which is determining the best operating levels for different generators, usually at the optimal cost, in order to meet the demand within a transmission network. Here, the authors investigate ML methods for AC Optimal Power flow (ACOPF) problem through two approaches of ACOPF: an end-to-end optimal generator settings prediction task, and a constraint prediction task to predict the optimal solution for the set of active constraints. Then, they validate both tasks on two test systems (IEEE 30-bus and IEEE 118-bus). Finally, they concluded a better performance on IEEE 118-bus than IEEE 30-bus system for the end-to-end prediction and that neural networks are highly accurate at determining the active constraint set.

Authors in [15] review the advanced machine learning techniques used for power system applications on electricity load, price forecasting, and wind power prediction. The authors presented a brief overview of neural network (NN) methods application to predict hourly electricity demand and price using similar day approach based on examples that apply data from the Victorian electricity market, Australia, and the PJM market. They also review a short-term wind forecasting by applying an adaptive neural fuzzy inference system (ANFIS) using an example from Tasmania, Australia. The major challenges concerning wind power prediction were underlined, such as variability and intermittency nature of wind power generation. Finally, the reviewed case studies results were discussed to conclude that ML techniques prove to be effective for forecasting applications in power system.

Electricity Load Forecasting Using Machine Learning

Forecasting electricity demand accurately is critical for the power system planning, operation, and policy making decisions. Large changes and uncertainty in electricity demand make the maintenance of demand supply balance more challenging for the power grid operators, as it becomes more complex to forecast the future demand with low error levels [16]. Therefore, more robust forecasting models are needed to give highly accurate load predictions. Machine learning approaches are widely applied and have proved improvements in forecasting methods.

In [17], authors compared the performance of three different forecasting methods - autoregressive integrated moving average (ARIMA), artificial neural network (ANN) and multiple linear regression (MLR) - to predict the electricity demand in Thailand. The data experimented in this study was the historical data related to Thailand's electricity demand (population, gross domestic product: GDP, stock index, revenue from exporting industrial products and electricity consumption) from 1986 to 2010. The research resulted in a better performance of ANN model among the other approaches.

The authors in [18] provided two approaches to forecast the energy consumption: an autoregressive integrated moving average (ARIMA) model and a non-linear autoregressive neural network (NAR) model. They compared the two models in order to evaluate their performance, which resulted in equal performance of both the models. However, in terms of simplicity, the ARIMA model was more appropriate to use.

Reference [19] proposes a multilayer deep-feed forward neural network (Deep-FNN) to predict yearly and monthly loads, while considering the weather conditions. The paper uses hourly load data from the New York Independent System Operator (NYISO) from 2010 to 2018 and weather data from the National Climatic Data Center (NCDC). Researchers compares the performance of 12 models based on different combination of activation functions and training algorithms. The built model uses test data for 7 and 30 records for the short-term forecast and 365 for the long-term forecast. Based on the mean absolute percentage error (MAPE) metric used for evaluation in this paper: Model number 7, which is a Deep-FNN with sigmoid function and resilient backpropagation algorithms showed the most accurate results for the short-term horizon, whereas, Model 8 having ReLu as activation function and Levenberg-Marquardt as training algorithm presented the best model among the other for long-term forecast.

1.3 Research Objective

The main objectives of this research are as follows:

- Presenting a detailed analysis of the COVID-19 implications on the electricity demand and prices by comparing electricity data of 2019 and 2020, in addition to the weather data. This work aims to provide electricity stakeholders and policymakers with lessons learned to take future precautions.
- Developing an FFNN model that uses time series and additional external features as inputs to investigate the impacts of the early stages of the pandemic on the electricity demand forecasting.
- Introducing Ontario's Market Renewal Program as a second case scenario where the potential efficiency improvement of Ontario's electricity market during COVID-19 is investigated. This section mainly focuses on the different pricing systems of Ontario's current market and the market renewal.

1.4 Research Outline

The rest of this research is organized as follows:

Chapter 2 presents some background information about the different concepts and terminologies used in the research to help the reader understand the rest of this paper. This chapter provides a general review of the electricity market structure and operation, then focuses on Ontario and New York's electricity markets being the case studies of this research. A background overview of the ML techniques in forecasting applications is presented, followed by particular information about the FFNN network model for load forecasting. The parameters of the training phase, along with model evaluation metrics used in this research are presented.

Chapter 3 provides a data-driven descriptive analysis of the COVID-19 impacts on Ontario's hourly electricity demand and price. The analysis starts with an annual overview, then it dives deeper into the monthly patterns of demand and price. The week days patterns, along with a daily K-means clustering of the hourly electricity demand is also presented.

Chapter 3 introduces the selection criteria and structure of the FFNN model to investigate the impacts of COVID-19 on the load forecast. The FFNN model is then evaluated using MAPE metric in three

different phases (before the pandemic, during the beginning of the pandemic, and during the pandemic).

Chapter 5 assesses the pandemic challenges under Ontario Market Renewal by comparing the changes in Ontario's current market demand and prices with the ones of New York's market, taking New York market's structure as a benchmark of the Market Renewal.

Chapter 6 presents the main conclusion and future work of the thesis.

Chapter 2

Background

This chapter offers a theoretical background review of the main concepts and research work presented in this thesis. First, an overview of the electricity market operation is provided along with the specific features of Ontario and New York electricity systems. Then, some background information about machine learning methods and comparison with traditional methods in forecasting applications are presented. Finally, the machine learning forecasting model used in this research, i.e. FFNN, and its main properties are discussed.

2.1 The Electricity Market Operation

The electricity market is designed to offer reliable electricity at the least cost and the best use of resources, while satisfying network constraints. The market solves a complex economic problem as it must send the right price signals to ensure efficient generation and future investment in resources. Figure 3 shows the basic components and flow of a traditional electricity market [20]. As shown, the electricity is first produced by the generating resources, then it is transmitted through transmission lines for export or to distribution utilities, responsible for providing electricity to consumers (businesses and homes) through low-voltage distribution lines. Electricity end-users represent the electricity demand, known as load. Recently, with the advent of distributed generation, demand nodes are able to produce electricity in the distribution system, which creates more complexity in the system operation.

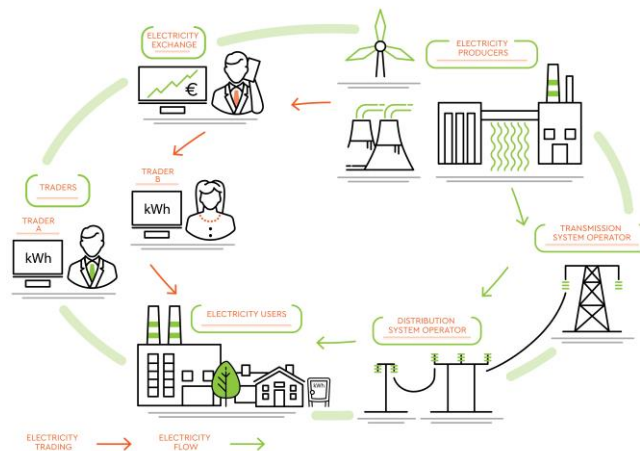


Figure 3: Electricity Market Structure [20]

There are different market service layers (MSL) that can differ in implementation and characteristics from one country or region's electricity market to another. Some examples of MSLs are [21]:

- Day-ahead market (DAM): In such markets, the next day hourly electricity production schedule (unit commitment) is determined. Electricity production companies and power plants submit their supply bids, whereas electricity suppliers and retailers submit their demand bids in the DAM.
- Capacity market: The resources capacity is related to their physical capability to provide energy ensuring adequacy for meeting system peaks. Long-term investments and provision of adequate resources that satisfy the capacity requirements take place in the capacity market.
- Real-time market (RTM): This market ensures that the energy supply and demand are balanced. Operators run a security-constrained economic dispatch every 5 minutes, resulting in real-time dispatch instructions for resources and prices throughout the operating day.
- Ancillary services: This market represents the different energy reserves to keep supply and demand balanced each second in case of a large generator failure, while satisfying all constraints. Reserves can be co-optimized with energy in the DAM and the RTM.

2.1.1 Ontario Electricity Market

The Ontario electricity market is a competitive wholesale electricity market that opened on May 1, 2002, operated by the IESO, and regulated by the Ontario Energy Board (OEB). It is a real-time electricity market (RTM) that sets uniform Market Clearing Prices (MCPs) on 5-minute intervals, they are then averaged to generate the Hourly Ontario Energy Price (HOEP). The MCP is determined without taking into account the power transmission physical limitations. Those transmission lines constraints, also called congestion, result in “constrained-on” and “constrained-off” payments to compensate market participants who were affected by difference in their dispatch instruction with and without the existence of congestion [22].

Ontario's electricity market is the only single-settlement market in North America, unlike the rest of the markets, which are two-settlement markets, meaning that it does not have a financially binding day-ahead market (DAM). The company that owns and operates Ontario's transmission network is Hydro One Inc. Ontario's market participants are categorized into dispatchable participants who pay the Market Clearing Price (MCP) and non-dispatchable participants who pay the Hourly Ontario Energy Price (HOEP) [23].

Ontario's current system design needs some improvements to increase the system efficiency by ensuring reliable supply at the lowest cost and support the grid in the future. Accordingly, the IESO and its stakeholders are in process for many years to address the current market's inefficiencies by introducing the market renewal program (MRP) [24].

Ontario Market Renewal

The Market Renewal Program (MRP) is the reformation of Ontario's current market that would include some features to improve the system efficiency and flexibility. Figure 4 shows the MRP initiatives, which are as follows [25]:

- A single schedule market (SSM): This market will replace the current two-schedule market to align between price and dispatch, by taking into consideration the transmission constraints. This market will result in eliminating the congestion management settlement credits (CMSC), which are out-of-market payments to recover the difference between the current two-schedule pricing systems and will introduce the locational marginal prices (LMPs).
- A day-ahead market (DAM): This market will be financially binding, which results in increasing the financial certainty to market participants, introducing a two-settlement system. It also aims to lower the cost of producing electricity and improves the resources commitment process, increasing the operational certainty to the IESO.
- Enhanced real-time unit commitment (ERUC): The ERUC will operate in the pre-dispatch phase in transition from the day-ahead to real-time. It will use optimization process that considers all costs of scheduling and dispatching resources, resulting in more informed and cost-effective unit commitment decisions to meet the demand.
- Capacity services: Ensure an efficient way to acquire the resources to meet long-term supply and demand needs at the lowest price. The implementing of the capacity auctions project will encourage greater competition, resulting in reduced costs and improved resources' reliability.



Figure 4: MRP Work Streams [25]

2.1.2 New York Electricity Market

The New York Independent System Operator (NYISO) was established in 1998 and started to run New York’s power grid and its wholesale electricity markets in November 1999 [26]. NYISO is a two-settlement locational based marginal price (LBMP) market, consisting of a day-ahead and real-time market. It uses a bid-based security constrained economic dispatch (SCED) and a security constrained unit commitment (SCUC) for energy, operating reserves and regulation co-optimization. It also includes transmission congestion contracts (TCC), which enable energy buyers and sellers to be aware of the transmission price fluctuations, and installed capacity markets (ICAP), which is main benefit is to ensure the availability of resources when needed to meet the peak demand [27].

2.2 Traditional vs Machine Learning Forecasting Techniques

With the evolving technology, artificial intelligence (AI) applications become more advanced and popular in the business world. Forecasting methods are one application of machine learning (ML) that has gained great interest in most fields and industries to guide their decision-making. ML-based forecasting methods have replaced traditional statistical forecasting techniques in several data analytics initiatives across businesses and sectors. Choosing the best forecasting technique to follow is crucial, as it can influence the time, cost, and complexity of the process (Figure 5).



Figure 5: Traditional vs ML Forecasting [28]

Conventional algorithms use statistical models to analyze a univariate dataset or a multivariate dataset that has finite, countable, and simple variables. When dealing with univariate datasets, the traditional methods can be more convenient to use, as they are easier to explain and simpler to compute. Some of the classical models used in forecasting univariate datasets with high accuracy are: moving average, simple exponential smoothing (SES), linear regression, ARIMA and SARIMAX. Figure 6 illustrates the typical steps for the traditional execution of forecasting [28].

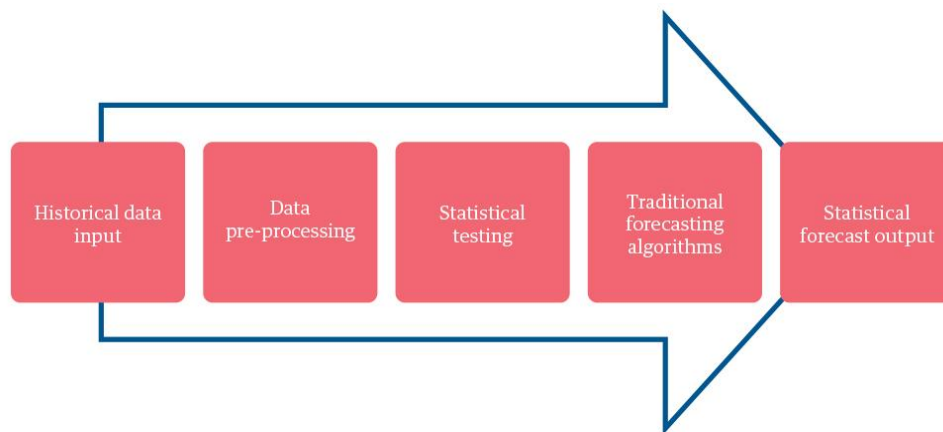


Figure 6: Traditional forecasting process [28]

Machine learning (ML) forecasting techniques mainly deal with large amount of data with more complex variables using non-linear algorithms to minimize the prediction error, which makes them more difficult to interpret than the traditional linear methods. Moreover, a combination of linear and

nonlinear algorithms can be used in ML forecasting to predict with even higher accuracy. Some of the ML models used in forecasting are: artificial neural networks (ANN), random forest, classification and regression trees (CART), and support vector regression. Figure 7 shows the process of ML forecasting methods starting by collecting the required data for the business problem, parsing and cleaning the data, then selecting the appropriate features to train the model. After the dataset is split into training and testing data, the ML model is built and trained. Next, the model performance is evaluated by comparing the actual and forecasted values of the data. Multiple models can be built and compared to select the most accurate one.

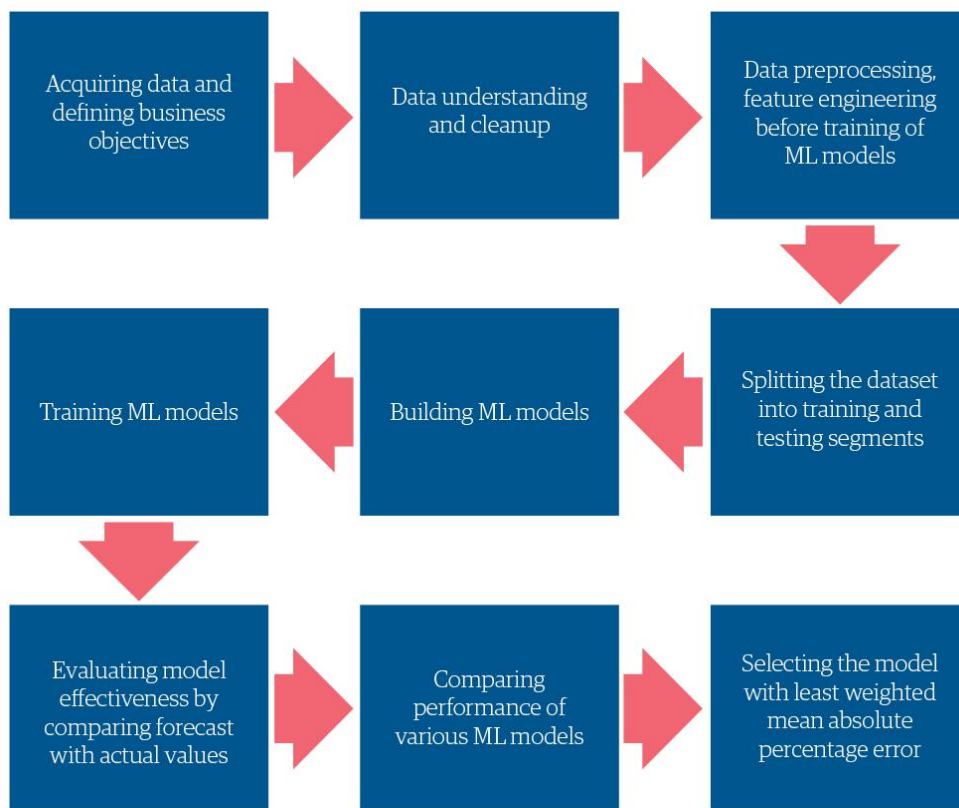


Figure 7: ML forecasting process [28]

ML is one of the applications of AI, however, basic ML models need some guidance when working with large amount of data, as it needs human intervention if the results of a prediction model come back inaccurate. Hence, the deep learning comes more powerful than machine learning. As shown in Figure 8 deep learning is a subset of ML while the latter is a subset of AI. Deep learning models use multi-layer structure algorithms that resemble the human brain, known as ANN, and can automatically

conclude the accuracy of a forecast model. As the size of the data increase, the deep learning networks keep improving [29].

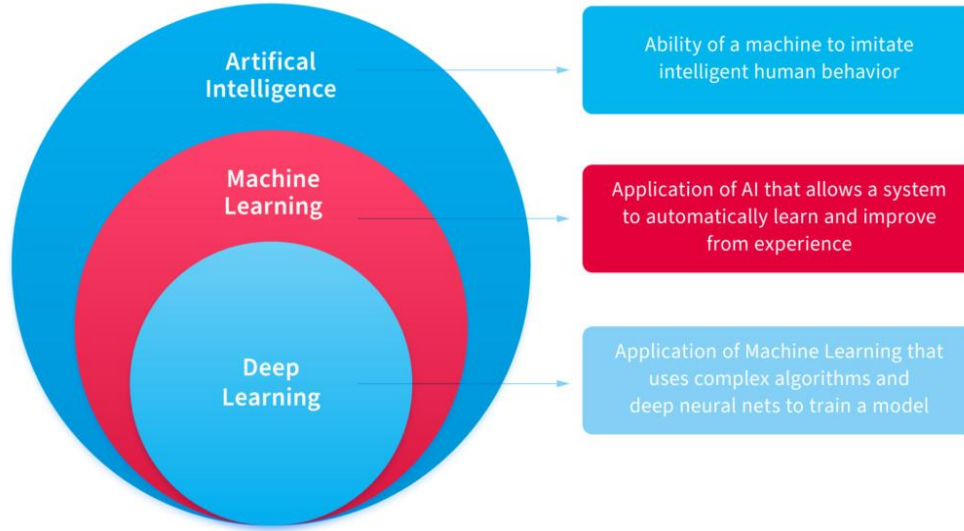


Figure 8: Artificial intelligence vs Machine leaning vs Deep learning [30]

2.2.1 Feed-Forward Neural Network Forecasting Model

Feed-Forward Neural Network (FFNN) is one type of Artificial Neural Network (ANN) used for supervised learning. A simple FFNN model consists of an input layer, hidden layer, and output layer. The main features of an FFNN model architecture are the layers, neurons (known as nodes), and activation [31]. With more complex data, a deeper and more parametrized neural networks are needed. This can be achieved with a deep feedforward neural network (DFNN), which has a higher number of hidden layers that can learn from the different input features, allowing the model to accurately predict the output based on those features.

As shown in Figure 9, the basic FFNN includes an input layer with input x_i variables, for $i > 0$. Each i^{th} input node is connected to each j^{th} node of the hidden layer by a weighting factor W_{ij} . Each neuron in the hidden layer performs a non-linear transformation by summing all the inputs, each multiplied by its corresponding weight. The summation is then used as an input for the activation function of the hidden layer. The output of a neuron h_j can be formulated as follows:

$$A_j = f_h(net_j) \quad (1)$$

where f_h is the activation function and net_j is the transformation function (summation unit) of the hidden layer.

The output layer of a FFNN has a similar structure as the hidden layer, except that its inputs are the outputs of the hidden layer. The output neuron y_k can be formulated as follows:

$$y_k = f_y(net_k) \quad (2)$$

where, f_y is the activation function and net_k is the transformation function (summation unit) of the output layer.

The activation function is a mathematical function that limits the range of the neuron's output to a finite value. The most common activation functions are: Linear, Sigmoid and Rectified Linear Unit (ReLU) [31] [32].

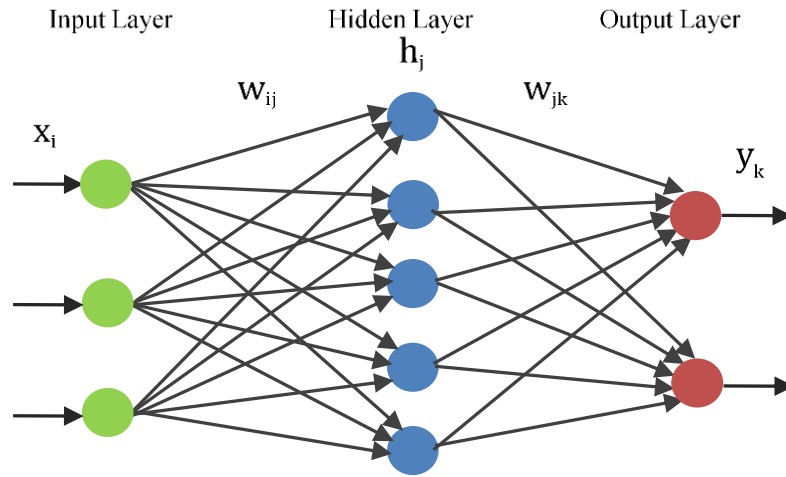


Figure 9: Feed Forward Neural Network Structure

ReLU activation function is the most commonly employed in deep learning models, especially for regression problems. If the input received is negative, the function returns 0, but for any positive value x , it returns that value back, which can be identified as [33]:

$$f(x) = \max(0, x) \quad (3)$$

The model proposed in this research is a short-term FFNN with three hidden layers to forecast the hourly load for the upcoming 15 days. The model's main purpose is to evaluate the load forecast during COVID-19. A short-term load forecast can range from 1 day to a couple of weeks ahead and has many use cases, including [34]:

- Operational planning of the power system for generation schedule which allows optimizing the mix of generating resources to meet the expected demand in an efficient production cost.
- Distribution operations to allow maintenance.
- For Demand Response Programs, where customers should reduce their energy consumption during peak demand when the energy is reduced in feeder circuits to avoid distribution overloads.
- Charge and discharge optimization of utilities Energy Storage (ES) patterns to balance the energy supply and demand.
- Make sure that there is a sufficient generation available to meet the peak demand [35].

2.3 Chapter Summary

A background overview of the main thesis concepts were presented in this chapter. Starting with some common background information about the electricity market operation, while focusing more specifically on Ontario and New York's electricity systems. Subsequently, a general comparison between forecasting methods using ML models and traditional statistical models was presented. Lastly, the main structure and features of a FFNN forecasting model, as an application of deep learning, were explained.

The next chapter offers an inclusive analysis of the COVID-19 impacts on Ontario's electricity market (hourly demand and prices). The changes in hourly demand and prices between the years 2019 and 2020 are investigated based on different granularity of the year, months, and days. Moreover, the weather data are examined to check for the effect of different temperature between both years. Finally, the main results and observations are presented to offer an extensive understanding of the implications on Ontario's electricity market throughout the year of 2020.

Chapter 3

Impacts of COVID-19 on Ontario's Electricity Market

In response to the outbreak of the COVID-19 in the year 2020, worldwide governmental measures, which included social distancing, business closure followed by working from home policy, and travel suspension were imposed to limit the spread of the virus. Such restrictions have caused drastic changes in the electricity sector, such as an initial drop in the overall load, shifts of the peak demand, changes in the energy-related emissions, and uncertain demand, which is more challenging to forecast. Therefore, understanding these variations is crucial for the future planning and operation of the electricity sector [36].

This chapter aims to present a comprehensive analysis of the pandemic impacts on Ontario's electricity market by comparing Ontario's electricity demand and hourly price trends in 2020 with those in 2019. The comparison is broken down into three main parts: annual overview, monthly and daily breakdown to understand the demand trends based on seasonal changes and consequent policy enforcements due to the pandemic. The temperature data is presented in Figure A - 1 of Appendix A: COVID-19 impacts on Ontario's electricity demand and price. In addition, in order to compare electric demand variations during low, mid, and peak periods, a classification method using K-means Clustering is implemented [37].

The electricity demand and HOEP data used in the analysis are collected from the IESO data repository [38]. The weather data are obtained from Meteoblue, which presents Toronto's hourly weather history data [39]. All the codes used in this section are presented in Appendix A: COVID-19 impacts on Ontario's electricity demand and price.

3.1 Ontario's Electricity Demand

This section describes the changes in Ontario's hourly electricity demand during the pandemic while taking into consideration the potential effects of weather conditions. The features selected for the analysis are date, time, Ontario's demand (MW), and temperature (Celsius) data for each hour of the day from the year 2019 to 2020. The obtained data, after checking for missing values, consists of 17544 observations.

3.1.1 Annual demand comparison 2019 vs 2020

This section includes an overall comparison between the years 2019 and 2020 electricity demand, including the interesting changes in the load profiles based on different clusters of months. Moreover, the mean hourly electricity load and the load duration curve of both years are analyzed.

To give an overview of the changes that happened to the hourly electricity demand in the year 2020 due to the pandemic, the demand data for both 2020 and 2019 are plotted against each other as illustrated in Figure 10. The weekdays are aligned for both years to create an accurate comparative analysis between weekdays and weekends.

Figure 10 compares Ontario's electricity demand for the years 2019 and 2020. As shown, the demand in the year 2020 has experienced some alterations compared to 2019, which can be identified through 4 different intervals of time illustrated by the red vertical lines. For example, from the 3rd week of March after the essential business closure and until the 3rd week of May, the load has dropped significantly compared to the load in 2019 as demonstrated in part 2 of Figure 10. On the contrary, as shown in part 3, the load has unexpectedly experienced a high rise from the end of May until the beginning of September. Subsequently, the electricity demand in 2020 started to follow approximately the same normal shape as 2019. These three classifications of the electricity demand are going to be justified more in detail in the next section, in which the monthly breakdown of demand is shown.

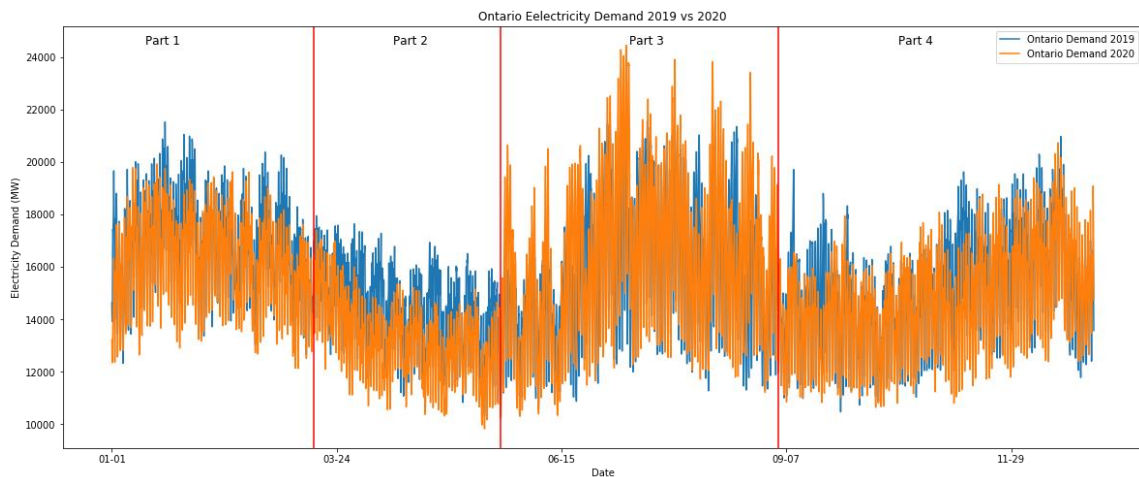


Figure 10: Ontario Hourly Electricity Demand of the year 2019 against the year 2020 (The date displayed on the x-axis is considered for the year 2020, but the same weekdays are applied for both years)

Next, the mean hourly electricity demand of each year is calculated by averaging the demand of each hour over the year. The resulted hourly electricity demand represents a typical day in 2019 and 2020, which can be used for comparisons between the two years.

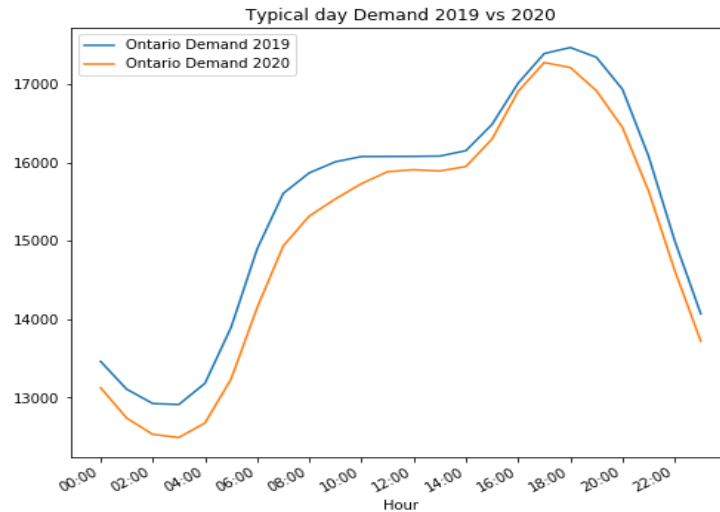


Figure 11: The electricity mean hourly demand of 2019 and 2020

As shown in Figure 11, generally there are two common peaks throughout the day: morning and evening peaks, where the evening peak is much higher than the morning one. Besides the overall drop in the 2020 peak load, the morning and evening peaks are also shifted. For example, in 2020, the morning peak occurs later in the day, while the evening peak occurs earlier in the day than in 2019. The reason for such transition in peak hours can be mainly due to the changes in individuals' daily routines initiated by schools and business closure and working from home regulations implemented during COVID-19. In the morning, the demand is affected mainly by the times where the essential businesses were closed, showing the highest drop in the load curve. As illustrated in Figure 11, the rate of electricity consumption is higher after 6:00 am in 2019, compared to 2020, in which individuals have more flexibility with starting their work as there is no more need for the time spent commuting to work. The gap between the two load curves is getting smaller in the evening, between 4:00 to 6:00 pm, as individuals' routines are the same during COVID-19 and pre-COVID-19.

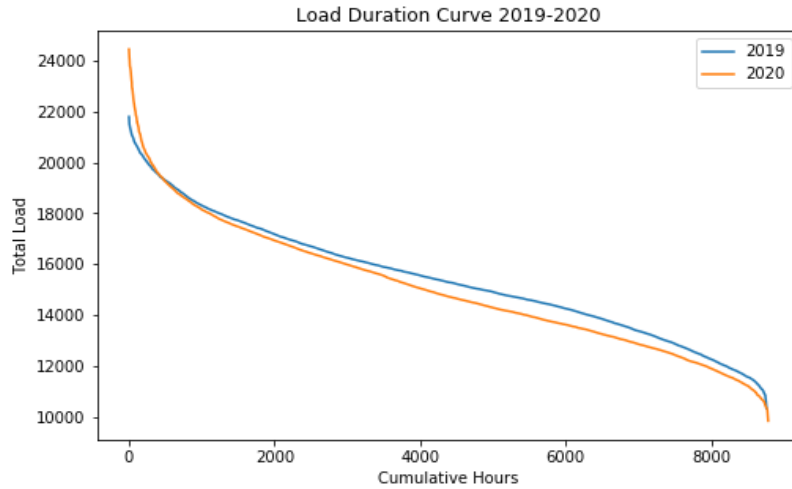


Figure 12: Load Duration Curve of the years 2019 and 2020

Lastly, the load duration curve is observed to give an overall view of the cumulative hourly electricity demand for the year 2019 and 2020. The load duration curve is crucial in the electric power domain, specifically in the planning phase, to identify the optimal capacity needed for generation. An annual load duration curve represents the load profile vs the time duration in hours where the load is arranged in a descending magnitude order, with the peak demand being the first point on the curve from the left. By reducing their peak demand, utilities can improve the efficiency of power generation [40].

Figure 12 demonstrates the highest peak in 2020 surpassing 24,000 MW while it was below 22,000 MW in 2019. This case is also confirmed by part 3 of Figure 10, where the load curve of 2020 is reaching higher demand in the Summer than 2019. On the other hand, the lowest peak is almost around 10,000 MW for both years, being slightly lower in 2020, which can be relevant to the decline that happened to the electricity demand in March and April due to the pandemic.

3.1.2 Monthly demand comparison 2019 vs 2020

In this section, the monthly electricity load is clustered into 3 categories as shown in Figure 10 to present the reduction, increase, and the recovery of the load between 2019 and 2020 (Note that as the COVID-19 impacts started to get more intense after the school closures in March 16th, the monthly analysis is ignoring the months of January and February), as follows:

- From the first week of March till the third week of May.
- From the last week of May till the first Thursday of September.

- From the first Friday of September till the last week of December.

Monthly demand comparison: March to May

On March 12th Ontario's government announced the closure of schools, then, on the 17th a state of Emergency was declared, followed by non-essential business closure on the 23rd [41]. As a result of these fast-paced regulations implemented to reduce the risks of the COVID-19 spread, energy consumption witnessed a significant drop. As published on the IESO News on April 30th, the overall electricity demand decreased by almost 12% [4]. This drop of load can be observed in Figure 13.

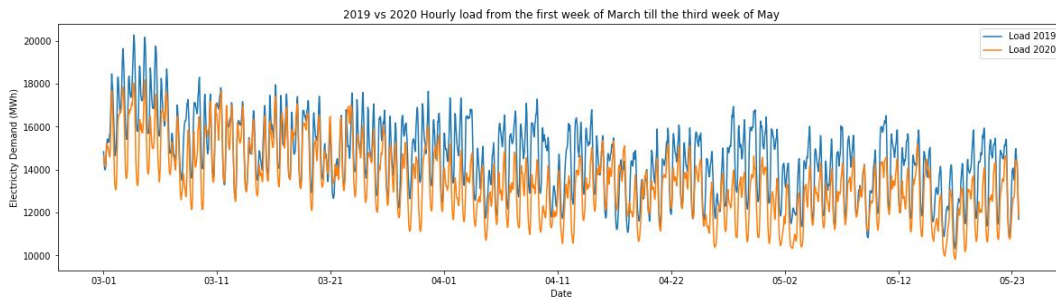


Figure 13: 2019 vs 2020 hourly load from the first week of March till the third week of May

Monthly demand comparison: May to September

As the weather became warmer and some businesses reopened, the electricity consumption started to ramp up once again by the mid of May. Consequently, towards the end of May, the demand of 2020 got significantly above 2019 demand rates. This phenomenon was predominant in the period from the last week of May till the first few days of September as can be noticed in Figure 14. One reason of the high peaks in June 2020 was the Industrial Conservation Initiative (ICI) ¹ Hiatus that was announced to help large industrial consumers across Ontario to recover from COVID-19 by focusing on producing more than reducing their peak demand in order to minimize their Global Adjustment costs [42]. In July 2020, the electricity demand jumped to its highest since July 17, 2013. Part of the demand increase in 2020 compared to 2019 was due to hotter days, consequently the increased usage of ACs. However, the weather did not have much impact on demand patterns as it was observed from the data (as presented in Figure A - 2 in Appendix A: COVID-19 impacts on Ontario’s electricity demand and price). Overall,

¹ The ICI is a program for large electricity consumers to shift their high demand to off-peak hours, thus reducing their Global Adjustment costs.

the recovery of the electricity demand in the Summer exceeded the expectation of the Ministry of Energy as well as the IESO [42].

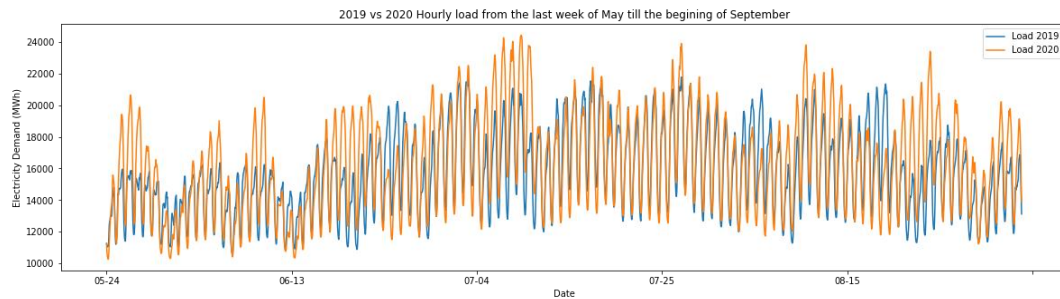


Figure 14: 2019 vs 2020 hourly load from the last week of May till the first Thursday of September

Monthly demand comparison: September to December

As COVID-19 cases started to rise again in September, the government of Ontario decided to suspend the reopening plan on the 8th of September 2020 for a period of 4 weeks [43]. This restriction, as shown in Figure 15, can be a main contributor to another decline in the demand in September 2020. By the end of September, the load followed the same pattern as in 2019, which was consistent for the rest of the year, except for the first half of November, in which the demand declined, due to a rise in the temperature around the 5th until almost the 20th of November 2020, reaching 15°C (as presented in Figure A - 3 of Appendix A: COVID-19 impacts on Ontario’s electricity demand and price).

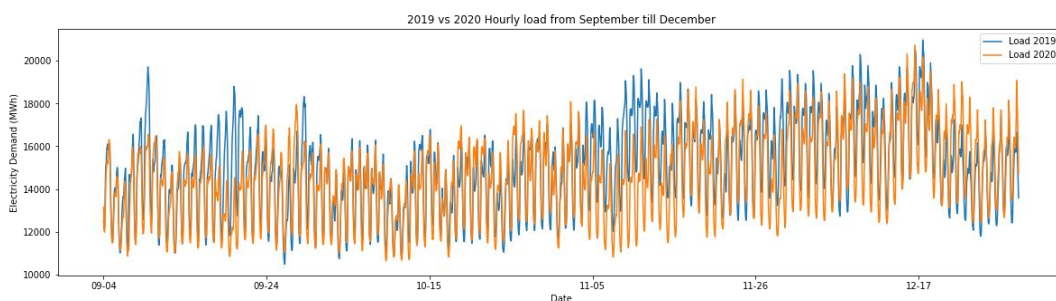


Figure 15: 2019 vs 2020 hourly load from the first Friday of September till the last week of December

Mean hourly load based on months

This section demonstrates the hourly load in a typical day for the three classifications (March-May, May-September, and September-December) mentioned in Section 3.1.2 comparing 2019 and 2020. Figure 16 presents the mean hourly demand of the first group of months (March to May) in dashed

lines, the second group (May to September) in dotted lines, and the third group (September to December) in solid lines, each for 2019 and 2020.

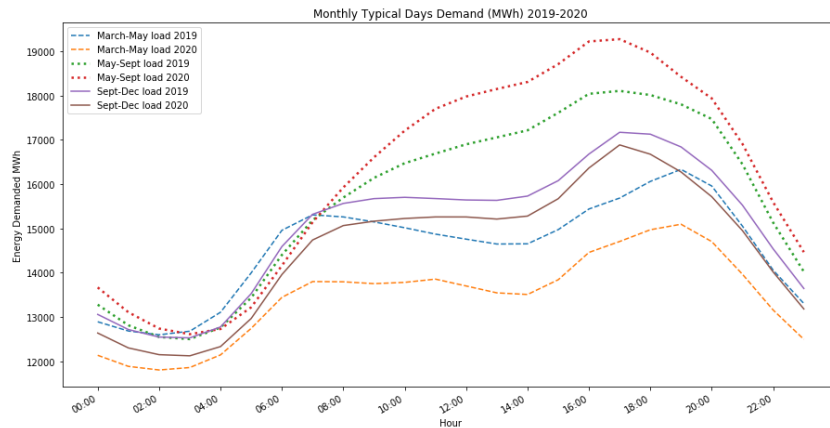


Figure 16: Mean hourly demand for each group of months for the years 2019-2020

As shown, the difference between the representations of days for each group of months indicates load drop in March and April 2020 with a more flattened morning consumption due to the mandatory lockdown and working from home regulations. Also, overall higher electricity demand is observed in the Summer days of the year 2020, reaching its highest between 4:00 and 6:00 pm with delayed morning peaks and sharper evening peaks. The demand patterns are not changed between the years and months between 12:00–6:00 am, except March and April. Moreover, the lines representing the months from September to December are demonstrating the closest load patterns between 2020 and 2019, showing that the electricity demand nearly returned to normal behavior.

3.1.3 Daily demand comparison 2019 vs 2020

This part compares the average hourly electricity demand for each day of the week by evaluating the daily load profiles in 2020 and 2019. Also, to visualize this comparison through different classifications of load profiles, the daily demand is clustered, using K-means Clustering. The data was selected from March till December.

Weekdays mean hourly load

Figure 17 displays 2 graphs of the mean hourly electricity demand for each day of the week for the years 2019 and 2020. By looking at the shown demand profiles, the general trends could be summarized as follow: the average morning and evening peaks were significantly higher in 2019, reaching around 19,000 MWh and over 20,000 MWh, respectively. Whereas in 2020, the maximum morning and

evening peaks were around 17,000 MWh and over 18,000 MWh, respectively. Additionally, most of the weekdays' demand patterns of 2020 are more converged and flattened than those of 2019.

Also as shown, the average energy consumption on the weekends is remarkably lower than the weekdays, especially in the morning and the afternoon, which can be expected due to schools and businesses normally functioning on weekdays. As for Sunday evenings, the demand ramps up, getting closer to Fridays' load pattern, reaching an average of 18,500 MW/h, in 2019. On the other hand, in 2020, the weekends are showing a slightly lower average electricity demand in the morning and the afternoon, with a peak on Sunday evenings almost the same as the weekdays, attaining more than 17,500 MW/h. This similarity could be the result of business closures and working from home mandates.

Finally, some distinctive trends can be noted for the different weekdays. For example, all the weekdays' curves of 2019 are adjacent except for Friday, where the afternoon and evening energy profile is lower than the other weekdays. This variation can mostly be due to the fact that some businesses close earlier on Fridays. In 2020, the load profiles look different than usual, as the Mondays, Tuesdays, and Fridays average hourly consumption are closer to each other and more flattened than those of Wednesdays and Thursdays. Another noticeable trend is the presence of additional peak hours in the afternoon, as can be seen on Tuesdays, Wednesdays, and Fridays. This fluctuation could be referred to the increase in residential electricity, which mainly occurs between 11:00 am and 5:00 pm as customers are staying at home.

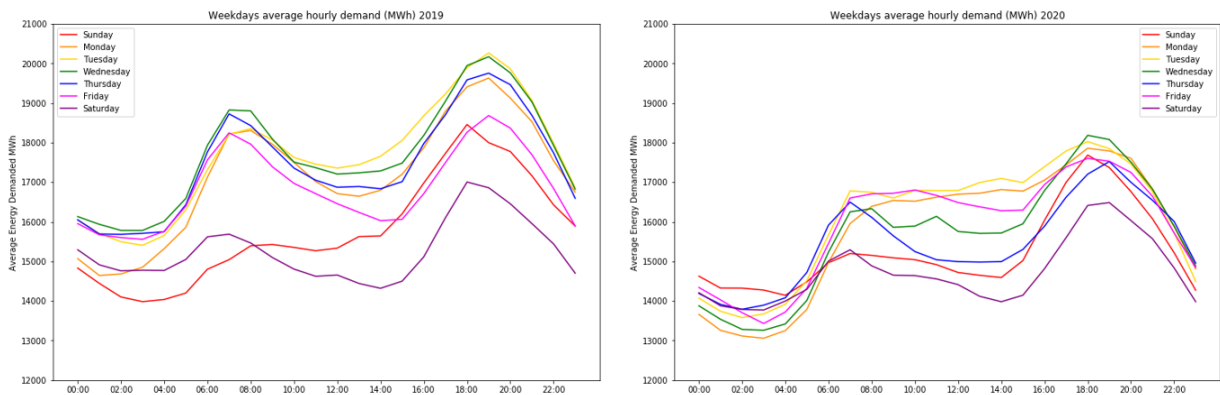


Figure 17: Mean hourly energy demand for each day of the week 2019-2020

Daily K-means clustering of hourly load

To dive deeper into the daily electricity consumption changes throughout the day, the K-means clustering algorithm is applied using Scikit-Learn Python package on the hourly load data of the years 2019 and 2020, separately [37]. The data used for the clustering is starting from the first Sunday of March till the last Tuesday of December, which makes it 304 days in total for each year. The optimal number of clusters is identified to be 3 clusters using the elbow method [44] as shown in Figure 18.

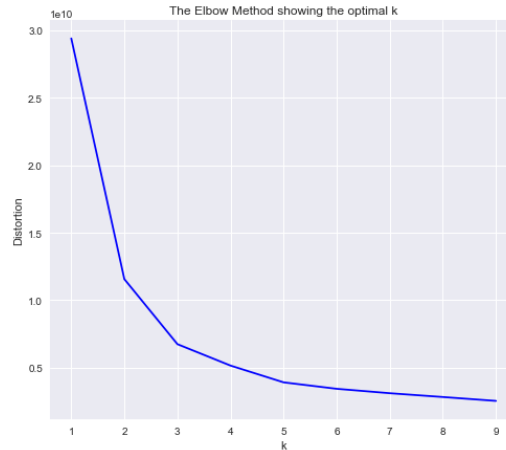


Figure 18: Elbow Method

The resulted three clusters of daily demand profile shown in Figure 19. There are three groups of daily demand profile, which can also be reflected on the mean hourly demand presented in Figure 16. Those clusters can be interpreted as follows: The green cluster representing the days with the highest peak load, with a delayed shift in the morning peak accompanied with an earlier shift in the evening peak. The blue and pink clusters represent days with moderate and base loads. Days with low demand could mainly be related to the mild-weather sunny days in both years, which is also confirmed by the March until May curve in Figure 16.

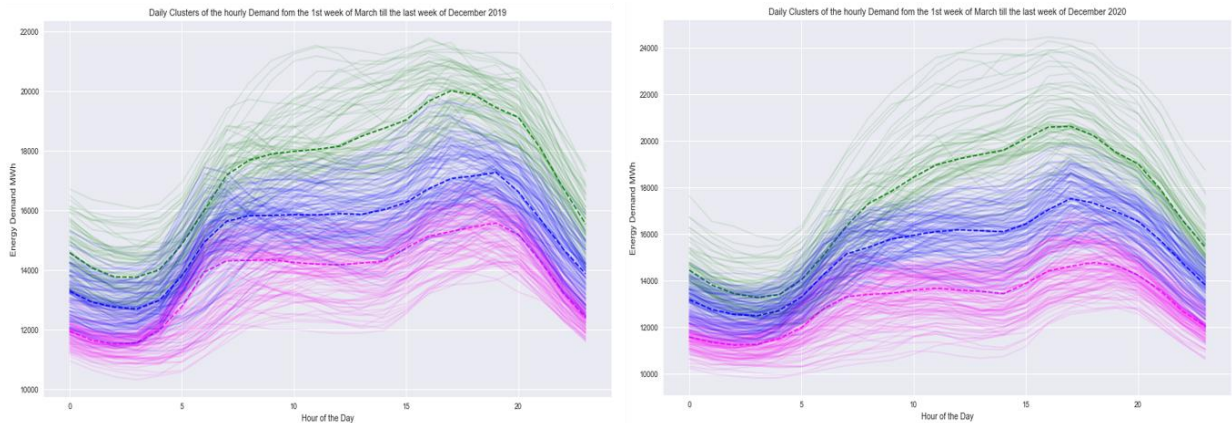


Figure 19: Daily K-means Clustering of Hourly Demand for the years 2019-2020

3.2 Ontario's Electricity Prices

This section evaluates the impact of pandemic on electricity prices. There are currently two types of pricing scheme in Ontario:

- Time of use (TOU) prices: Most of Ontario's residential and small business consumers pay TOU rates, which depend on when they use the electricity. Therefore, TOU prices have a direct impact on the consumption of costumers [45]. Figure 20 demonstrates the different periods of the electricity TOU rates (off-peak, mid-peak, and on-peak) based on Summer and Winter times [46].

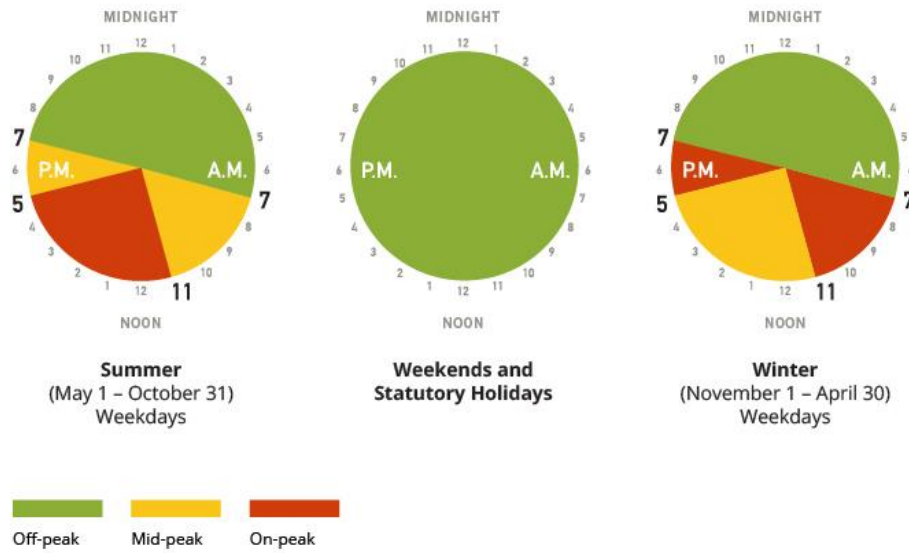


Figure 20: Electricity time-of-use rate periods

- Ontario’s HOEP: It is the average of the twelve market clearing prices, which are set on a 5-minutes interval. The HOEP is paid by large consumers and local distribution companies (LDCs) who then regain their profit back from business customers that pay the wholesale (TOU) market price [47].

In order to study the impact of COVID-19 on prices, this section uses data frame with features, such as date, time, and HOEP data for each hour of the day from the year 2019 till 2020. The data description is displayed and checked for any missing values. The used data frame consists of 26304 observations, containing no missing values.

3.2.1 Time of Use (TOU) Price

Electricity consumption throughout the day is reflective of the hourly electricity prices, the higher the price is, the lower the consumption is. In this section, the impact of changes in the TOU rates, resulted from the regulations during the pandemic is investigated.

In 2020, Ontario Energy Board (OEB) revised TOU prices to support customers, who were impacted by the consequences of the closures. The first emergency policy initiated on the 24th of March 2020 and was extended till May 31st, in which, the government of Ontario refined the electricity price for TOU

customers to the Regulated Price Plan (RPP) at 10.1 ¢/kWh for all hours of the day. The initiated RPP was equivalent to the off-peak price of the original TOU prices.

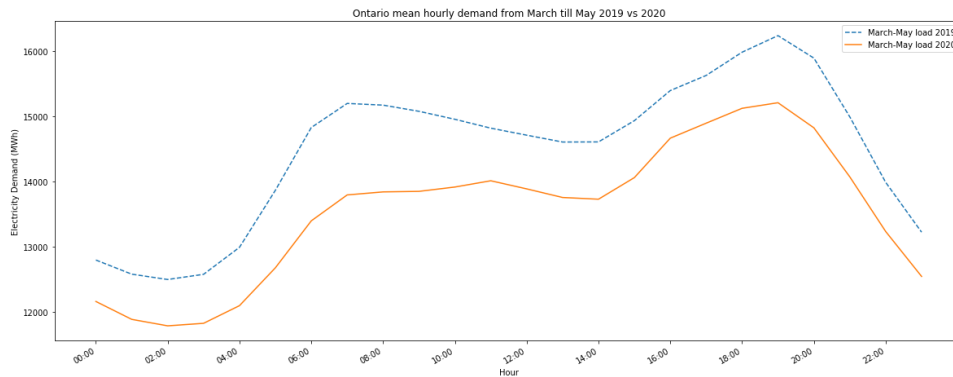


Figure 21: Mean hourly load from March till May 2019 vs 2020

As shown in Figure 21, the load pattern in 2020 was changed, especially from morning till noon, in which the load in 2019 dropped after the morning peak at 8:00 am, while it kept slightly increasing till 11:00 am, in 2020. This means that with the fixed TOU rates and working from home mandates, the consumers were not concerned about their consumption.

When the government of Ontario gradually started to reopen the businesses, the electricity prices were fixed at 12.8 ¢/kWh for all hours of the day from the 1st of June 2020 until the 31st of October 2020 for TOU customers. Figure 22 displays the mean hourly demand during this period, where it shows a load pattern that is almost the same in both years. In terms of magnitude, the average of demand in both years were almost the same from 8:00 pm till 8:00 am, while in 2020 the average load exceeded the load in 2019 during 8:00 am till 8:00 pm. This increase in demand contained a sharper evening peak in 2020. It is evident that with a higher fixed price and the businesses reopening, the load is getting closer to normal. However, with a continued working from home policy, the residential electricity consumption is still affecting the peak hours.

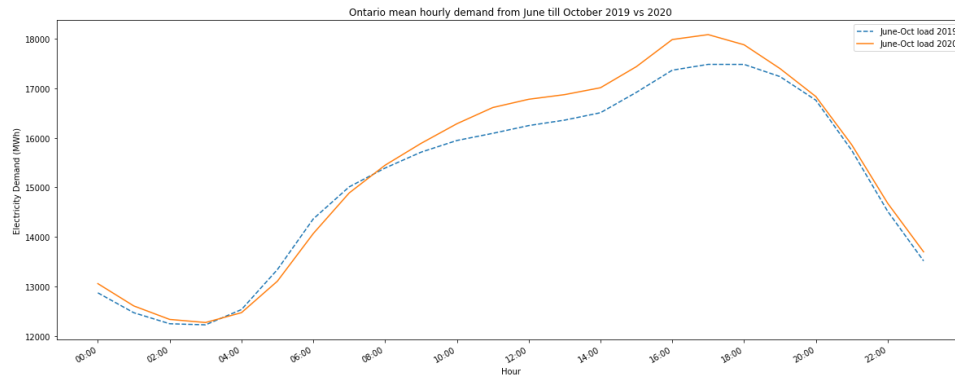


Figure 22: Mean hourly load from June till Oct 2019 vs 2020

On November 1st 2020, the prices were revised to their original values before the pandemic based on the Winter TOU scheme. As shown in Table 1, there were three different TOU prices depending on off-peak, mid-peak, and on-peak hours [48].

Winter TOU Price Periods	November 1, 2020 TOU Prices
Off-Peak (Weekdays 7 p.m. – 7 a.m., all day weekends and holidays)	10.5 ¢/kWh
Mid-Peak (Weekdays 11 a.m. – 5 p.m.)	15.0 ¢/kWh
On-Peak (Weekdays 7 a.m. – 11 a.m. and 5 p.m. – 7 p.m.)	21.7 ¢/kWh

Table 1: November 1st, 2020 electricity price rates (Source: OEB)

As shown in Figure 23, the mean hourly load pattern from November till December in 2020 is the most identical to the one in 2019, comparing to other periods, as consumers became more sensitive to the time of their consumption, and therefore, adjusted their behavior to benefit from price changes.

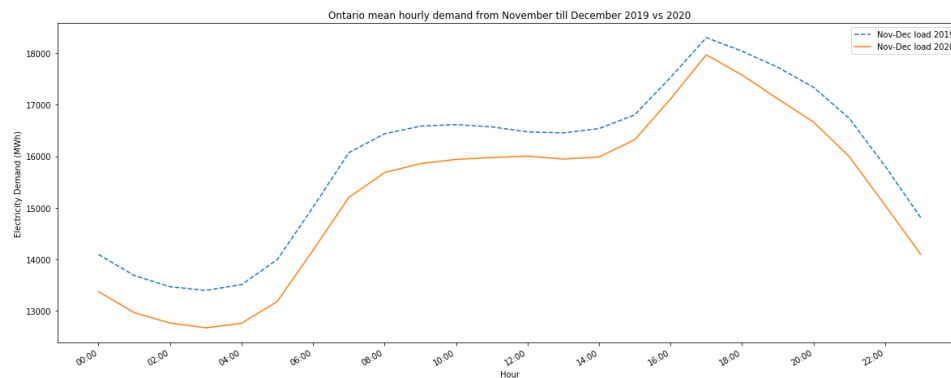


Figure 23: Mean hourly load from Nov till Dec 2019 vs 2020

3.2.2 HOEP Pricing

To evaluate the impact of pandemic, this section focuses on HOEP prices and compares them on an annually and monthly basis.

Annual price comparison 2019 vs 2020

Figure 24 compares the HOEP in 2019 vs 2020. The timelines reflecting HOEP in 2019 and 2020 are aligned to refer to same weekdays and weekends. Generally, the prices in 2020 were lower than those of 2019 for most of the days, and fewer number of high peaks were observed in 2020 data.

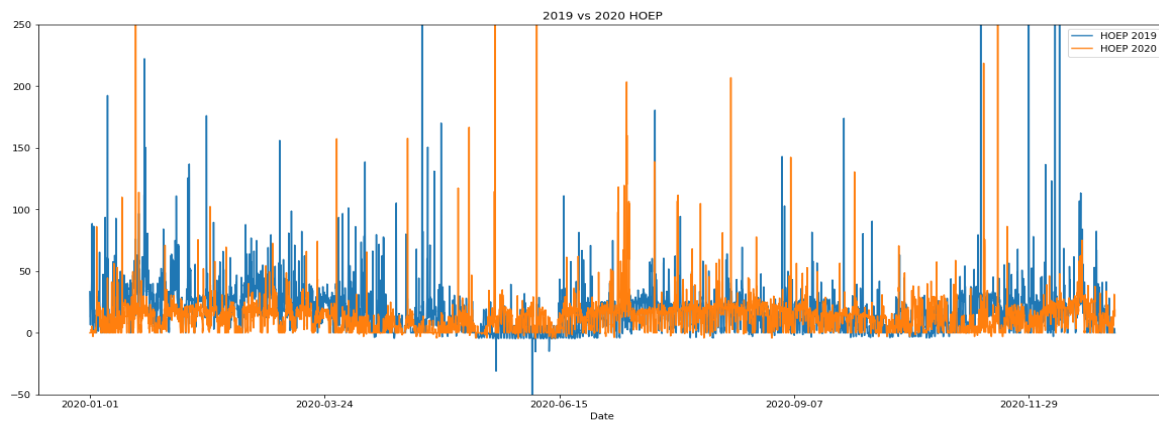


Figure 24: Ontario Hourly Electricity Price of the year 2019 against the year 2020 (The date displayed on the x-axis is considered for the year 2020, but the same weekdays are applied for both years)

Furthermore, the mean hourly electricity price for both years are plotted against each other in Figure 25. As shown, the overall average hourly price of 2020 was lower than the one in 2019. Also, the peak prices indicate an unusual trend in 2020 with two peaks in the morning (16.5 \$/MWh, and 17.5 \$/MWh), and two peaks in the evening (19.5 \$/MWh, and 16.0 \$/MWh). Whereas in 2019, there was one peak price in the morning, at 8:00 am, of 22.5 \$/MWh, and one in the evening, at 8:00 pm, of 25.0 \$/MWh.

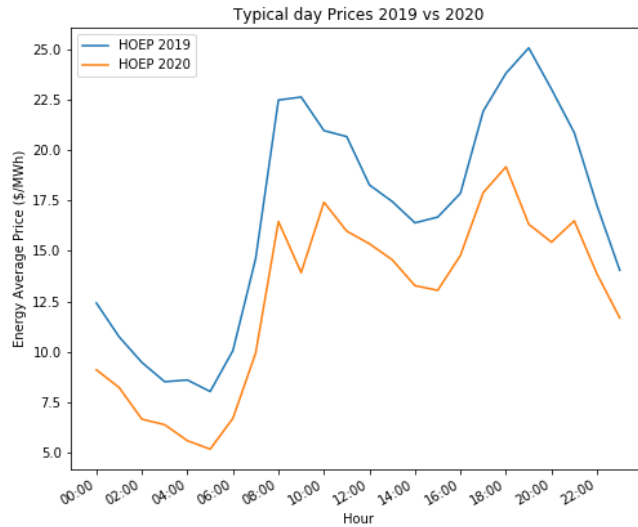


Figure 25: Ontario hourly electricity mean hourly price of 2019 and 2020

Monthly price comparison 2019 vs 2020

To further investigate the changes in HOEP from 2019 to 2020, the monthly breakdown of the electricity price is shown in Figure 26, by averaging every two months mean hourly price. This approach would help study the changes in peak prices related to the weather conditions and regulations in more details. The objective is to discover whether this trend happened directly due to COVID-19 or there were other external factors that affected the prices.

Figure 26 below demonstrates the typical day of each two months of the year 2019 and 2020 against each other. For example, the first graph is the mean hourly prices of the months January and February, the second graph of March and April, the third is of May and June, and so on. By looking at the trends in all graphs, it can be confirmed that peak prices can happen during different times of the day, even in 2019. Moreover, the lower price in 2020 can be observed in January and February graph, before the start of the pandemic. Hence, the unusual trends in hourly prices are not all directly dependent on the COVID-19 as they can also be impacted by the weather conditions. After reviewing the temperature data, it turns out that the Winter of 2020 was warmer than the Winter of 2019, with an average lowest temperature of about 4°C vs 1°C, and average highest temperature of almost 10°C vs 8°C, respectively. Such weather conditions resulted in a lower electricity demand in 2020 which in turn yielded less hourly prices.

Moreover, the main contributor to lower prices in March and April of 2020, beside a slightly warmer Spring, was the decrease in demand due to the COVID-19 restrictions and business closure. For the graphs representing prices in May till October, the average prices experienced a rise, surpassing those of 2019 in some hours. This variation could also be referred to the demand recovery in the Summer and Fall with almost the same weather conditions for both years. Finally, November and December prices, as indicated in the last graph, are approximately closer between 2019 and 2020. In addition to the COVID-19 recovery, the temperature data showed a relatively warmer average day for both months in the year 2020, which resulted in electricity demand rates similar to the ones of 2019. Thus, a closer average prices for both years.

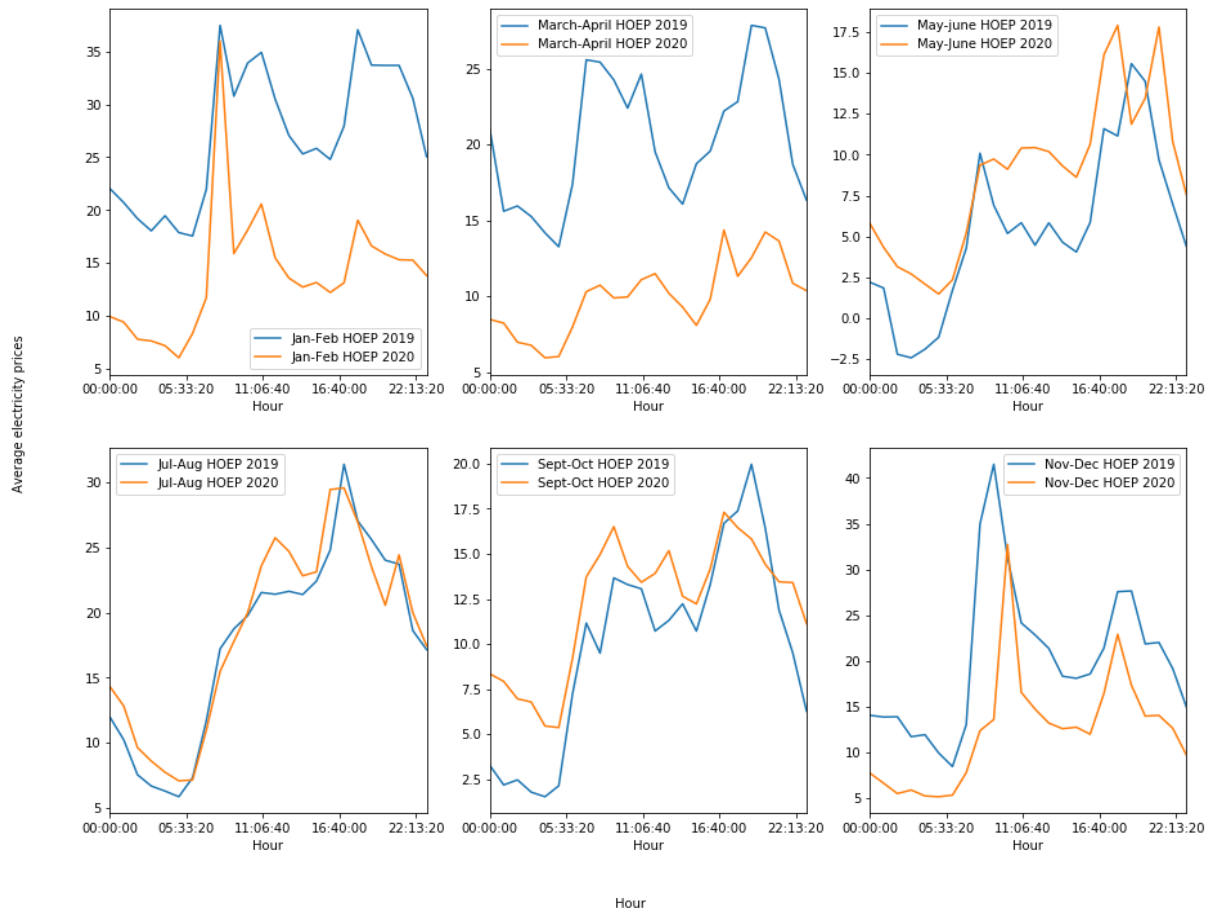


Figure 26: Mean hourly electricity price of each 2 months of the year 2019 vs 2020

3.3 Chapter summary

In this chapter, the impacts of the pandemic on Ontario's hourly electricity demand and prices were investigated. Overall, it was shown through the data analysis that both the demand and price trends underwent several alterations in 2020, when compared to 2019. The most interesting observations were a drop in the electricity demand and prices in March and April of 2020 as a response of the early stage of COVID-19 restrictions and closures, followed by an unexpected increase in load and prices starting from May 2020 and till the end of the Summer. Finally, in the Fall and Winter of 2020 the average load and price data indicated approximately the same trends as the ones of 2019.

Moreover, the changes in TOU prices and HOEP were investigated to reflect the changes in the demand. The alternation between the Tier threshold and the fixed TOU prices showed a direct influence on the consumer's demand patterns. The overall changes in the HOEP were aligned with those of the demand in terms of magnitude. However, those are not the final market prices that costumers pay as they don't count for the global adjustment costs, as will be discussed in Chapter 5.

In the next chapter, the impact of the pandemic on the robustness of forecasting methods under extreme events is studied. This evaluation is done by comparing the performance of a FFNN forecast model in three different time intervals: before the spread of the virus, during the early stage of the pandemic, and finally, during the recovery period. Both the demand and weather data are combined in the same data frame to be used in the forecast model.

Chapter 4

Impacts of COVID-19 on Ontario's Load Forecast

Forecasting the electricity load is crucial for the reliable operations of the power systems. Therefore, constructing an accurate forecasting model becomes more challenging due to the inherent characteristics of the daily operations of the systems, which are prone to rare events such as pandemic. The ML-based forecasting models are shown to perform better than other statistical prediction methods, as they can learn the patterns and structure of the data to predict future even with less error [36].

There are different types of forecast models that can be used to predict electricity demand, some are linear statistical models such as autoregressive integrated moving average (ARIMA) and (SARIMA), and others are non-linear models, like Neural Network (NN). In recent years, the application of NN techniques for load forecasting has gained much attention among the other different techniques due to its ability to learn complex non-linear relationships between the inputs and outputs, whereas the linear models, like ARIMA, depends on historical data, based on limited features [49] and [50]. The comparison between the performance of the different types of forecast models are presented in [17] and [51], indicating better performance of Artificial Neural Network (ANN) compared to other linear methods.

4.1 Forecast Model Selection

In this research, based on the electricity demand analysis, a Feed-Forward Neural Network (FFNN) forecast model is chosen to consider different features, impacting the demand, such as seasons, days, hours, and weather to predict the hourly demand. The related Ontario's weather data, including temperature, wind direction, wind speed, and humidity, is paired with Ontario's demand data in the forecast model. The model provides comparisons of the resulted forecast between before and during pandemic.

The provided analysis relies on historical demand data from January 2018. The data used in this model consists of 27528 rows and 8 columns, which are: date, time, hour, Ontario demand, temperature, humidity, wind speed, and wind direction, starting from the 1st of January 2018 till February 2021. First, the data is examined for missing values, then more features are added to the data such as, the

year, the season, the months, and the days to be used as input variables in the model. In order to find the relevant features for the analysis a feature selection method, considering the correlation between input and output layers is used. Six features are chosen as input variables as will be discussed in Section 4.2.

Three Keras sequential models are built with different training and testing data splits in Python 3.7.12, using Tensorflow library. The models are trained for three different time intervals. The first interval (January 2018 – January 2020) is to predict the demand before the spread of the coronavirus, the second (January 2018 – March 2020) is to study the performance of prediction methods during the lockdown, and the last interval (January 2018 – January 2021) is to examine the impact of pandemic on prediction models after the recovery from the COVID-19 in 2021. The data is split such that there would be 15 days in each interval for test set and the rest is used for training set. All the codes used in this section are presented in Appendix B.

4.2 FFNN Model Structure

The initial model included one input layer, one hidden layer, and one output layer. Different combinations of numbers of layers, neurons, epochs, and batch sizes are examined to better tune the model. After building and testing the model for several times with different topologies, the best outcome is achieved using the following architecture of the three FFNN models:

- An input layer including 6 input variables which are: temperature, humidity, wind speed, season, weekday, and hour.
- Three hidden layers consisting of 100 neurons each.
- An output layer that includes a single neuron which is Ontario's demand.
- The **ReLU** is used as an activation function, **adam** as an optimizer, and the **mean squared error** as the loss function.
- The **epoch**, which is the number of time to run the model is set to 100.
- The **batch size** which means to divide the input data into a number of batches and process each in parallel is set to 10.

4.3 Forecast Model Performance and Evaluation Method

To evaluate the performance of the model, the Mean Absolute Percentage Error (MAPE) is calculated

for each of the models to indicate the percentage of the error between the predicted, F and actual, A values for the training and testing datasets [52], as follows:

$$MAPE = \frac{1}{n} * \Sigma \left(\frac{|A-F|}{|A|} \right) * 100 \quad (4)$$

Where, n is the size of the sample.

4.3.1 Model performance: pre-pandemic

The pre-pandemic model is trained over pre-pandemic historical demand data (Jan 2018 – Jan 2020) and tested over pre-pandemic period of Jan 15, 2020 – Jan 29, 2020. As shown in Figure 28 the performance of the test data in base case scenario is extremely accurate, MAPE = 3.21%, as illustrated in Table 2.

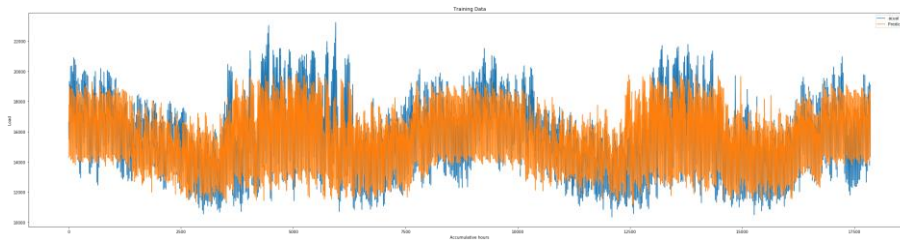


Figure 27: Train data from Jan 1st 2018 till Jan 14th 2020

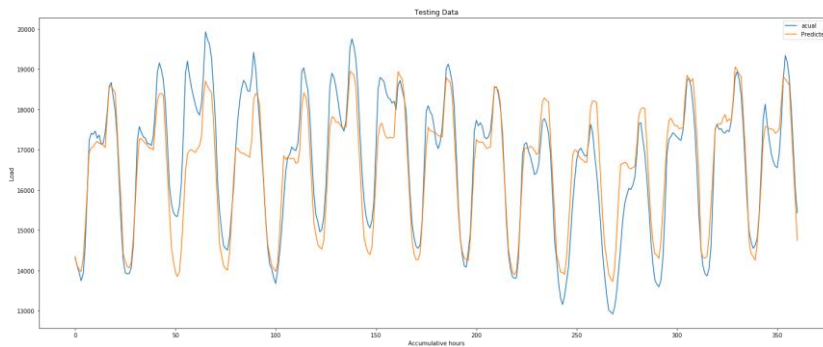


Figure 28: Test data from Jan 15th 2020 till Jan 29th 2020

4.3.2 Model performance: beginning-pandemic

Next, a second model is trained using the same FFNN architecture, using training data, before pandemic (Jan 2018 - March 2020), and then tested over the data in the beginning of pandemic, March 25, 2020 – April 8, 2020. Although the training error in Figure 29 is acceptable (MAPE = 6.76%), as shown in Figure 30 and Table 2, the test performance declined significantly, due to the sudden changes in demand. The resulted MAPE during this period is 13.86%.

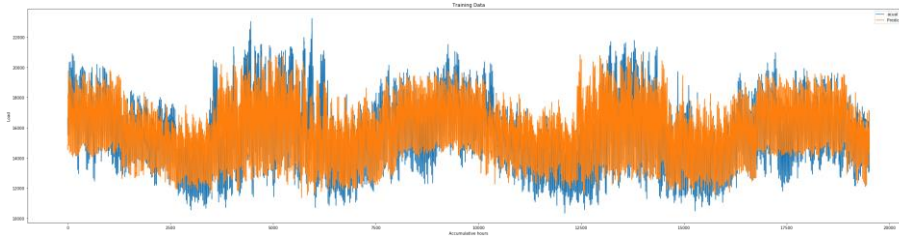


Figure 29: Train data from the 1st of Jan 2018 till the 24th of March 2020

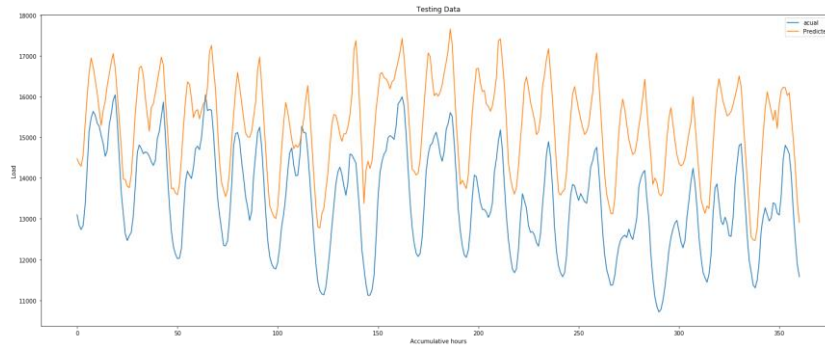


Figure 30: Test data from the 25th of March 2020 till the 8th of April 2020

4.3.3 Model performance: during-pandemic

The FFNN model is retrained adding the data from pandemic (Jan 2018 – Jan 2021), as shown in Figure 31 and tested over the data from Jan 25, 2021 – Feb 8, 2021, during which the load behavior was stabilized. As shown in Figure 32, the retrained model, with the additional data from pandemic, performs with much higher accuracy (MAPE = 4.23%).

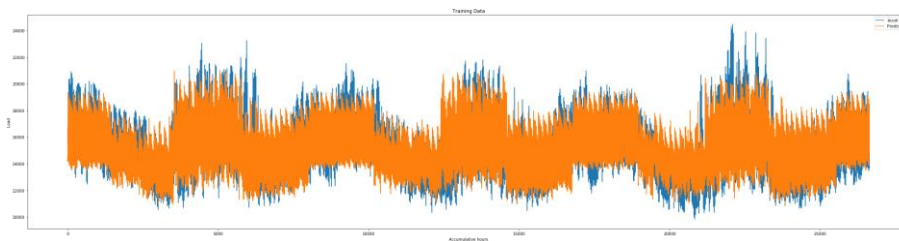


Figure 31: Train data from the 1st of Jan 2018 till the 24th of Jan 2021

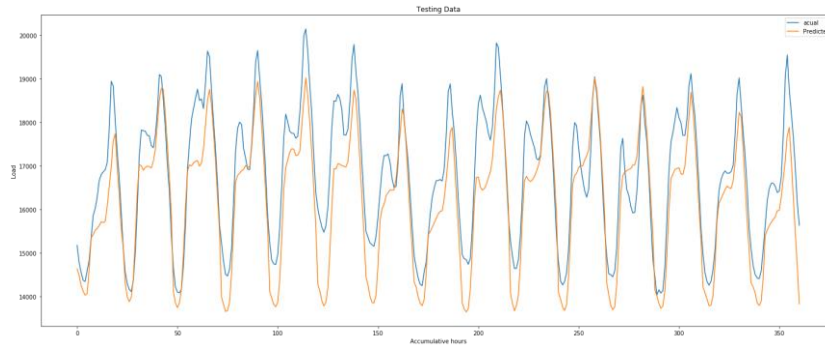


Figure 32: Test data from the 25th of Jan 2021 till the 8th of Feb 2021

The results show good performance of the FFNN model, even during the beginning of COVID-19. As noted in [53], the evaluation of the accuracy of NN models, using MAPE, can be categorized into the 4 following categories:

- Highly accurate forecasting if the MAPE <10.
- Good forecasting if the MAPE is between 10 and 20.
- Reasonable forecasting if the MAPE is from 20 to 50.
- And an inaccurate forecasting if the MAPE >50.

A summary of the MAPE comparisons among the three models is given in Table 2 (The percentages in the table were rounded to 2 decimal places).

Models	Train data MAPE	Test data MAPE
Before COVID-19	6.58%	3.21%
During COVID-19	6.76%	13.86%
After the recovery	6.69%	4.23%

Table 2: MAPE scores for the three models

By comparing the test data results to the typical MAPE index, models 1 and 3 are showing an excellent performance with small percentage error, categorizing them as “highly accurate forecasting model”. The worst result, which is associated with the 2nd model, is still labeled as “good forecasting model”.

4.3.4 Model Performance, using Time Series Cross Validation: in the beginning of the pandemic

To examine, the model performance for the second model (during the early stage of the pandemic) a cross validation on a rolling basis is used [54]. For this purpose, a 5-folds cross validation technique is performed on the test data while the training data is from January 1st, 2018 to March 15th, 2020 and the test data is from March 16th, 2020 until March 29th, 2020, for the first fold. For each of these intervals,

the last test data points are then added as part of the training dataset and subsequent data points are included in the test data of the next fold. Finally, the average accuracy of the 5-folds cross validation is calculated. Table 3 below illustrates each of the 5-fold intervals used, the accuracy of each fold, and the average accuracy for the overall cross validation performance.

Folds	Training data	Test data	MAPE: Cross-validation over test data
1	Jan 1, 2018 - Mar 15, 2020	Mar 16, 2020 – Mar 29, 2020	6.4%
2	Jan 1, 2018 - Mar 30, 2020	Mar 31, 2020 – Apr 13, 2020	13.6%
3	Jan 1, 2018 - Apr 14, 2020	Apr 15, 2020 – Apr 28, 2020	10.7%
4	Jan 1, 2018 – Apr 29, 2020	Apr 30, 2020– May 13, 2020	13.1%
5	Jan 1, 2018 - May 14, 2020	May 15, 2020– May 28, 2020	14.0%
Average Accuracy (MAPE)			11.6 %

Table 3: Time Series 5-folds Cross Validation

As shown in the above table, the main model here is represented by the 5th fold. The average accuracy presented by the cross-validation method is 11.6%, indicating higher accuracy than the actual model’s MAPE of 14% accuracy. The cross validation gives a better observation of the data points by using them in both the training and the testing datasets.

4.4 Chapter Summary

Overall, the results from the FFNN model were showing a highly accurate electricity demand predictions in normal conditions, whether before the COVID-19 or after- the partial recovery of the electricity demand at the beginning of 2021. However, during the pandemic, the forecast model performance was remarkably affected. Expectedly, the accuracy of the model got worse due to the sudden load drop that took place in March and April 2020, yet the results looked promising for future improvements.

The upcoming chapter represents the assessment of Ontario’s Market Renewal under the COVID-19 situation. One main aspect of the Market Renewal is having a locational marginal price (LMP) system, as well as a zonal forecasting system. This approach could present an effective strategy of improving the pricing system and the market efficiency.

Chapter 5

Ontario's Market Renewal Evaluation Under Pandemic

As mentioned in chapter 2, MRP aims to achieve a more efficient, reliable, and affordable electricity market. Therefore, the COVID-19 remarkable impacts on the electricity system represent an effective opportunity to check how the MRP would have performed if it was in place during the pandemic. To carry out this evaluation, the impacts of the COVID-19 on an equivalent market (New York ISO) that benefits from MRP structure is assessed and compared to Ontario's current market, which has not implemented MRP mechanism yet. The following criteria are considered to have the two markets comparable:

- Weather conditions: The geographical location of the two markets are very close to each other. Hence, they have similar weather conditions [55].
- Energy consumption profiles: Both markets have similar demand profiles across industrial and household consumption, and very close average seasonal hourly demand patterns. As can be seen in Figure 33 (New York graph is borrowed from [56] and a similar graph is executed using Ontario's data using Python 3.7.12) the average hourly demand curve shape of each season of the year 2020 for both cities is quite similar.
- Generation capacity: The north zone in New York has similar generation capacity to Ontario, with higher renewables and nuclear generation capacities. The two markets have almost the same total generation capacity, marking around 38,500 MW in the year 2020 [57] [56].
- Pandemic restrictions: Both jurisdictions followed almost the same timelines for the different restriction declarations [41] [58].
- Other common features: The MRP structure which will be implemented in Ontario in the future is close to New York's LMP-based market.

Based on the preceding criteria, New York's electricity market proved to be an adequate benchmark to be compared with the MRP. However, the total average demand of New York is higher than Ontario, which can be reasonable due to the difference in population between the two cities. Moreover, it seems that the implications of the pandemic on New York energy consumption during the Spring were very close to those of the Fall, whereas in Ontario the load drop during Spring was the most significant.

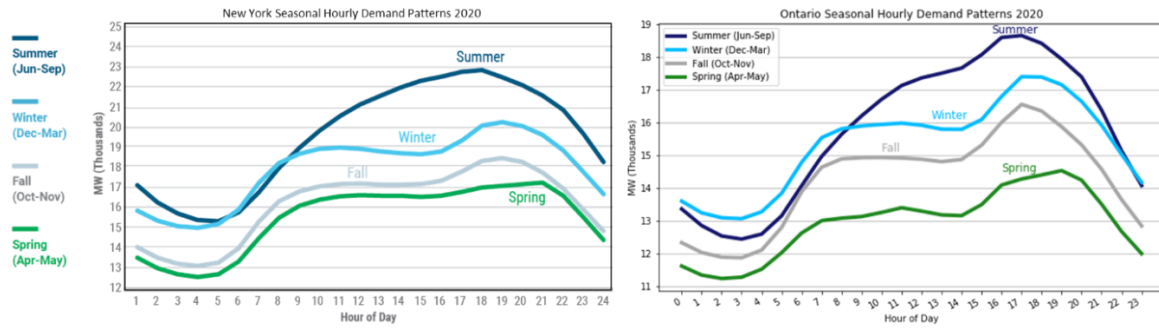


Figure 33: NY vs ON 2020 Seasonal Hourly Demand Patterns

To start the comparison, 5 different zones from New York’s market were selected, as follows:

1. North Country.
2. Western New York.
3. Central New York.
4. Capital District.
5. Mid-Hudson.

The comparison between the two markets is concise to the mean hourly electricity demand and prices of two groups of months. First one is March and April of 2019 vs 2020, and the second one is May and June of 2019 vs 2020. This segmentation enables a deeper look into the changes that happened to both markets during the early stage of COVID-19 in March and April causing a significant load drop, followed by the unexpected rise in demand during May and June. Finally, the percentage difference of the average electricity costs between 2019 and 2020 are calculated for different hours to compare how consumers’ bills were affected during the pandemic based on the different pricing system of each city.

5.1 Ontario’s load vs New York’s locational load

Figure 34 demonstrates the comparisons between Ontario’s average load and New York’s two zones (Central and West) average loads in 2019 and 2020. The averages are calculated for March and April, and May and June, both of 2019 and 2020. New York’s West and Central zones are only displayed for more clarification of the comparison. As shown in the figure, the load patterns of New York’s zones, specifically the Central region are relatively like Ontario’s load patterns. However, some zones look more flattened than the others, such as the West and North regions (a graph of New York’s five zones is presented in Figure A - 4 of Appendix C: Ontario vs New York’s electricity markets)

Moreover, the locational loads are demonstrating a difference in how the demand was affected by the pandemic based on different regions. For example, the Central and the West areas are showing the most impacted demand profiles, whereas the Capital and the Hudson Valley regions have experienced a less severe load drop. On the other hand, the North region has experienced a higher demand rates in 2020 compared by those of 2019. These observations mean that when dealing with a locational market, the uncertainty in the demand could be analyzed and managed more accurately, based on the load of each zone, than when dealing with a whole province load, as in the case of Ontario.

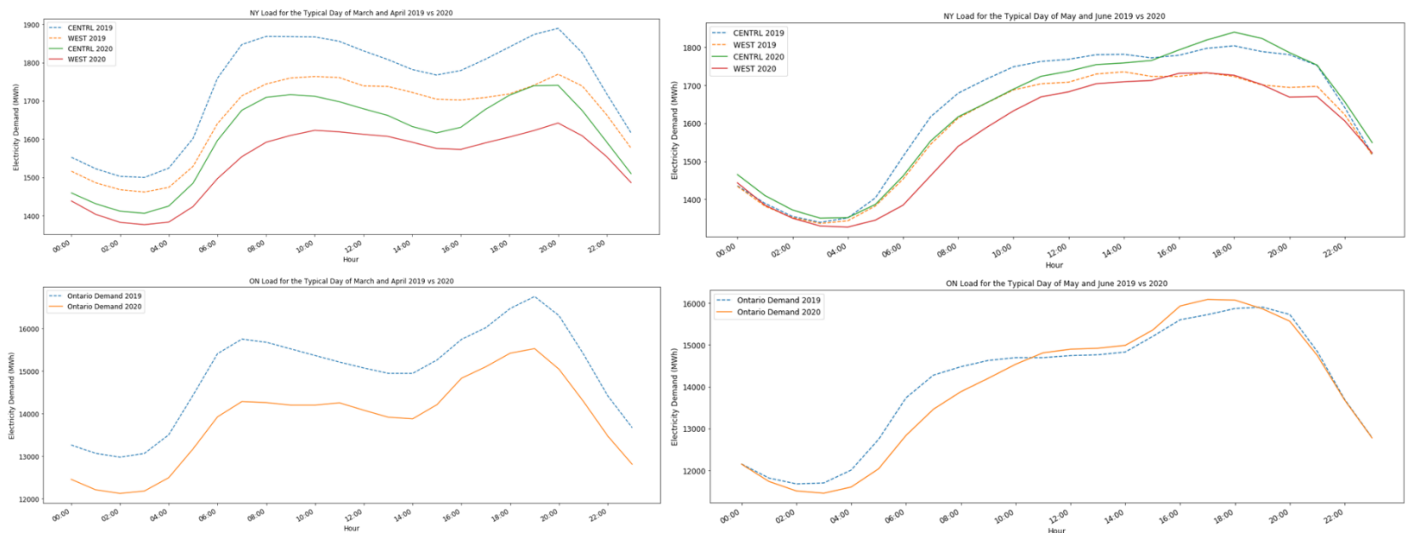


Figure 34: NY and ON average hourly load 2019 and 2020

5.2 Ontario’s HOEP vs New York’s LBMP

This section presents a comparison between the changes in Ontario’s mean hourly electricity prices and New York locational marginal prices. The HOEP is compared with and without adding the Global adjustment payments to represent the actual prices of electricity and the final uniform prices that customer pays, which is referred here as “Adjusted HOEP”.

Global Adjustment (GA)

GA is an additional cost, covering the province’s new electricity infrastructure, resources maintenance, and conservation programs delivery costs to ensure the availability of electricity supply in the long term. GA is calculated each month to reflect the difference between the HOEP and the additional payments for energy contracts paid for some generators, and regulated generation. Generally, there is an inverse effect between GA and HOEP, meaning that when HOEP is lower, GA gets higher, and conversely.

Figure 35 below demonstrates the comparisons between Ontario’s average actual and adjusted HOEP and New York’s five average LBMP in 2019 and 2020. Same as the demand, the averages are calculated for March and April, and May and June, both of 2019 and 2020. As shown, New York’s LBMP and Ontario’s actual HOEP dropped significantly in March and April 2020, reflecting the changes in the load during this period. However, the HOEP experienced a remarkable rise when adding the GA payments, which resulted in inefficiency between the final prices that consumers paid and what they actually consumed.

In May and June, LBMP still showed some reductions, while the HOEP underwent an increase. With the GA, the HOEP remarkably decreased, which is compatible with in the inverse relation between the HOEP and GA, as well as the ICI program that resulted in reducing large consumers GA during this time, as mentioned in Section 3.1.2.

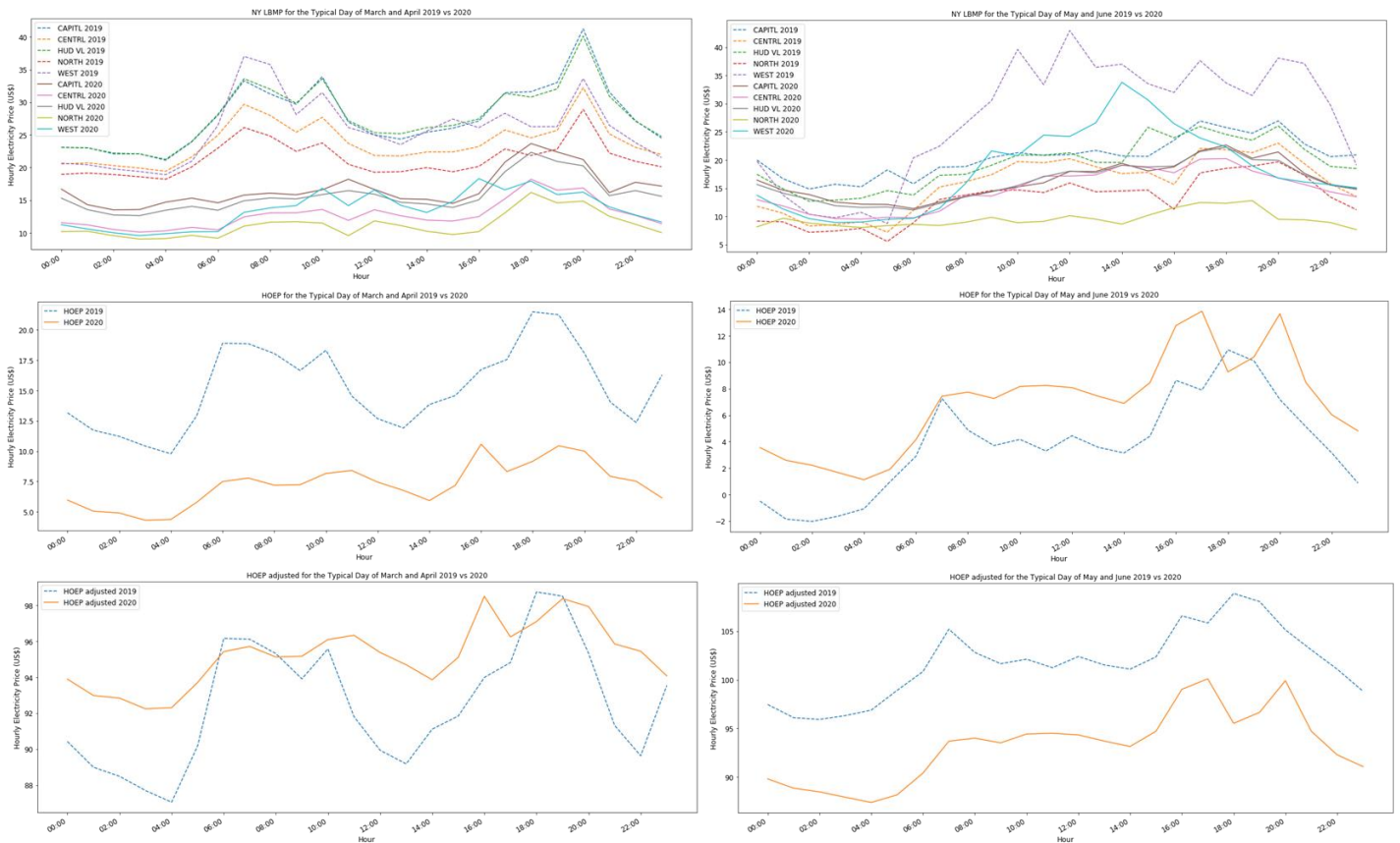


Figure 35: NY and ON average hourly prices 2019 and 2020

5.3 Formulating Average Hourly Cost of Electricity Index

The hourly energy cost is the price of the total energy consumed at this hour. It is calculated by multiplying the electricity demand (MW/h) at an hour (x) by the price of electricity (\$/MW) at the same hour. Here, the difference indexes between the average energy costs of Ontario and New York’s 5 zones are formulated for March and April, and May and June, both of 2019 and 2020. A comparison between Ontario and New York zones difference in electricity cost at the same hour will help to review which market had a more efficient pricing system, as it will show if the hourly demand of each area is reflected on its hourly price during the pandemic. For this comparison, the adjusted HOEP is used.

The energy cost index for an average hour is calculated as follows:

$$\text{Generation cost} = \text{HOEP adjusted} \times \text{Hourly demand} \quad (5)$$

$$\text{Difference index} = \frac{(\text{2020 generation cost} - \text{2019 generation cost}) * 100}{\text{2019 generation cost}} \quad (6)$$

	March-April %			May-June %		
	8 am	2 pm	8 pm	8 am	2 pm	8 pm
Capital	-52.2%	-43.6%	-51.7%	-27.4%	-2.3%	-17.0%
Central	-57.3%	-51.0%	-51.8%	-17.7%	-7.1%	-26.6%
Hudson	-56.4%	-49.7%	-52.6%	-29.4%	-7.5%	-24.9%
North	-44%	-47.9%	-47.2%	-32.2%	-36.9%	-49.0%
West	-70.3%	-52.6%	-55.2%	-43%	-10.1%	-56.6%
Ontario	-9.2%	-4.3%	-5.2%	-12.3%	-6.9%	-5.9%

Table 4: Percentage difference index of electricity cost

Table 4 illustrates the percentage of difference between what consumers paid in three different average hours of March and April, and May and June in 2019 vs 2020. As shown, in March and April the average electricity costs for all the five nodes of New York were significantly impacted, showing a decrease of around 50% and more. However, the percentage change in Ontario’s consumer payments presented in the last row is the lowest, indicating a negligible change in the electricity costs during the most severe stage of COVID-19, where the demand faced a significant drop. This difference conclude a misalignment between what energy consumers use and what they pay.

As shown in May and June column of Table 4, consumers were still paying less in 2020 compared to 2019, even in Ontario. The average difference in payments of these months were highly variant from one zone in New York to another, showing how each group of consumers were impacted differently. In Ontario the percentage differences were slightly more than March and April. Overall, Ontario and New York's consumers paid less than what they consumed in May and June of 2020.

5.4 Chapter Summary

This chapter used the COVID-19 outbreak as a case study to highlight the main inefficiencies in Ontario's current pricing system. While the GA represented a barrier to pricing transparency and market efficiency resulting in increase in consumer bills, the LMP pricing system proved to be in the best interest of consumers as it represented the final prices with no hidden costs. Therefore, Ontario's current market reformation is crucial to address those inefficiencies.

As mentioned in [24], the MRP enhancements will result in significant reduction of transfer payments caused by excess of marginal value and uplifts in market prices that do not reflect actual costs, as well as investment cost savings. Moreover, the MRP aims to reduce or eliminate CMSC payments, and day-ahead/real-time cost guarantees. Such initiatives will help reduce the GA and any out of market payments, resulting in more transparent and fair pricing for electricity costumers.

The next chapter highlights the main thesis conclusion and suggests future work to improve the research and benefit from the potential opportunities that emerged during the pandemic.

Chapter 6

Conclusion & Future Work

Since the COVID-19 has acted as a rare event that caused unprecedented challenges in the operation of the electricity market and changes in the electricity demand, many lessons have been learnt by the system operators and researchers. In this section, the outcomes of this research are summarized and recommendations for future work is outlined.

6.1 Conclusion

This research offered an extensive analysis of the COVID-19 implications on Ontario's hourly electricity demand and prices to give a comprehensive vision of the unexpected changes in the energy consumption of the year 2020. The study showed significant load drop during March and April 2020 and unforeseen demand rise in the Summer of 2020. In addition to a discussion on the changes in consumer's behavior, the weather data was examined to better investigate the unexpected variation in demand.

As for the pricing of electricity, the TOU prices were first investigated to show the difference between the Tier threshold and the fixed TOU prices on affecting the consumer's demand patterns. Then, the HOEP (without counting for GA) were looked at, showing some changes that were aligned with those of the demand. However, the HOEP were more complicated to interpret as they showed a multiple peaks pattern that is not consistent.

The research also compared the accuracy of forecasting methods before, beginning and during the pandemic, to investigate the impacts of COVID-19 on load forecasting. It suggested that a FFNN model could result in good forecast of demand even in the beginning of the pandemic.

Moreover, Ontario's MRP was assessed during the pandemic by comparing Ontario's current electricity market and New York electricity market. The results showed a more efficient and transparent performance of a LMP market versus a uniformed price market.

The analysis presented in this thesis aims to provide energy stakeholders and policymakers with lessons learned for better planning of the electricity amidst the pandemic. It also proposed an effective forecasting model that accepts more inputs to be tested for future improvement. Moreover, it highlights

the importance of Ontario's electricity market reformation to address the inefficiencies in the current pricing system that were revealed in comparison with an LMP system during COVID-19.

6.2 Future Work

Given the fact the COVID-19 is still ongoing and its impacts on the electricity sector are considered as long-term impacts, some restrictions and customer behavior are becoming the 'new normal'. Moreover, the probability of the emerging new variants is still threatening the state of the electricity market. Therefore, there are many opportunities for future research to handle the pandemic unforeseen challenges, as outlined below:

Planning for electric grid: This research is planned to be expanded by creating scenarios for planning models, considering rare events impacting the operation of electric grids, and using insights gained from this study. Such rare events require more resilient electric systems, and through this work, we plan to investigate strategies and planning tools required for the robust operations of the grid. For instance, one option might be promoting micro-grids, or peer-to-peer networks to reduce the peak demand from the system. Another way to boost the resiliency is the integration of diverse generation resources and distributed generation paired with storage.

Improving forecasting models: There are many areas of life that have been impacted by the pandemic consequent restriction, imposing some changes in people daily activities, hence, changing in customers' electricity consumption. Therefore, the changes in mobility, transportation, or employment data will be considered to the proposed forecast model and tested for future improvement.

Opportunities for more clean energy: This research can be expanded to study the performance of generation mix and changes in greenhouse gas emissions (GHG) during COVID-19. This analysis could also be applied to crises from extreme weather associated with climate change. The assessment of potential transition to more nuclear and renewable power supply during rare events, stimulates higher investments in clean energy, which leads to the achievement of the long-term climate goals.

Market renewal opportunities: With the availability of more data, such as locational prices data for Ontario, further investigations can be done to assess the MRP during rare events. For example, applying forecasting models on LMP and locational demand instead of HOEP and the province-wide demand, compare the performance of both models, and check the robustness of locational forecasting models.

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Appendices

Appendix A: COVID-19 impacts on Ontario's electricity demand and price

All the codes were executed on Python 3.7.12.

In this section, some codes are borrowed from: <https://www.kaggle.com/nicholasjhana/eda-energy-demand-analysis>

Importing the required libraries:

```
import numpy as np
import pandas as pd
import random as rd
import matplotlib.pyplot as plt
import plotly.graph_objects as go
import plotly.express as px
import csv

import sklearn
from sklearn.cluster import KMeans
import sklearn.metrics as sm
from sklearn import datasets
from sklearn.metrics import confusion_matrix, classification_report

from pylab import plot, show
from numpy import vstack, array
from numpy.random import rand
from scipy.cluster.vq import kmeans, vq
from math import sqrt
%matplotlib inline
```

1. Ontario's electricity demand analysis

1.1. Annual Comparison:

Importing and examining data:

```
#Importing the data
df= pd.read_csv ('Demand-Temp(2018-2020).csv', usecols=['Date', 'Time',
'Ontario Demand', 'Temperature'])
df= df.loc[(df['Date'] >= '2019-01-01') & (df['Date'] <= '2020-12-31')]

print (df.describe().transpose())
print (df.info())
```

	mean	std	min	25%	\	count
Ontario Demand	17544.0	15237.510203	2390.995025	9831.000000	13450.000000	

```
Temperature      17544.0      12.903312      7.627233      -3.749471      6.838
029
```

```

                50%                75%                max
Ontario Demand  15039.000000  16860.000000  24446.000000
Temperature     12.480529     18.430529     36.12053
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 17544 entries, 8760 to 26303
```

```
Data columns (total 4 columns):
```

```

#   Column                Non-Null Count  Dtype
---  ----
0   Date                   17544 non-null  object
1   Time                   17544 non-null  object
2   Ontario Demand         17544 non-null  int64
3   Temperature            17544 non-null  float64
```

```
dtypes: float64(1), int64(1), object(2)
```

```
memory usage: 685.3+ KB
```

```
None
```

Plotting 2019 vs 2020 demand data:

```

#Comparing 2019 demand to 2020 demand
df19= df.loc[(df['Date'] >= '2019-01-02') & (df['Date'] <= '2019-12-31')]
df20= df.loc[(df['Date'] >= '2020-01-01') & (df['Date'] <= '2020-12-29')]
df19=df19.rename(columns = {'Ontario Demand':'Ontario Demand 2019'})
df20=df20.rename(columns = {'Ontario Demand':'Ontario Demand 2020'})

#Plot both years against each other
ax= df19.plot(x="Date", y="Ontario Demand 2019", kind="line", figsize=(25,
8))
df20.plot(x="Date", y="Ontario Demand 2020", figsize=(20,8), ax=ax,
title=("Ontario Eelectricity Demand 2019 vs 2020"))
ax.legend(["Demand 2019","Demand 2020"])

squad = ['00', '01-01', '03-24','06-15','09-07','11-29']
ax.set_xticklabels(squad, minor=False)
ax.set_ylabel="Electricity Demand (MW)"

xpoints = [1800,3456, 5928]

for p in xpoints:

    plt.axvline(p, color='red')

plt.legend()
ax.text(300, 24500, 'Part 1', fontsize=12, color='black')
ax.text(2500, 24500, 'Part 2', fontsize=12, color='black')
ax.text(4600, 24500, 'Part 3', fontsize=12, color='black')
ax.text(7000, 24500, 'Part 4', fontsize=12, color='black')
plt.show()
```

Plotting 2019 vs 2020 temperature data:

```
#Comparing 2019 Temperature to 2020 Temperature
df19= df.loc[(df['Date'] >= '2019-01-02') & (df['Date'] <= '2019-12-31')]
df20= df.loc[(df['Date'] >= '2020-01-01') & (df['Date'] <= '2020-12-29')]
df19=df19.rename(columns = {'Temperature':'Temperature 2019'})
df20=df20.rename(columns = {'Temperature':'Temperature 2020'})

#Plot both years against each other
ax= df19.plot(x="Date", y="Temperature 2019", kind="line", figsize=(25, 8))
df20.plot(x="Date", y="Temperature 2020", figsize=(20,8), ax=ax,
title=("Ontario Temperature 2019 vs 2020"))
ax.legend(["Temperature 2019", "Temperature 2020"])

squad = ['00', '01-01', '03-24', '06-15', '09-07', '11-29']
ax.set_xticklabels(squad, minor=False)
ax.set_ylabel("Temperature (C)")

xpoints = [1800, 3456, 5928]

for p in xpoints:

    plt.axvline(p, color='red')

plt.legend()
ax.text(300, 36.5, 'Part 1', fontsize=12, color='black')
ax.text(2500, 36.5, 'Part 2', fontsize=12, color='black')
ax.text(4600, 36.5, 'Part 3', fontsize=12, color='black')
ax.text(7000, 36.5, 'Part 4', fontsize=12, color='black')
plt.show()
```

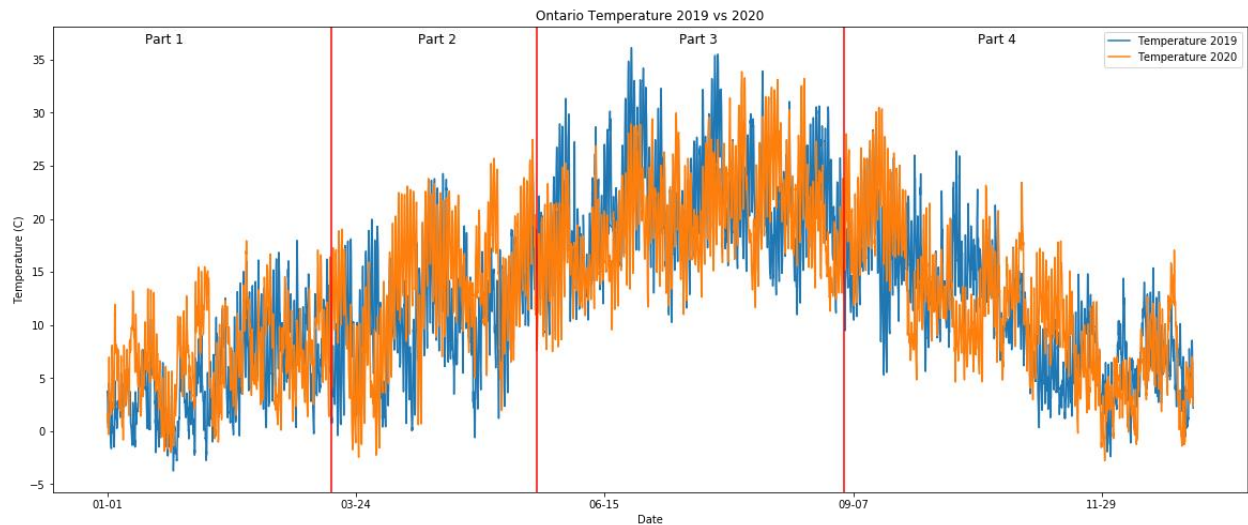


Figure A - 1: Hourly Temperature data 2019 vs 2020

Mean hourly load: 2019 vs 2020

```
#Calculating the mean hourly load for each year
f19['Datetime'] = pd.to_datetime(df19['Date'] + ' ' + df19['Time'])
df19 = df19.drop(['Date', 'Time'], axis=1)
df19['Datetime'] = pd.to_datetime(df19['Datetime'])

df20['Datetime'] = pd.to_datetime(df20['Date'] + ' ' + df20['Time'])
df20 = df20.drop(['Date', 'Time'], axis=1)
df20['Datetime'] = pd.to_datetime(df20['Datetime'])

hour = pd.to_timedelta(df19['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
df19 = df19.groupby(hour).mean()
df19 = df19[['Ontario Demand 2019']]

hour = pd.to_timedelta(df20['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
df20 = df20.groupby(hour).mean()
df20 = df20[['Ontario Demand 2020']]

#Plotting the data
ax= df19.plot(figsize=(8, 7), x_compat=True)
df20.plot(figsize=(8,7), ax=ax, x_compat=True, title=("Typical day Demand
2019 vs 2020"))
ax.legend(["Toal Load 2019", "Toal Load 2020"])

hour=[0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22]
ax.set_xticks(hour)
```

```
squad = ['00:00', '02:00',
'04:00', '06:00', '08:00', '10:00', '12:00', '14:00', '16:00', '18:00', '20:00', '22:
00']
ax.set_xticklabels(squad, minor=False)
ax.legend()
plt.show()
```

Load duration curve: 2019 vs 2020

```
#group data by year
group_year = df_all['Ontario Demand'].groupby(pd.Grouper(freq='A'))

#set figure and axis
fig, axs = plt.subplots(1, 1, figsize=(8,5))

for name, group in group_year:
    sorted_demand_count =
pd.Series(group.values).sort_values(ascending=False).reset_index()
    sorted_demand_count.drop('index', axis=1, inplace=True)

#plot the data
axs.plot(sorted_demand_count)
axs.set_xlabel('Cumulative Hours')
axs.set_ylabel('Total Load')
axs.set_title('Load Duration Curve 2019-2020')
axs.legend(['2019', '2020'])
```

1.2. Monthly comparison:

For the sake of this analysis, the monthly breakdown starts from the month of March to explore the load drop in 2020 due to the lockdown and the essential business closure as a result of the COVID-19.

From March till May

```
# Plotting the load drop that happend from the 1st week of March till the
second half of May
df19_34= df.loc[(df['Date'] >= '2019-03-03') & (df['Date'] <= '2019-05-25')]
df19_34=df19_34.rename(columns = {'Ontario Demand':'Load 2019'})
df20_34= df.loc[(df['Date'] >= '2020-03-01') & (df['Date'] <= '2020-05-23')]
df20_34=df20_34.rename(columns = {'Ontario Demand':'Load 2020'})

ax= df19_34.plot(x="Date", y="Load 2019", kind="line", figsize=(20, 5))
df20_34.plot(x="Date", y="Load 2020", ax=ax, title=("2019 vs 2020 Hourly
load from the first week of March till the third week of May"))

squad = ['00', '03-01', '03-11', '03-21', '04-01', '04-11', '04-22', '05-
02', '05-12', '05-23']
ax.set_xticklabels(squad, minor=False)
ax.set_ylabel="Electricity Demand (MWh)"
```

From May till August

```
# The load has experienced a significant rise from the last week of May till
the end of the summer.
df19_58= df.loc[(df['Date'] >= '2019-05-26') & (df['Date'] <= '2019-09-05')]
df19_58=df19_58.rename(columns = {'Ontario Demand':'Load 2019'})
df20_58= df.loc[(df['Date'] >= '2020-05-24') & (df['Date'] <= '2020-09-03')]
df20_58=df20_58.rename(columns = {'Ontario Demand':'Load 2020'})

ax= df19_58.plot(x="Date", y="Load 2019", kind="line", figsize=(20, 5))
df20_58.plot(x="Date", y="Load 2020", ax=ax, title=("2019 vs 2020 Hourly
load from the last week of May till the begining of September"))

squad = ['00', '05-24', '06-13','07-04','07-25','08-15']
ax.set_xticklabels(squad, minor=False)
ax.set_ylabel="Electricity Demand (MWh)"
```

Temperature comparison from May till August

```
# Checking the temperature data from the last week of May till the begining
of September
df= pd.read_csv ('Demand-Temp(2018-2020).csv', usecols=['Date', 'Time',
'Ontario Demand', 'Temperature'])
df
df19_ = df.loc[(df['Date'] >= '2019-05-26') & (df['Date'] <= '2019-09-05')]
df19_=df19_.rename(columns = {'Temperature':'Temperature 2019'})
df20_ = df.loc[(df['Date'] >= '2020-05-24') & (df['Date'] <= '2020-09-03')]
df20_=df20_.rename(columns = {'Temperature':'Temperature 2020'})

ax= df19_.plot(x="Date", y="Temperature 2019", kind="line", figsize=(20, 5))
df20_.plot(x="Date", y="Temperature 2020", ax=ax, title=("2019 vs 2020
Hourly temperature from the last week of May till the begining of
September"))

squad = ['00', '05-24', '06-13','07-04','07-25','08-15']
ax.set_xticklabels(squad, minor=False)
ax.set_ylabel="Electricity Demand (MWh)"
```

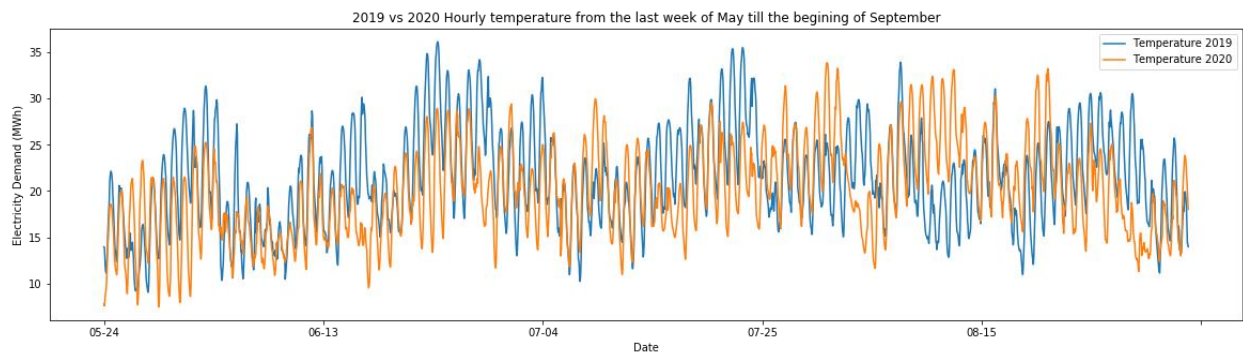


Figure A - 2: Hourly Temperature from May till September 2019 vs 2020

From September till December

```
# Starting form September and until the end of the year 2020, the overall
load almost returned back to the normal (2019) trends.
df19_912= df.loc[(df['Date'] >= '2019-09-06') & (df['Date'] <= '2019-12-
31')]
df19_912=df19_912.rename(columns = {'Ontario Demand':'Load 2019'})
df20_912= df.loc[(df['Date'] >= '2020-09-04') & (df['Date'] <= '2020-12-
29')]
df20_912=df20_912.rename(columns = {'Ontario Demand':'Load 2020'})

ax= df19_912.plot(x="Date", y="Load 2019", kind="line", figsize=(20, 5))
df20_912.plot(x="Date", y="Load 2020", ax=ax, title=("2019 vs 2020 Hourly
load from September till December"))

squad = ['00', '09-04', '09-24','10-15','11-05','11-26', '12-17']
ax.set_xticklabels(squad, minor=False)
ax.set_ylabel="Electricity Demand (MWh)")
```

Temperature comparison from November till December

```
#Checking the temperature data in November and December
df= pd.read_csv ('Demand-Temp(2018-2020).csv', usecols=['Date', 'Time',
'Ontario Demand', 'Temperature'])
df
df19_ = df.loc[(df['Date'] >= '2019-11-06') & (df['Date'] <= '2019-12-31')]
df19_ =df19_.rename(columns = {'Temperature':'Temperature 2019'})
df20_ = df.loc[(df['Date'] >= '2020-11-04') & (df['Date'] <= '2020-12-29')]
df20_ =df20_.rename(columns = {'Temperature':'Temperature 2020'})

ax= df19_.plot(x="Date", y="Temperature 2019", kind="line", figsize=(20, 5))
df20_.plot(x="Date", y="Temperature 2020", ax=ax, title=("2019 vs 2020
Hourly temperature in November and December"))
```

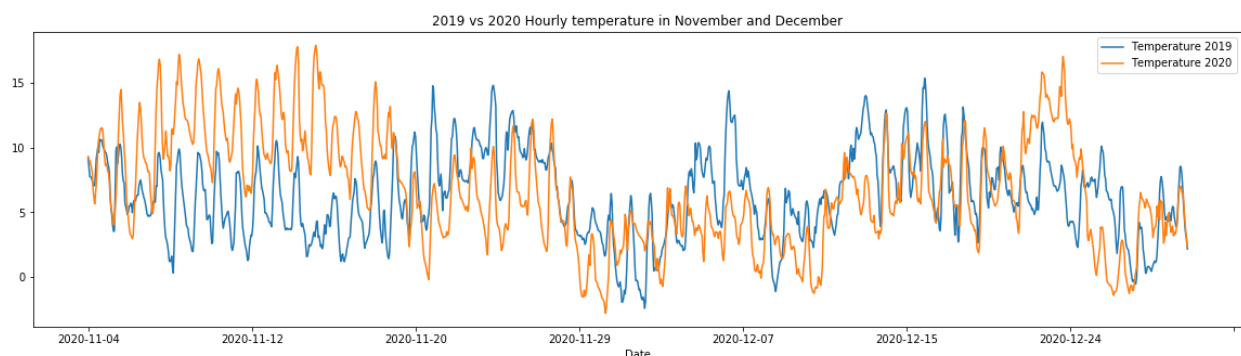


Figure A - 3: Hourly Temperature from November till December 2019 vs 2020

Mean Hourly Demand for each cluster of months

```
#Creating new datasets with each group of months from each year separately
df_m19= df.loc[(df['Date'] >= '2019-03-03') & (df['Date'] <= '2019-05-25')]
df_m19=df_m19.rename(columns = {'Ontario Demand':'March-May load 2019'})
df_j19= df.loc[(df['Date'] >= '2019-05-26') & (df['Date'] <= '2019-09-05')]
df_j19=df_j19.rename(columns = {'Ontario Demand':'May-Sept load 2019'})
df_s19= df.loc[(df['Date'] >= '2019-09-06') & (df['Date'] <= '2019-12-31')]
df_s19=df_s19.rename(columns = {'Ontario Demand':'Sept-Dec load 2019'})
df_m20= df.loc[(df['Date'] >= '2020-03-01') & (df['Date'] <= '2020-05-23')]
df_m20=df_m20.rename(columns = {'Ontario Demand':'March-May load 2020'})
df_j20= df.loc[(df['Date'] >= '2020-05-24') & (df['Date'] <= '2020-09-03')]
df_j20=df_j20.rename(columns = {'Ontario Demand':'May-Sept load 2020'})
df_s20= df.loc[(df['Date'] >= '2020-09-04') & (df['Date'] <= '2020-12-29')]
df_s20=df_s20.rename(columns = {'Ontario Demand':'Sept-Dec load 2020'})

#Set a Datetime index
df_m19['Datetime'] = pd.to_datetime(df_m19['Date'] + ' ' + df_m19['Time'])
df_m19 = df_m19.drop(['Date', 'Time'], axis=1)
df_m19['Datetime'] = pd.to_datetime(df_m19['Datetime'])

df_j19['Datetime'] = pd.to_datetime(df_j19['Date'] + ' ' + df_j19['Time'])
df_j19 = df_j19.drop(['Date', 'Time'], axis=1)
df_j19['Datetime'] = pd.to_datetime(df_j19['Datetime'])

df_s19['Datetime'] = pd.to_datetime(df_s19['Date'] + ' ' + df_s19['Time'])
df_s19 = df_s19.drop(['Date', 'Time'], axis=1)
df_s19['Datetime'] = pd.to_datetime(df_s19['Datetime'])

df_m20['Datetime'] = pd.to_datetime(df_m20['Date'] + ' ' + df_m20['Time'])
df_m20 = df_m20.drop(['Date', 'Time'], axis=1)
df_m20['Datetime'] = pd.to_datetime(df_m20['Datetime'])

df_j20['Datetime'] = pd.to_datetime(df_j20['Date'] + ' ' + df_j20['Time'])
df_j20 = df_j20.drop(['Date', 'Time'], axis=1)
df_j20['Datetime'] = pd.to_datetime(df_j20['Datetime'])

df_s20['Datetime'] = pd.to_datetime(df_s20['Date'] + ' ' + df_s20['Time'])
df_s20 = df_s20.drop(['Date', 'Time'], axis=1)
df_s20['Datetime'] = pd.to_datetime(df_s20['Datetime'])
```

```
#Getting the mean hour of each day of the months
hour = pd.to_timedelta(df_m19['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
df_m19 = df_m19.groupby(hour).mean()
df_m19 = df_m19[['March-May load 2019']]

hour = pd.to_timedelta(df_j19['Datetime'].dt.hour, unit='H')
```

```

hour.name = 'Hour'
df_j19 = df_j19.groupby(hour).mean()
df_j19 = df_j19[['May-Sept load 2019']]

hour = pd.to_timedelta(df_s19['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
df_s19 = df_s19.groupby(hour).mean()
df_s19 = df_s19[['Sept-Dec load 2019']]

hour = pd.to_timedelta(df_m20['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
df_m20 = df_m20.groupby(hour).mean()
df_m20 = df_m20[['March-May load 2020']]

hour = pd.to_timedelta(df_j20['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
df_j20 = df_j20.groupby(hour).mean()
df_j20 = df_j20[['May-Sept load 2020']]

hour = pd.to_timedelta(df_s20['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
df_s20 = df_s20.groupby(hour).mean()
df_s20 = df_s20[['Sept-Dec load 2020']]

```

```

#Merge all clusters in one dataframe
df_m = pd.merge(df_m19, df_m20, how="left", on="Hour")
df_mo= pd.merge(df_m, df_j19, how="left", on="Hour")
df_mon= pd.merge(df_mo, df_j20, how="left", on="Hour")
df_mont= pd.merge(df_mon, df_s19, how="left", on="Hour")
df_months= pd.merge(df_mont, df_s20, how="left", on="Hour")

#Plot the data
fig, ax = plt.subplots()

df_months['March-May load 2019'].plot(ax=ax, linestyle='dashed',
x_compat=True)
df_months['March-May load 2020'].plot(ax=ax, x_compat=True,
linestyle='dashed')
df_months['May-Sept load 2019'].plot(ax=ax, x_compat=True,
linestyle='dotted')
df_months['May-Sept load 2020'].plot(ax=ax, x_compat=True,
linestyle='dotted')
df_months['Sept-Dec load 2019'].plot(ax=ax, x_compat=True)
df_months['Sept-Dec load 2020'].plot(figsize=(15,8), ax=ax, x_compat=True,
title=("Monthly Typical Days Demand (MWh) 2019-2020"))

hour=[0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22]
ax.set_xticks(hour)

```

```
squad = ['00:00', '02:00',
'04:00', '06:00', '08:00', '10:00', '12:00', '14:00', '16:00', '18:00', '20:00', '22:
00']
ax.set_xticklabels(squad, minor=False)
ax.set_ylabel('Energy Demanded MWh')
ax.legend()
plt.show()
```

1.3. Daily comparison:

For this comparison the mean hourly electricity demand of each day of the week was calculated for 2019 and 2020 in two different Excel sheets, each for one year.

```
#Import the data
dw19= pd.read_csv ('weekdays hourly average 2019.csv')
dw20= pd.read_csv ('weekdays hourly average 2020.csv')
```

```
#Plot 2019 week days
fig, ax = plt.subplots()

dw19['Sunday'].plot(ax=ax, x_compat=True, color='red')
dw19['Monday'].plot(ax=ax, x_compat=True, color='darkorange')
dw19['Tuesday'].plot(ax=ax, x_compat=True, color='gold')
dw19['Wednesday'].plot(ax=ax, x_compat=True, color='green')
dw19['Thursday'].plot(ax=ax, x_compat=True, color='blue')
dw19['Friday'].plot(ax=ax, x_compat=True, color='magenta')
dw19['Saturday'].plot(figsize=(12, 8), ax=ax, x_compat=True, color='purple',
title="Weekdays average hourly demand (MWh) 2019")

hour=[0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22]
ax.set_xticks(hour)
squad = ['00:00', '02:00',
'04:00', '06:00', '08:00', '10:00', '12:00', '14:00', '16:00', '18:00', '20:00', '22:
00']
ax.set_xticklabels(squad, minor=False)
ax.set_ylabel('Average Energy Demanded MWh')
ax.legend()
plt.ylim(12000, 21000)
plt.show()
```

```
#Plot 2020 week days
fig, ax = plt.subplots()

dw20['Sunday'].plot(ax=ax, x_compat=True, color='red')
dw20['Monday'].plot(ax=ax, x_compat=True, color='darkorange')
dw20['Tuesday'].plot(ax=ax, x_compat=True, color='gold')
dw20['Wednesday'].plot(ax=ax, x_compat=True, color='green')
dw20['Thursday'].plot(ax=ax, x_compat=True, color='blue')
dw20['Friday'].plot(ax=ax, x_compat=True, color='magenta')
```

```

dw20['Saturday'].plot(figsize=(12, 8), ax=ax, x_compat=True, color='purple',
title=("Weekdays average hourly demand (MWh) 2020"))

hour=[0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22]
ax.set_xticks(hour)
squad = ['00:00', '02:00',
'04:00', '06:00', '08:00', '10:00', '12:00', '14:00', '16:00', '18:00', '20:00', '22:
00']
ax.set_xticklabels(squad, minor=False)
ax.set_ylabel('Average Energy Demanded MWh')
ax.legend()
plt.ylim(12000, 21000)
plt.show()

```

Daily K-means clustering

The K-means clustering is performed on the Hourly electricity demand for the total number of days (365) for the years 2019 and 2020. The purpose of this analysis is to identify the different groups of days sharing the same characteristics.

Some of the codes used in this section were borrowed from: <https://towardsdatascience.com/clustering-electricity-profiles-with-k-means-42d6d0644d00>

```

#K-means clustering for 2020 data (From 1st week of March till the last week
of December)
plt.style.use('seaborn')

#1-Importing data
df= pd.read_csv ('Demand-Temp(2018-2020).csv', usecols=['Date',
'Time', 'Ontario Demand'])
df_clust19= df.loc[(df['Date'] >= '2020-03-01') & (df['Date'] <= '2020-12-
29')]

df_clust19['datetime'] = pd.to_datetime(df_clust19['Date'] + ' '+
df_clust19['Time'])
df_clust19 = df_clust19.drop(['Date', 'Time'], axis=1)
df_clust19 = df_clust19.set_index('datetime')

# Creating an index column consisting of the hours of the day

df_clust19['Hour'] = df_clust19.index.hour
df_clust19.index = df_clust19.index.date

clust19_pivot = df_clust19.pivot(columns='Hour')

ax= clust19_pivot.T.plot(figsize=(15, 8), legend=False, color='blue',
alpha=0.08, title=('Hourly Demand of each day of the year 2020 from the 1st
week of March till the last week of December'))

```

```
squad = ['0', '0', '5', '10', '15', '20']

ax.set_xticklabels(squad, minor=False)
ax.set_xlabel('Hour of the day')
ax.set_ylabel('Energy Demanded MWh')
```

The Elbow Method is used to know the optimal number of clusters

Code is borrowed from: <https://predictivehacks.com/k-means-elbow-method-code-for-python/>

```
elbow_method = []
K = range(1,10)
for k in K:
    kmeanModel = KMeans(n_clusters=k)
    kmeanModel.fit(clust19_pivot)
    elbow_method.append(kmeanModel.inertia_)

plt.figure(figsize=(8,7))
plt.plot(K, elbow_method, 'bx-')
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method showing the optimal k')
plt.show()
```

```
#The elbow method is showing that the optimal number is 3.

kmeans = KMeans(n_clusters=3)
clusters_found = kmeans.fit_predict(X)
clusters_found_sr = pd.Series(clusters_found, name='clusters')
clust19_pivot = clust19_pivot.set_index(clusters_found_sr, append=True )

fig, ax= plt.subplots(1,1, figsize=(15,8))
colors_list = ['magenta', 'green', 'blue']
clusters_values =
sorted(clust19_pivot.index.get_level_values('clusters').unique())

for cluster, color in zip(clusters_values, colors_list):
    clust19_pivot.xs(cluster, level=1).T.plot(
        ax=ax, legend=False, alpha=0.1, color=color, label= f'Clusters
{cluster}'
    )
    clust19_pivot.xs(cluster, level=1).median().plot(
        ax=ax, color=color, alpha=0.9, ls='--'
    )

squad = ['0', '0', '5', '10', '15', '20']

ax.set_xticklabels(squad, minor=False)
ax.set_title('Daily Clusters of the hourly Demand fom the 1st week of March
till the last week of December 2020')
ax.set_ylabel('Energy Demand MWh')
ax.set_xlabel('Hour of the Day')
```

Appendix B: FFNN load forecasting model

Some codes are borrowed from: <https://soumilshah1995.blogspot.com/2019/08/project-data-analysis-and.html>. The same codes were used on three different train and test data splits: before COVID-19, beginning of COVID-19, and during COVID-19.

Importing the required libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pprint
from sklearn.preprocessing import MinMaxScaler
from keras.layers import Dropout
import keras
from keras.models import Model
from keras.models import Sequential
from keras.layers import Dense, Input, LSTM, Embedding, Dropout, Flatten
from tensorflow.keras import regularizers
from sklearn.preprocessing import StandardScaler
from keras.layers.wrappers import TimeDistributed
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import cross_val_score

%matplotlib inline
```

Importing the data, then adding extra features, such as seasons, years, months, and days.

```
#Reading the data
d=pd.read_csv('Demand-Temp(2018-2021).csv', parse_dates=True)
d['Datetime'] = pd.to_datetime(d['Date'] + ' ' + d['Time'])
d = d.drop(['Date', 'Time'], axis=1)
d.drop('Market Demand', inplace=True, axis=1)

#Adding some features to the data
d['season'] = (d['Datetime'].dt.month%12 + 3)//3
seasons = {
    1: 'Winter',
    2: 'Spring',
    3: 'Summer',
    4: 'Autumn'
}
d['season_name'] = d['season'].map(seasons)
data = d
data["Month"] = pd.to_datetime(d["Datetime"]).dt.month
data["Year"] = pd.to_datetime(d["Datetime"]).dt.year
data["Date"] = pd.to_datetime(d["Datetime"]).dt.date
data["Time"] = pd.to_datetime(d["Datetime"]).dt.time
data["Week"] = pd.to_datetime(d["Datetime"]).dt.week
```

```

data["Day"] = pd.to_datetime(d["Datetime"]).dt.day_name()
data['weekday'] = data['Datetime'].dt.dayofweek
data = d.set_index("Datetime")
data.index = pd.to_datetime(data.index)
print(data.info())

```

```

<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 27528 entries, 2018-01-01 00:00:00 to 2021-02-20 23:00:00
Data columns (total 15 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Hour                  27528 non-null  int64
1   Ontario Demand       27528 non-null  int64
2   Temperature           27528 non-null  float64
3   Humidity              27528 non-null  int64
4   Wind_Speed            27528 non-null  float64
5   Wind_Direction       27528 non-null  float64
6   season                27528 non-null  int64
7   season_name          27528 non-null  object
8   Month                27528 non-null  int64
9   Year                  27528 non-null  int64
10  Date                  27528 non-null  object
11  Time                  27528 non-null  object
12  Week                  27528 non-null  int64
13  Day                   27528 non-null  object
14  weekday               27528 non-null  int64
dtypes: float64(3), int64(8), object(4)
memory usage: 3.4+ MB
None

```

Check the correlation between the different features (forecast model inputs) and Ontario's hourly electricity demand (forecast model output)

```

data.corr()['Ontario Demand']
Hour                0.443695
Ontario Demand     1.000000
Temperature         0.110930
Humidity            -0.255567
Wind_Speed          0.155522
Wind_Direction     0.032042
season              -0.173858
Month               -0.090840
Year                -0.047345
Week                -0.088437
weekday             -0.173873
Name: Ontario Demand, dtype: float64

```

FFNN model before COVI-19:

Splitting the data into train and test datasets

```

#Split the data into train and test datasets
import pandas as pd
startdate=pd.to_datetime("2018-01-01").date()

```



```

startdate = pd.to_datetime("2020-01-15").date()
enddate = pd.to_datetime("2020-01-30").date()
train=data.loc[startdate:enddate]
test=data.loc[startdate:enddate]

```

Selecting the desired features from the data to train and test the model

```

#Select the required variables from the data
test=test[['Ontario Demand', 'Temperature', 'Wind_Speed', 'Humidity', 'Hour',
'season', 'weekday']]
train=train[['Ontario Demand', 'Temperature', 'Wind_Speed', 'Humidity',
'Hour', 'season', 'weekday']]

```

Creating output and input dataframes each for the train and test data

```

#Creating a train and test dataframes
y_train=pd.DataFrame(train['Ontario Demand'])
y_train
y_test=pd.DataFrame(test['Ontario Demand'])

x_train=pd.DataFrame(train[['Temperature', 'weekday', 'Hour', 'season',
'Humidity', 'Wind_Speed']])
x_train
x_test=pd.DataFrame(test[['Temperature', 'weekday', 'Hour', 'season',
'Humidity', 'Wind_Speed']])

#Convert to Numpy Array
x_train = np.array(x_train)
y_train = np.array(y_train)
x_test = np.array(x_test)
y_test = np.array(y_test)

```

```

#Scale the data
sc = StandardScaler()
sc.fit_transform(x_train)
x_train = sc.transform(x_train)
x_test = sc.transform(x_test)
x_train

```

Building and running the model

```

def model1(reg):
    model = Sequential()

    #input layer
    model.add(Dense(6, activation = 'relu', input_dim = 6))

    #hidden layer
    model.add(Dense(units = 100, activation =
'relu', kernel_regularizer=regularizers.l2(reg)))

    #hidden layer

```

```

model.add(Dense(units = 100, activation = 'relu'))

#hidden layer
model.add(Dense(units = 100, activation = 'relu'))

#output layer
model.add(Dense(units = 1))

# Compiling
model.compile(optimizer = 'adam', loss = 'mean_squared_error', metrics
=['mean_squared_error'])
return model

```

```

model=model1(0.3)
# Fitting the NN to the Training set
model.fit(x_train, y_train, batch_size = 10, epochs = 100)

model.summary()

```

Generate the train and test prediction and visualize the data

```

y_pred_train= model.predict(x_train)
y_pred_train

```

```

y_pred_test = model.predict(x_test)
y_pred_test

```

```

# Plot the training actual and predicted values
figg, ar = plt.subplots(figsize=(40,10))
ar.plot(y_train,label='actual')
ar.plot(y_pred_train,label='Predicted')
plt.ylabel('Load')
plt.xlabel('Accumulative hours')
plt.title('Training Data')
plt.legend()
plt.show

```

```

# Plot the test actual and predicted values
figg, ar = plt.subplots(figsize=(25,10))
ar.plot(y_test,label='actual')
ar.plot(y_pred_test,label='Predicted')
plt.ylabel('Load')
plt.xlabel('Accumulative hours')
plt.title('Testing Data')
plt.legend()
plt.show

```

Evaluate the train and test predictions

```

#Mean absolute percentage error of the train data
def mape(y_train, y_pred_train):

```

```
    """Calculates MAPE given y_true and y_pred"""
    y_train, y_pred_train = np.array(y_train), np.array(y_pred_train)
    return np.mean(np.abs((y_train - y_pred_train) / y_train)) * 100
mape(y_train, y_pred_train)
```

```
#Mean absolute percentage error of the test data
def mape(y_test, y_pred_test):
    """Calculates MAPE given y_true and y_pred"""
    y_test, y_pred_test = np.array(y_test), np.array(y_pred_test)
    return np.mean(np.abs((y_test - y_pred_test) / y_test)) * 100
mape(y_test, y_pred_test)
```

Appendix C: Ontario vs New York's electricity markets

Seasonal Hourly Demand Patterns: 2020

```
#Creating new datasets with each group of months from each year separately
dfp= df.loc[(df['Date'] >= '2020-01-01') & (df['Date'] <= '2020-12-31')]

df_jf20= dfp.loc[(dfp['Date'] >= '2020-06-01') & (dfp['Date'] <= '2020-09-30')]
df_jf20=df_jf20.rename(columns = {'Ontario Demand':'Summer (Jun-Sep)'})
df_ma201= dfp.loc[(dfp['Date'] >= '2020-12-01') & (dfp['Date'] <= '2020-12-31')]
df_ma202= dfp.loc[(dfp['Date'] >= '2020-03-01') & (dfp['Date'] <= '2020-03-31')]
frames= [df_ma201,df_ma202]
df_ma20=pd.concat(frames)
df_ma20=df_ma20.rename(columns = {'Ontario Demand':'Winter (Dec-Mar)'})
df_mj20= dfp.loc[(dfp['Date'] >= '2020-10-01') & (dfp['Date'] <= '2020-11-30')]
df_mj20=df_mj20.rename(columns = {'Ontario Demand':'Fall (Oct-Nov)'})
df_ja20= dfp.loc[(dfp['Date'] >= '2020-04-01') & (dfp['Date'] <= '2020-05-31')]
df_ja20=df_ja20.rename(columns = {'Ontario Demand':'Spring (Apr-May)'})

#Set a Datetime index
df_jf20['Datetime'] = pd.to_datetime(df_jf20['Date'] + ' ' + df_jf20['Time'])
df_jf20 = df_jf20.drop(['Date','Time'], axis=1)
df_jf20['Datetime'] = pd.to_datetime(df_jf20['Datetime'])

df_ma20['Datetime'] = pd.to_datetime(df_ma20['Date'] + ' ' + df_ma20['Time'])
df_ma20 = df_ma20.drop(['Date','Time'], axis=1)
df_ma20['Datetime'] = pd.to_datetime(df_ma20['Datetime'])

df_mj20['Datetime'] = pd.to_datetime(df_mj20['Date'] + ' ' + df_mj20['Time'])
df_mj20 = df_mj20.drop(['Date','Time'], axis=1)
df_mj20['Datetime'] = pd.to_datetime(df_mj20['Datetime'])

df_ja20['Datetime'] = pd.to_datetime(df_ja20['Date'] + ' ' + df_ja20['Time'])
df_ja20 = df_ja20.drop(['Date','Time'], axis=1)
df_ja20['Datetime'] = pd.to_datetime(df_ja20['Datetime'])
```

```
#Getting the mean hour of each day of the months
hour = pd.to_timedelta(df_jf20['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
df_jf20 = df_jf20.groupby(hour).mean()
df_jf20 = df_jf20[['Summer (Jun-Sep)']]

hour = pd.to_timedelta(df_ma20['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
```

```

df_ma20 = df_ma20.groupby(hour).mean()
df_ma20 = df_ma20[['Winter (Dec-Mar)']]

hour = pd.to_timedelta(df_mj20['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
df_mj20 = df_mj20.groupby(hour).mean()
df_mj20 = df_mj20[['Fall (Oct-Nov)']]

hour = pd.to_timedelta(df_ja20['Datetime'].dt.hour, unit='H')
hour.name = 'Hour'
df_ja20 = df_ja20.groupby(hour).mean()
df_ja20 = df_ja20[['Spring (Apr-May)']]

```

```

#Merge the three clusters in one dataframe
df_s = pd.merge(df_jf20, df_ma20, how="left", on="Hour")
df_sea= pd.merge(df_s, df_mj20, how="left", on="Hour")
df_season= pd.merge(df_sea, df_ja20, how="left", on="Hour")

#Plot the data
fig, ax = plt.subplots()

df_season['Summer (Jun-Sep)'].plot(ax=ax, x_compat=True, linewidth=4, color='midnightblue')
df_season['Winter (Dec-Mar)'].plot(ax=ax, x_compat=True, linewidth=4, color='deepskyblue')
df_season['Fall (Oct-Nov)'].plot(ax=ax, x_compat=True, linewidth=4, color='darkgrey')
df_season['Spring (Apr-May)'].plot(figsize=(10,6), ax=ax, x_compat=True, linewidth=4, color='forestgreen', title=("Ontario Seasonal Hourly Demand Patterns 2020"))

hour=[0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23]
ax.set_xticks(hour)

squad = [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23]
squad2 = [10,11,12,13,14,15,16,17,18,19,20]
ax.set_xticklabels(squad, minor=False)
ax.set_yticklabels(squad2, minor=False)
ax.set_ylabel('MW (Thousands)')
ax.set_xlabel('Hour of Day')
ax.legend()
ax.yaxis.grid()
ax.text(15.5, 18730, 'Summer', fontsize=12, color='midnightblue')
ax.text(12.5, 16100, 'Winter', fontsize=12, color='deepskyblue')
ax.text(10, 15100, 'Fall', fontsize=12, color='darkgrey')
ax.text(16, 14500, 'Spring', fontsize=12, color='forestgreen')
plt.show()

```

Comparison between NY 5 zones average load of March and April 2019 vs 2020, and May and June 2019 vs 2020.

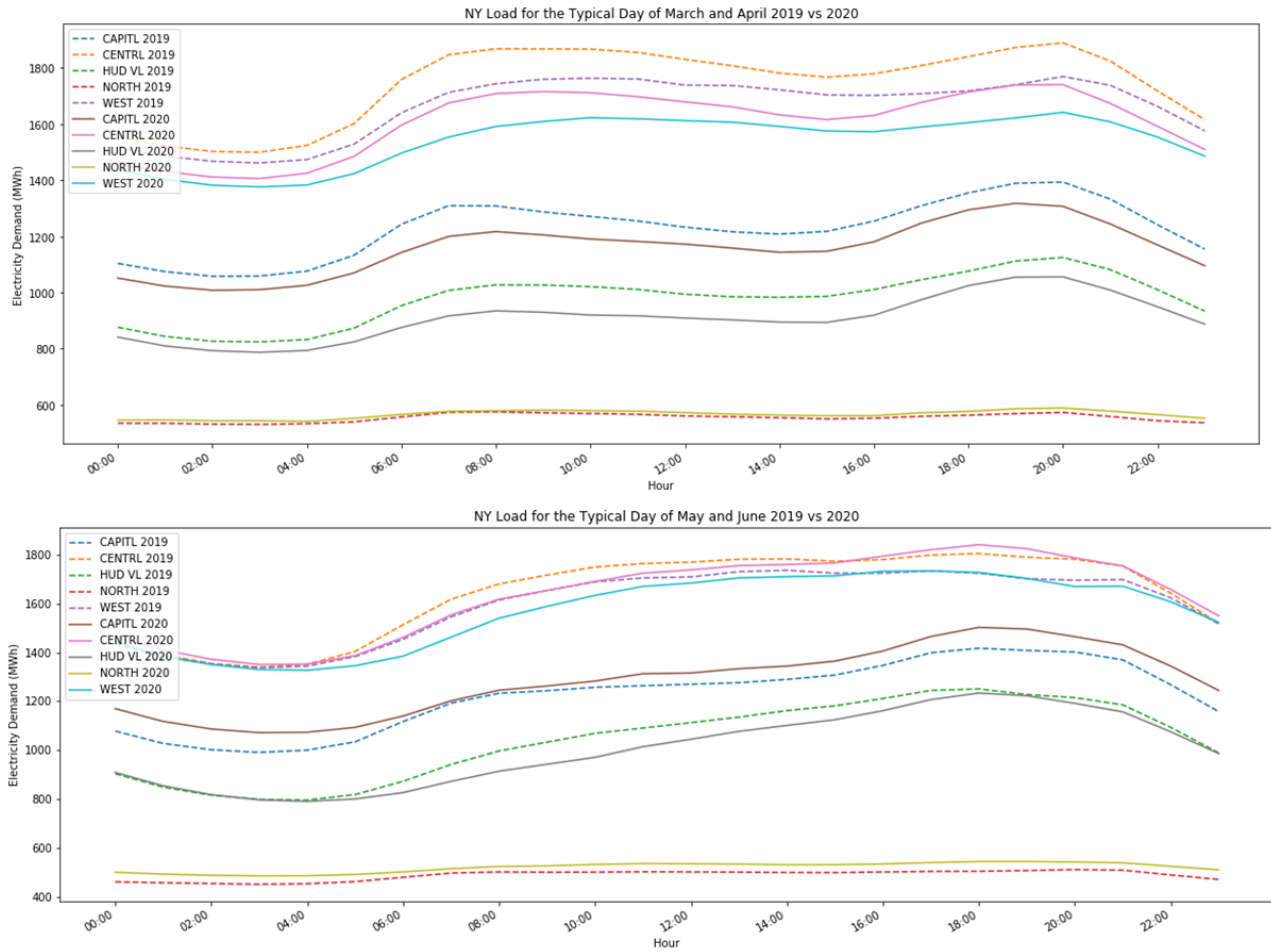


Figure A - 4: NY zones average load comparisons