7-7-2020

Demand Curve Modeling for the Utility of the Future

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Demand Curve Modeling for the Utility of the Future

by

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A Thesis

Submitted to the Faculty of Graduate Studies

though the Department of Civil and Environmental Engineering

in Partial Fulfilment of the Requirements for

the Degree of Master of Applied Science at the

University of Windsor

Windsor, Ontario, Canada

Demand Curve Modeling for the Utility of the Future

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DECLARATION OF CO-AUTHORSHIP/PREVIOUS PUBLICATIONS

I hereby declare that this thesis incorporates material that is result of joint research, as follows:

Chapters 2, 3 and 4 of the thesis were written under the supervision of Dr. Miller and Dr. Carriveau. In all cases, the key ideas, primary contributions, data analysis, interpretation, and writing were performed by the author. The contribution of the co-authors was primarily through the provision of supervision as well as feedback on refinement of ideas and editing of the manuscript.

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This thesis includes three original papers that have been previously published/submitted for publication in peer reviewed journals, as follows:

Thesis Chapter	**Publication**	**Publication Status**
Chapter 2	N. MacMackin, L. Miller, and R. Carriveau, "Modeling and disaggregating hourly effects of weather on sectoral electricity demand," *Energy*, vol. 188, 2019.	Published
Chapter 3	N. MacMackin, L. Miller, and R. Carriveau, "A simple Parameterized Model to Advance Visualization of Utility Load Curves for Strategic Systems Planning," *Utility Policy*.	Under Review
Chapter 4	N. MacMackin, L. Miller, and R. Carriveau, "Investigating Distribution Systems Impacts with Clustered Technology Penetration and Customer Load Patterns," *International Electrical Power & Energy Systems*.	Under Review

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ABSTRACT

Electricity systems are undergoing significant changes. Demands are shifting in magnitude and temporal distribution due to developing policies and technologies such as electric vehicles, heat pumps, embedded generation and energy storage, while an increasingly renewable supply is intermittent and less flexible. As such, there is currently great uncertainty in the industry and future business pathways may vary significantly from the current paradigm. This research focused on developing a set of models which can be used by utility companies to leverage their smart meter data and gain insights into possible future impacts and opportunities.

The thesis presents a series of novel models, developed and implemented with data provided from a utility in Southern Ontario. First, a regression model was developed to leverage the full value of utility smart meter data by disaggregating residential and commercial sector demands into base, heating and cooling end uses. The use of a variable temperature changepoint only marginally improved prediction accuracy, but significantly shifted disaggregation results, particularly at hourly resolution. This model was also applied for weather normalization, assessment of technology change and projection under different climate scenarios. A second model used this and additional data from literature to project long term utility level average and peak seasonal load curves. A dynamic interface with parameterized controls allowed real-time visualization of technology and policy impacts on the demand curve. A set of eight literature-based scenarios were also projected to demonstrate the extreme range of impacts predicted by different literature. These led to the conclusion that unmanaged technology penetration can lead to significant challenges such as increased peaks, large ramp rates and lower utilization. An analysis was then performed at finer geographic resolution, investigating impacts on representative distribution system transformers. First, the current variation in local technology penetration was examined, showing a significantly skewed distribution with many transformers having up to ten times the average rates. Clustering was then used to identify a set of eight diverse, representative transformer load profiles. Future scenarios were modeled, demonstrating that the impacts of technology and optimal mitigation techniques vary significantly between regions of the distribution system. Finally, the dynamic utility load curve model was also updated to project demands for the representative transformer groups identified. This allows users to simultaneously assess local impacts and mitigation strategies, as well as aggregate effects on the overall system demands. Together these works combine to provide a valuable toolset and significant insight into potential system impacts.

DEDICATION

This work is dedicated to my parents and the rest of my family and friends for their love, support and patience, as well as to my coach Gary Malloy who was always there through times of accomplishment and disappointment.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my advisor Dr. Rupp Carriveau and co-advisor Dr. Lindsay Miller for providing me the opportunity to work on this project and their guidance and support throughout. They have provided me many opportunities to engage with and learn from numerous industry stakeholders, as well as given me international exposure during my trip to Germany. I would also like to express my gratitude to Dr. Paul Henshaw and Dr. Narayan Kar for their knowledge and feedback. Additionally, I would like to thank ENWIN Utilities Ltd. for their collaboration throughout the process. Finally, I would like to acknowledge the Ontario Ministry of Colleges and Universities and the Natural Sciences and Engineering Research Council of Canada (NSERC) for their support in the form of funding.

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LIST OF ABBREVIATIONS

ACs	Air conditioners
CDs	Cooling degrees
CDDs	Cooling degree days
CDHs	Cooling degree hours
CLEEN2040	Climate Led Energy Evolution Network 2040
CPPAs	Corporate Power Purchase Agreements
CV	Coefficient of variation
CWEC	Canadian Weather Year for Energy Calculation
DST	Daylight savings time
EH	Electric heating
EIA	U.S. Energy Information Administration
ES	Energy storage
EVs	Electric vehicles
HDs	Heating degrees
HDDs	Heating degree days
HDHs	Heating degree hours
HPs	Heat pumps
HumSDCH	Humidex Summer cooling degree hours
HW	Hot water
IEA	The International Energy Association
IESO	Independent Electricity System Operator
LST	Local standard time
MAPE	Mean absolute percent error
microFIT	micro Feed in Tarif program
MILP	Mixed integer linear programming
NEB	Canadian National Energy Board
NHTS	National Household Travel Survey
NREL	National Renewable Energy Laboratory

NSERC	Natural Sciences and Engineering Research Council of Canada
OPO	Ontario Planning Outlook
SCDHs	Summer cooling degree hours
5hHDHs	5-hour average heating degree hours
5hCDHs	5-hour average cooling degree hours
3dHDDs	3-day average heating degree days
3dCDDs	3-day average cooling degree days

CHAPTER I: INTRODUCTION

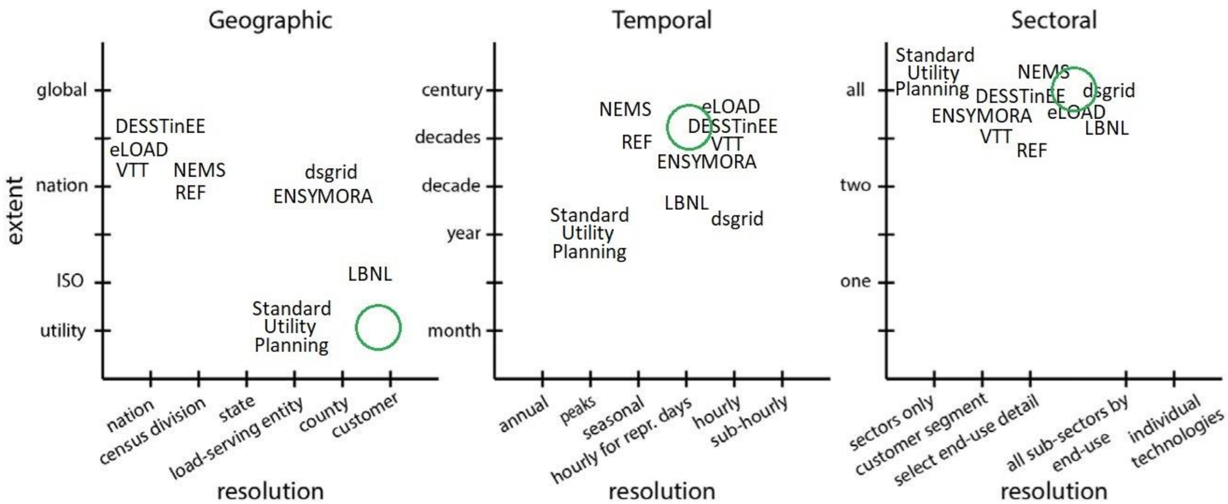
1 BACKGROUND

Climate change is currently one of the largest political topics on a global scale and focus on mitigating its effects has continuously grown in recent years. In the center of this debate is the future of energy markets and energy systems, as efforts are made to reduce dependence on fossil fuels and shift to more sustainable sources. This involves focusing on efficiency, development of intermittent renewable energy sources such as wind and solar, and the transition of end-uses such as transportation and heating towards electricity. Such initiatives are already impacting the magnitude and distribution of daily electricity demand, as discussed by the Canadian National Energy Board (NEB) [1], as well as numerous other authorities concerned over highly variable demand such as California's 'duck curve' [2]. The low flexibility of some clean generation assets is resulting in supply balancing challenges for system operators. Furthermore, the erosion of demand due to embedded generation has led to significant discussion around the potential for a 'utility death spiral' [3]. One utility in the United States even saw three major companies representing 5% of their total demand forfeit significant exit fees in 2015 in order to leave the utility and independently source renewable supply [4]. While new demands from electric vehicles (EVs) and electric heating (EH) such as heat pumps (HPs) could offset some of the lost revenues, they also may increase peak demands, requiring investment in expensive peaking generation and distribution assets. These significant shifts in the temporal distribution of the demand curve only exacerbate the supply and demand balancing problems discussed previously.

A significant complicating factor in the impending challenge is the large degree of uncertainty around both future regulatory measures and technology development. Utility Dive found the most commonly cited concern of utility workers in the past two year's surveys to be uncertainty in market conditions and regulations [5]. Also, depending on which authority or scenario is considered, projections for technology deployment vary significantly. For example, the NEB's 2018 report [6] and the joint Institut de l'énergie Trottier and e3 Hub report [7] lead to estimations of Canadian EV penetration between 5-10% in 2030 in all scenarios, whereas the IESO's 2015 Planning Outlooks C & D [8] project penetrations equivalent to over 14%. These variations can even be large between scenarios by the same authority: NEB reference case scenario EV sales [6] combined with the vehicle ages in Ontario [9] lead to an estimated 12.6% penetration by 2040, compared to the technology case where this value is surpassed by 2030 and estimated to reach 44.9% by 2040. Likewise, the Independent Electricity System Operator's (IESO) four planning outlook projections vary significantly, with residential EH penetration decreasing slightly to 17% in one scenario, and more than doubling to 42% in another. Furthermore, the projections can change quickly from year to year, as shown by the technology case in the 2017 NEB Energy Market assessment projecting 25 GW of solar power by 2040 [10], compared to only 14 GW one year later in the 2018 technology scenario results [6]. In order to avoid risk, properly plan for future energy systems and develop policy, the potential implications of these scenarios need to be modeled and evaluated.

Historically, short-term, high resolution models have been used for operations planning, while longer-term predictions of bulk and peak demands were used for capacity planning [11]. However, due to the expected demand curve changes, these may no longer be sufficient for adequate policy planning. As a result, several organizations have developed detailed models for long-term changes in electricity supply and demand at much higher resolution. The U.S. Energy Information Administration (EIA) [12] and National Renewable Energy Laboratory (NREL) [13], [14] have developed bottom up models which use specific end-use curves to construct the total demand up to a national scale. These can be used to assess future energy sector scenarios based on sector and technology change, and demand growth. Other research attempted to partially reduce this extreme complexity and data requirement by separating only specific end-uses from sector load curves. Boßmann and Staffell used the models DESSTinEE and eLOAD to project scenarios for Germany and the UK in 2050 [15]. Meanwhile, the Lawrence Berkeley National Laboratory's LBLN-Load model used customer clusters, disaggregating weather related demands with a temperature changepoint model and allocating other significant demands based on end-use datasets [16]. A set of Danish studies simplified still further using only sector load curves and adding demand for the new technologies of EVs and heat pumps to assess the impact on local and national electricity demand curves and systems [17]–[19]. A similar approach was also used for other Scandinavian countries by Koreneff et al. [20]. This literature provides a variety of insights and modeling techniques at varying levels of detail. However, the vast majority are focused at the national scale with varying degrees of local resolution. Furthermore, the Danish study showed that national datasets resulted in underestimation of local extremes.

Figure I-1 uses a framework adapted from an NREL presentation on their detailed dsgrid model [21] to present a variety of energy models in terms of their extent and resolution in three categories: geographic, temporal and sectoral. The extent refers to the upper limit of model scope within that category, while the resolution indicates the lower level of detail included. It can be seen that the majority of models do not have high geographic resolution and focus mainly at the national scale. Meanwhile, the standard utility planning is quite limited in resolution across all three categories. The models with highest resolution require extreme volumes of data and computation, and once again generally focus on spanning up to large geographic extents. While many utilities now have a wealth of information from the proliferation of smart meter data, they may not have the expertise and resources to analyze it. For these reasons, the focus of this thesis is to develop a set of relatively simple models which will allow for a utility to easily use their data to gain insights into their customer base and the potential challenges or opportunities which may arise under the vast array of potential future scenarios. Such models and analyses will offer the opportunity to assess local mitigation techniques and make informed investments and policy decisions. The scope and resolution of this study is marked by the green circle on the adapted figure.



NEMS	[12]	dsgrid	[13]	REF	[14]	DESSTinEE	[15]	Standard Utility Planning	[11]
eLOAD	[15]	LBNL	[16]	ENSYMORA	[17-18]	VTT	[20]		

Figure I-1: Energy Model Literature Resolution Summary [21]

2 METHODOLOGY

Many utilities currently have smart meters recording customer demand data, however submetering of individual end uses is uncommon and typically limited to specific studies of limited sample size. Therefore, Chapter II focuses on developing a model to disaggregate specific end uses from the aggregate customer groups (sectors in this case), which can then be used in further modeling processes. Specifically, a temperature changepoint model based on nonlinear regression is developed to differentiate heating, cooling and base demand. The model implements several novel techniques to improve the fit of the data: using average temperature data of varying temporal resolutions to capture short and long term weather effects, using a varying changepoint temperature for each hour of the day to reflect behaviour changes, and implementing three probit models to reflect seasonal installation of portable air conditioners. While flexible for application on any data, this method was applied to residential and commercial sector customer data from a utility partner in southern Ontario. In addition to disaggregation, once fitted the model can then be used to project demand of a weather normalized year, or under different climate change scenarios. The disaggregated loads could also be used to asses the impact of changing technology mixes in space conditioning. This model was applied in both respects in the following chapters.

Chapter III details a model designed to visually project average and peak seasonal daily load curves for a utility. The method assumes that sector demand will not change significantly in hourly distribution except where influenced by specific policy or technology changes. Thus, representative hourly curves for each sector could be scaled based on projected demand changes, while a set of modifying parameters are identified and associated with specific technology end-use load curves. All of the identified factors are parametrized in dynamic controls which can be adjusted in real time to show the impacts on daily demand curves. The dynamic nature allows the opportunity to quickly assess a wide range of scenarios, identifying each parameter's impact and their potential interactions. The parameters included as controls in the model are as follows:

- sector and specific end-use growth rates
- EV penetration and charging pattern
- residential and commercial rooftop PV penetration and orientation
- residential and commercial EH penetration
- residential and commercial electric hot water (HW) penetration
- residential and commercial electric cooling penetration
- average temperature increase (due to climate change)
- energy storage (ES) capacity
- industrial Corporate Power Purchase Agreements (CPPAs)
- microgrid communities

This model was once again calibrated with data from the southern Ontario utility partner. Both the residential and commercial data were disaggregated using the model discussed in Chapter II, then weather normalized and projected for alternate climate scenarios. PV generation data was also provided by the utility and extrapolated depending on the scenario, based on estimated regional potential. Most other parameters were based on simplified data from other sources. Using this model eight scenarios for 2040 were presented as a case study: four adapted from the IESO's planning outlooks [8], and four developed based on a variety of literature sources. The vast difference in results between scenarios, all based on literature projections, demonstrated the uncertainty in the industry and extreme range of potential outcomes. This highlights the requirement for this form of flexible, dynamic modeling for risk assessment, evaluation of mitigation techniques and informed planning.

An investigation into even finer geographical resolution, at the transformer level, is detailed in Chapter IV. This chapter examines the effects of localized clustering at the transformer level and how future technology penetration scenarios may impact the distribution system. To begin the variability in current localized technology penetration rates was assessed across different transformers in the utility partner's service area. PV penetration was estimated based on the meter data provided by the utility, while residential and commercial EH penetration rates were estimated by clustering customers to identify those with EH. These results justified examination of extreme penetration scenarios in later steps, as even if the impacts are not expected to occur on a broader scale for many years, local effects may be seen much earlier. Next, the current normalized load curves of all transformers were clustered into groups using k-means. The resulting representative clusters showed significant differences in seasonality and daily demand distribution, demonstrating the need to consider a diverse set of conditions when evaluating future impacts on the distribution system. These differences can be explained by similar localized clustering of technology use and customer behaviours. The representative cluster set was then used as the basis for a similar application of modeling future scenarios as in Chapter III, this time assessing distribution system impacts. Average characteristics of each cluster were used to establish the baseline demand, while specific end-use curves were added for technologies such as EV, PV, EH and ES. The results for each cluster were presented, as well as the aggregated impact on the total demand. The wide range of scenarios investigated allowed for identification of potential mitigation techniques to defer future capacity investment in different transformer clusters. Furthermore, comparing the impact on the local and total demand allows for the crafting of policies and decisions which benefit both the distribution level and overall electricity system.

An additional Appendix C is also included, detailing updates made to the model presented in Chapter III in order to incorporate the finer resolution investigation of Chapter IV. This updated version presents the projected seasonal average and peak load curves for the total utility and each of the transformer clusters. It also includes several additional parameters such as local relative growth and penetration rates, and heat pump penetration.

The three chapters in this thesis combine to provide a valuable modeling toolset for electricity system planners and operators. Using the wealth of smart meter data currently available to most utilities, these models can be calibrated and applied to quickly asses a wide range of scenarios. Their relatively simple parameterized design requires minimal computational and additional data resources. The insights gained through such evaluation can significantly aid in future planning and policy development.

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CHAPTER II: MODELING AND DISAGGREGATING HOURLY EFFECTS OF WEATHER ON SECTORAL ELECTRICITY DEMAND

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N. MacMackin, L. Miller, and R. Carriveau, "Modeling and disaggregating hourly effects of weather on sectoral electricity demand," *Energy,* vol. 188, 2019.

1 INTRODUCTION

Reliability in the energy system is of utmost importance and requires significant planning and forecasting. Accurate short-term forecasts are required to ensure adequate, and where possible, optimal unit commitment. Long-term forecasts are also required to aid in capacity planning and ensure that the system will have sufficient generation and transmission assets to meet future demand when and where required. Furthermore, the composition and complexity of national grids is changing with higher penetration of non-dispatchable renewable energy systems such as wind and solar, changing end uses such as electrical vehicles and heat pumps, and the implementation of energy storage. As energy systems become more challenging to manage, regulators and investors must decide which policies and technologies to develop or prepare for, increasing the importance of proper planning and accurate forecasts.

The introduction of smart-meters has increased the granularity of data collected from our energy systems which has improved some forecasting accuracy. Individual customer metering data on a fine temporal resolution is available in many regions and recorded by many utilities in the Canadian province of Ontario. Paatero and Lund developed detailed bottom-up models using individual appliance loads and use patterns produced from empirical probabilistic equations [1]. Another study applied this form of model with Danish data, specifically focusing on the potential for load control of appliances [2]. Meanwhile, Sandels, Widén and Nordström used similar appliance data, along with Markov chains to determine use patterns, and a physical model to predict heating demands [3]. However, these models require large volumes of detailed data from submetering of individual appliances or end-uses. Such data richness is presently not common, and studies from one region cannot always be applied to another without validation. Even within a country or province technology use patterns or penetration rates may vary significantly.

Weather can be a principal cause for seasonal and daily variation in electricity demand, and the lack of end-use data for space heating and cooling makes it challenging to forecast these effects. This is particularly important for assessing the impact of climate change or technological development. One study examined the factors effecting electricity demand in the cities of Athens and London and identified that temperature is the most significant factor, but that the response to weather varies significantly [4]. In each city minimum demands were seen at different temperatures (20 °C and 16 °C respectively), highlighting the importance of regional analysis and the development of an adaptive model which can be applied to different regions. Hart and Dear similarly assessed the weather sensitivity at a further refined appliance level, identifying how specific end-uses varied with temperature [5]. An understanding of these relationships has led to the development of various models to disaggregate weather-related demands and project future effects. These include the use of Fourier series, neural networks, and regression. One paper used Fourier and additional orthonormal functions to model residential weather-independent demands, while implementing a dynamic response model to simulate weather-dependent loads [6]. Ji, Xu and Ye proposed a model where Fourier series are used to predict lighting-plug demands which are then subtracted from total demand to find HVAC demands [7]. The validated these results with actual data for four commercial buildings, however did not propose a model to predict future weather effects. Niu, O'Neil and O'Neil used a modified Fourier series which incorporated temperature effects to disaggregate HVAC from base demands, then examined various data driven algorithms to predict future weather effects from this data [8]. Another study used neural networks to predict short-term electricity consumption in households, examining the effects of various climate parameters and specifically focusing on the influence of air conditioning [9]. Swan and Ugursal provided a good review of these modeling techniques as well as numerous others, highlighting the advantages and disadvantages of each method [10]. While neural networks can provide high accuracy, their black-box nature makes it difficult to interpret the results and project for different scenarios. Regression models, which can be used for both disaggregation and prediction, are preferred for their simplicity and interpretability.

Hong, Wilson and Xie focused on regression with polynomial functions of temperature, along with dummies to indicate the time of day and day type, in order to predict future demand and normalize monthly projections [11]. This study produced accurate predictions for hourly demand, as well as monthly peak demand but did not look to disaggregate the demand. Hobby and Shoshitaishvili predicted the effect of temperature on electricity consumption at each hour of the day using a cubic function [12]. The resulting demand was disaggregated as weather-related demand, while additional analysis was applied to further disaggregate the non-weather related demands. However, the weather-related demand was not identified specifically as heating or cooling. Several other studies have simplified the relationship between demand and temperature by breaking the temperature range into segments, and assuming linear relationships between variables within each segment. This has been applied to individual commercial customers, breaking the temperature distribution into 10°F temperature ranges from 50 to 100°F [13]. Going further, a study of residential customers recognized that the transition points for temperature relationships may change between customers. This study used three line segments with varying transition points fitted to the specific data and was able to identify five specific parameters for each house [14]. These included the average effects of temperature changes in cooling and heating seasons, and the typical “activity load” at times of occupancy. Birt, et al. suggested this model could help utilities to identify candidate homes for demand side management programs but did not focus on projecting future demand [14].

One common method simplifies the relationship between temperature and demand still further, using a single changepoint where the average consumer in a region transitions from heating to cooling. Along with these methods comes the terminology of heating degree days (HDDs) and cooling degree days (CDDs) which represent the number of degrees the average daily temperature is below or above (respectively) the changepoint temperature. In these studies HDDs and CDDs are the main inputs into the regression models. This type of model is very simple and functions well for aggregate demand where finer variations in customer behaviors are masked. Multiple studies have used this method to assess the impact of climate change scenarios in various regions. Mahmood, Saleemi and Amin used a model relating HDDs and CDDs to monthly electricity demand in the Kirachi district of Pakistan to examine the impact of increasing temperatures [15]. Another study examined monthly energy demands under climate change conditions and emphasized the importance of regional analysis due to the differences in sectoral compositions, infrastructure and climate [16]. Auffhammer, Baylis and Hausman examined a daily timescale, projecting the impacts of RCP4.5 and RCP8.5 conditions on both peak and average daily demand for multiple regions in the United Sates, and projected disproportionate growth in peak demand in most regions [17]. Kipping and Trømburg applied similar regression models with HDDs and other data to analyse Norwegian residential and commercial demand at hourly resolution, with a specific focus on heating demand [18–21]. The models also included the difference in HDD value between consecutive days as a parameter in the regression model. Analyses of individual houses and aggregate data showed that this variable accounted for thermal conservation on back to back cold days. HDDs facilitate disaggregation of base demand and heating demand and when combined with survey response data, the approach enabled identification of the demand associated with each type of heating system [18]. This information is valuable for projecting how demand may change in the future due to non-climate related factors, such as changes in technology penetration rates. Kipping and Trømburg then showed that the regression models using average daily temperature produced comparable results to models with hourly weather data [19]. In this study heating degree hours (HDHs) and cooling degree hours (CDHs) were calculated by the same method as HDDs and CDDs, simply using hourly data. The same daily model was also applied to model and disaggregate commercial building demand, comparing electrically heated and district heated buildings [20] and to disaggregate residential and commercial demand (heating & base) from regional aggregate demand [21]. These models demonstrate a simple disaggregation method for aggregate data which allows for projection of changing climate and technology conditions.

This study supports specific objectives of the Climate Led Energy Evolution Network 2040 (CLEEN2040), a progressive, look-head network focused on preparing energy stakeholders for the range of potentially disruptive modifiers that will impact energy systems between now and 2040. A priority objective of this network is the development of progressively determinant technoeconomic demand models for representative stakeholders, from system operators to end users, that can ultimately be used to generate a spectrum of what-if scenarios intended to mitigate risk. In particular, this paper presents change point regression models to disaggregate utility level demand in the Canadian Province of Ontario and allow for projection of future demand curve dynamics at an hourly resolution. A model will be developed using the residential sector demand data, then also applied to the commercial sector to test its cross applicability. While the electricity demand in the Kipping and Trømburg's data from Norway varies mostly due to heating demand, Ontario data shows a significant heating and cooling season. This paper also presents several new techniques for improving the model fit including the use of multiple temperature parameters at varying time resolutions, varying changepoints dependent on the time of day and day type (similar to the concept of using different fitted functions in [12]), and Probit analysis to model the usage of portable space conditioning devices.

2 MATERIALS AND METHODS

The following sections will detail the materials and methods used to develop the model. First the data used is presented in Section 2.1, followed by the regression model in Section 2.2, and finally the disaggregation method in Section 2.3.

2.1 DATA

The data used in this study includes one full year (2017) of hourly demand readings for 80,156 residential customers and 8,278 commercial customers of a utility in Southern Ontario, as well as the corresponding hourly climate data from the Government of Canada historical records [22]. The datasets include customers of all building types and subsectors. The total hourly values from these datasets can be seen plotted on a scatter plot with colours indicating each month in Figure II-1 and Figure II-2. The data was recorded in local standard time (LST) and adjusted for daylight savings time (DST) between March 12th and November 5th, to best reflect patterns in customer behaviour. Ten days of commercial customer data showed significant drops in demand and were suspected to contain measurement errors, thus were omitted. Several hours of temperature data were also missing, however there was never more than two sequential missing values, so the blanks were filled through linear interpolation between the preceding and following hours. All temperature data was shifted forward one hour to best match up with demand so that the temperature at hour 7:00 was matched with the demand occurring between hour 7:00 and 8:00 (labeled 8:00). Finally, the sunrise and sunset times for each day in 2017 were also collected from the National Research Council of Canada sunrise/sunset calculator [23].

The coefficients found in preliminary linear regression of demand data against temperature data showed that in times of both cooling and heating, the increase in demand associated with a change in temperature was over three times as much in the residential sector compared to the commercial sector (p-values = 0 in all cases). This is also evident from examining the data in Figure II-1and Figure II-2. Similarly, the proportion of variance explained by temperature in this preliminary analysis was much higher in the residential sector ($R^2 = 0.59$ vs. 0.40). For this reason, in the remaining sections of this methodology only residential data will be presented as this was the dataset used for development of the model. The model was then applied to the commercial data by the same method, with both results included in Section 3.

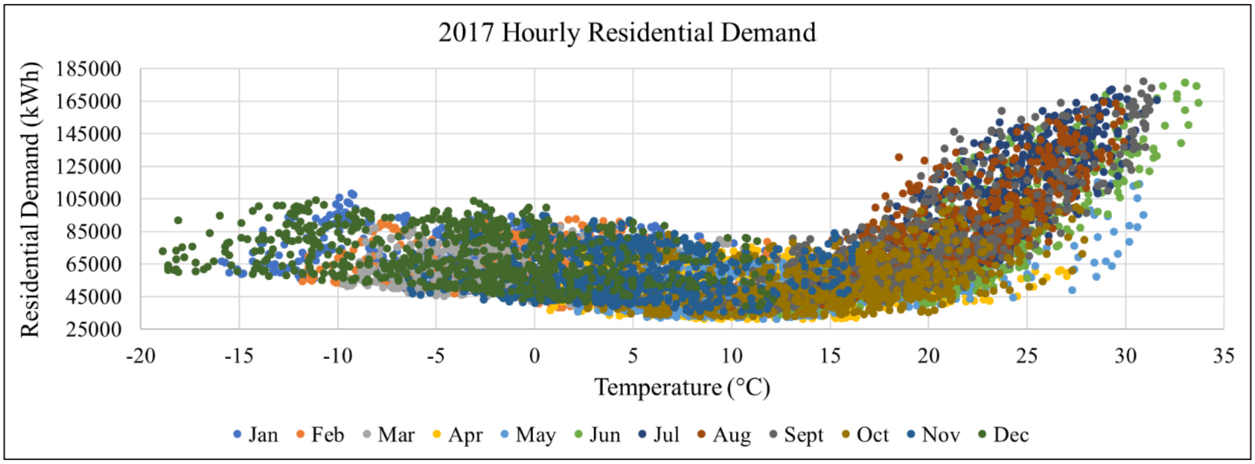

Figure II-1: Aggregate 2017 Hourly Residential Electricity Demand

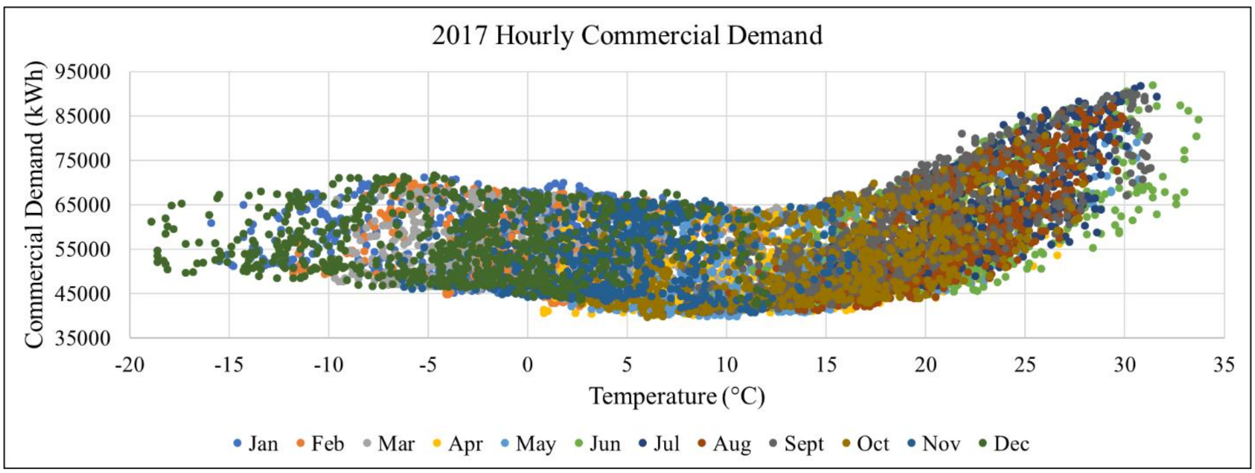

Figure II-2: Aggregate 2017 Hourly Commercial Electricity Demand

2.2 REGRESSION MODEL

This paper presents a multiple regression model for relating hourly electricity demand to climate and weather data. As is detailed in the following sections, a separate set of parameters, or sub-model, is developed for each hour of the day on both weekdays and weekends/holidays (48 total). The overall model uses Eq. (1), where the time t and day type w indicate the sub-model:

$$D_{d,w,t} = \sum_{i=B1}^{i=B6} \beta_{i,w,t}\, x_{i,d,t} + Pos\left(\sum_{i=H1}^{i=H2} \beta_{i,w,t}\, x_{i,d,t}\right) + Pos\left(\sum_{i=C1}^{i=C6} \beta_{i,w,t}\, x_{i,d,t}\right) + \epsilon_{d,t} \quad \text{Eq. (1)}$$

where:

D_d = the hourly electricity on the d^{th} day of the year

$x_{i,d}$ = the values on the d^{th} day for the i variables which influence electricity demand and are described in the subsequent sections

β_i = the slope coefficients for the i variables influencing electricity demand from regression

$\epsilon_{d,t}$ = the random error

In each sub-model there are 14 variables (including 5 dummies), with those corresponding to base demand ranging from *i=B1* to *B6*, those to heating from *i=H1 to H2*, and those related to cooling from *i=C1 to C6*. No intercept is required as it would be redundant with the dummy variables for day type described later. Note that although there are ten total day types, only five day-type dummies are required in each sub-model as they are each either a weekday or weekends/holiday sub-model. The function *Pos( )* replaces all negative values with zero. During initial testing the model did not include this function and an ordinary least squares linear regression was performed, however on days with certain conditions the model would occasionally predict a negative cooling demand which is not possible. Therefore, this constraint was added to the model to improve the accuracy of disaggregation, and was found to also improve both the regression and cross validation results. All of the parameters included in the regression model are summarized in Table II-1 and detailed in the following sections. When ordinary least squares linear regression was performed all included parameters had p-values less than 0.01 in multiple sub-models, although not necessarily all. Note the Holiday-Midweek dummy includes holidays falling on a Tuesday, Wednesday or Thursday. This was used due to the low number of holidays which fall on these days and lack of sufficient data to include each day separately. Each set of sub-model coefficients was fitted in Python using the Optimize.Minimize function from the SciPy library [24] with the modified Powell method [25], solving for the minimum squared error. Thus the objective function which was minimized was the negative coefficient of determination between actual and predicted demand values and. The methodology is summarized in Figure II-3.

Table II-1:Regression Model Parameters

	Climate Parameters	Dummy Day Variables
Weekday Models	**H1-2:** HDH, 3dHDD **C1-6:** CDH, 5hCDH, 3dCDD, CDH*3dCDD, SDCH, HumSCDH, **B6:** Daylight	**B1-5:** Monday, Tuesday, Wednesday, Thursday, Friday
Weekend Models		**B1-5:** Holiday-Monday, Holiday-Midweek, Holiday-Friday, Saturday, Sunday

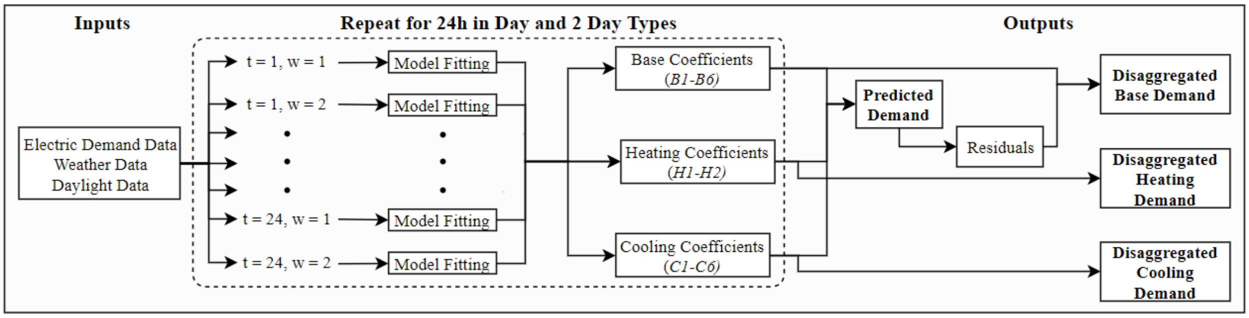

Figure II-3: Methodology Summary

2.2.1 CLIMATE PARAMETERS

To model the effect of weather and disaggregate the space conditioning demands, the model mainly depends on CDDs and HDDs as input data. Several previous papers have shown that including temperature data from not only the current day, but also previous ones increases the accuracy of the model. Similarly, this model incorporates temperature data from several timespans, namely the current hour temperature, the past five-hour average temperature and the past 72-hour average temperature. This allows for the model to better accommodate for thermal conservation and the effects of fast short-term temperature changes, as well as longer term, slower changes. Testing showed that using the 5-hour and 72-hour average temperature, as opposed to the average of only the day before, or two days before provided the best model fit. This suggests that incorporating the full historical data over these periods allowed for the best representation of medium and longer-term temperature effects.

Each of these average temperature values was separated into the cooling and heating effects, as detailed in 2.2.1.1. Thus, six temperature variables were developed: HDH, CDH, 5-hour average HDHs (5hHDH) and CDHs (5hCDH), and 3-day average HDDs (3dHDD) and CDDs (3dCDD). However, it was found that 5hDHD was not significant in the model and thus was excluded. Interaction variables between these temperature effects were also included, but testing suggested that the heating portion of the model required no interaction effects. For cooling the interaction between CDH and 3dCDD was found to improve model results significantly. The increased complexity for cooling is expected due to the higher variability seen at high temperatures compared to low temperatures (see Figure II-1).

Previous studies have calculated degree days and hours with a consistent changepoint temperature, typically ranging approximately from 15 to 18°C [16-19], although often lower (12 to 14°C) for studies using commercial sector data [17], [20-21]. For example, the Government of Canada data uses a changepoint of 18°C [22]. This may suffice for models using only daily average temperature, however at finer resolutions this may not be adequate. Factors such as occupancy and activity would affect the requirement for heating or cooling and thus the changepoint temperatures. For this reason, the following section details the identification of varying changepoints for sub-models. The model was run with the varying changepoints, as well as a range of constant changepoints to assess whether varying the changepoint improved results.

Preliminary results showed poor fit in the spring and summer periods, suggesting that cooling effects were still not being modeled adequately. Figure II-1shows that there is a very large demand variance at higher temperatures. Some months in the spring (April and May particularly) had several days which reach high temperatures, but the demand did not increase as significantly as in the summer. This effect can also be seen to a lesser degree in June. In the utility's region many houses have portable air conditioners (ACs) such as in-window units, as opposed to central systems. It was assumed that these portable units were either not installed, or not turned on in months with only a few hot days, thus a model to account for their usage was established. This is detailed in Section 2.2.1.2 and led to the establishment of a new set of variables labelled summer cooling degree hours (SCDHs) to account for the effect of these portable air conditioning devices. Humidity was also found to influence demand in the evening/nighttime of these summer periods (p-value < 0.01 in 17 sub-models), thus humidex values were included using a similar method.

2.2.1.1 CHANGEPOINT TEMPERATURES AND DEGREE HOURS/DAYS

It is assumed that the changepoint between heating and cooling degree days is the temperature at which, on average, a customer has very little to zero heating or cooling demand. If temperature moves below or above this value, demand begins to increase as the customer begins heating, or cooling respectively. Based on this assumption, the changepoint is the temperature with lowest demand. Figure II-4 shows the hourly residential electricity demand graphed against temperature at 3:00AM and 3:00PM on weekdays, and weekends/holidays. By comparing the morning and afternoon distributions it is evident the minimum demand occurs at different temperatures (approximately 10 and 16°C respectively), and thus so does the change point. Furthermore, the increased demand due to changing temperatures is shown to be much less significant through the early morning. These shifting changepoints and effects can be explained by differences in human behaviour and occupancy throughout the day and it was hypothesized that developing a separate model for each hour of the day would allow for these factors to be reflected and improve the model fit. These human behaviour factors also vary between weekdays and weekends/holidays; therefore, it was assumed that treating these days separately would also improve fit. The variation between weekends and weekdays is not as clear from Figure II-4, however several hourly changepoints for weekends were just over 1 °C degree lower in the morning, and almost 1 °C degree higher in the early afternoon. These periods correspond to the times at which there would be the largest difference between day types in household occupancy and behaviour. Similarly, when simple linear regression was performed, the slopes observed during heating and cooling periods varied slightly between weekdays and weekends/holidays. Therefore, 48 total sub-models were produced for the 24 hours of the day and two day types. The benefit of this method is also significant given the noticeable discrepancy between the changepoint temperatures determined and the values used in the Government of Canada data.

The changepoints were determined by splitting the data into the 48 sets discussed previously, fitting it with a polynomial and finding the local minimum point of this polynomial (within the range of 5 to 22°C). Cross validation showed that a sixth order polynomial provided the most accurate estimate of the minimum point, without overfitting to the data. It should be noted that the effect of temperature also varies depending on the temporal granularity considered. For example, at 4:00 PM on weekdays the minimum demand was seen at temperatures of approximately 16°C, whereas the minimum demand corresponded to a three-day average temperature of approximately 12°C. Therefore, this process was repeated to determine changepoints for each temporal resolution of temperature data as well. Once a changepoint temperature was found, the heating and cooling degree hours/days could be calculated using the following equations:

$$DH_{t,R,d} = Max(Tc_{t,d,R,w} - T_{t,d,R,w}, 0) \qquad \text{Eq. (2)}$$

$$DC_{t,R,d} = Max(T_{t,d,R,w} - Tc_{t,d,R,w} , 0) \qquad \text{Eq. (3)}$$

where $DH_{t,R,d}$, $DC_{t,R,d}$, $T_{t,d,R,w}$ and $Tc_{t,d,R,w}$ are the average degree heating hours/days, average degree cooling hours/days, average temperature and changepoint temperature at time t, on the d^{th} day of the year, using time resolution R (one hour, five hour or 3 day average), and day type w.

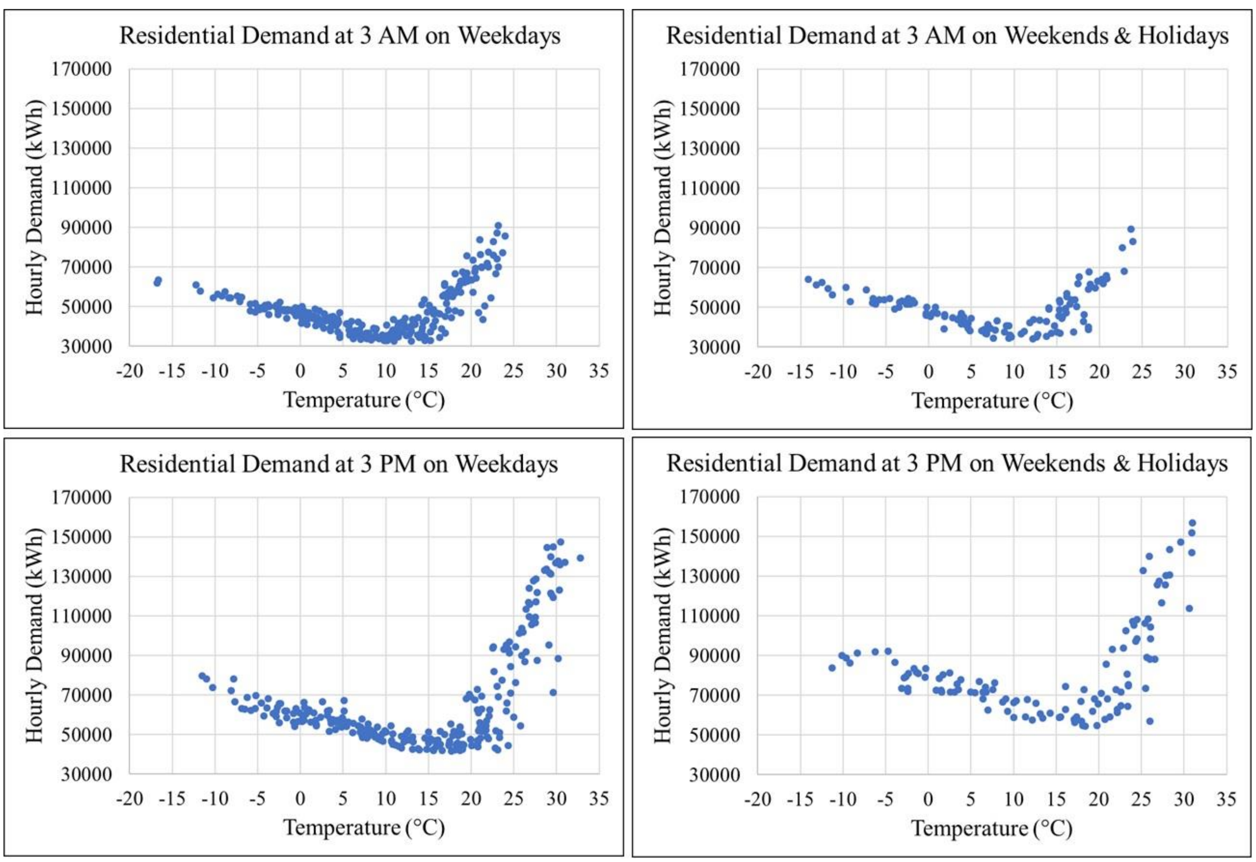

Figure II-4: The Time Dependent Effect of Temperature on Residential Demand

2.2.1.2 PROBIT ANALYSIS

Probit analysis relates the percentage of a sample responding to an environmental variable to the value of the variable. Previous studies have used this method to model the patterns of air conditioning use [5,9]. These studies have used a sigmoidal response function to relate usage to both degree days and humidex. In this model two separate sigmoid functions were fitted to average temperature variables using the following equation:

$$P_{m,d,t} = \frac{1}{1+e^{-n(T_{avg}-T_{50})}} \qquad \text{Eq. (4)}$$

where $P_{m,d,t}$ indicates the percentage response at month m, day d and time t, n and T_{50} are constants and T_{avg} is the variable to which the function is fitted. As previously discussed, many customers in the utility region have portable in-window air-conditioning units which are installed and turned on temporarily as required. It was assumed that each of these steps would be a response to changing temperatures over different time horizons. Thus, the sigmoid functions representing installation and removal of portable units were fitted as a response to the average temperature of the past week, while the response of turning these units on and off was fit to the past 24 hour average temperature. For the installation and turning on/off Probit models it was assumed that 5% of users would respond once the average temperature had reached the maximum hourly changepoint temperature (approximately 16°C). The removal model assumed all but 5% of units would be removed once the average temperature reached the minimum hourly changepoint temperature (approximately 10°C). Finally, it was assumed for all models that 95% of the sample would respond once the average temperature reached the 95th percentile value of the year. Each sigmoid function was fitted to the two data points, finding the constants *n*, and T_{50} shown in Table II-2.

Table II-2: Fitted Sigmoid Functions for Air Conditioning Probit Analysis

	5% Response Temp. (°C)	95% Response Temp. (°C)	Fitted Sigmoid Constant n	Fitted Sigmoid Constant T_{50}
Installation (Avg. Weekly Temperature)	16	22.77	0.8698	19.38
Removal (Avg. Weekly Temperature)	10	22.77	0.4611	16.38
Tuned on (Avg. Daily Temperature)	16	24.22	0.7164	20.11

It was assumed that once a customer had installed their portable AC units they would not remove them due to a slight temperature drop, until the summer cooling season had ended. Inspection of the data suggested that the increased response to CDHs and CDDs seen in the summer continued through September, beginning to decline in October. Therefore, the installation (Eq. (5)) and removal (Eq. (6)) models were adapted to the following:

$$For\ m \leq 9: \ \ P_{m,d,t} = Max\left(\frac{1}{1+e^{-n(T_{avg}-T_{50})}}\ ,\ P_{m,d,t-1}\right) \qquad \text{Eq. (5)}$$

$$For\ m \geq\ 10\text{:}\ \ P_{m,d,t} = Min\left(\frac{1}{1+e^{-n(T_{avg}-T_{50})}}\ ,\ P_{m,d,t-1}\right) \qquad \text{Eq. (6)}$$

where m is the month of the year. The installation percentage increases through the spring to a peak in the summer, using Eq. (5) and the installation constants. In the fall, installation percentage then declines as temperature decreases, using Eq. (6) with the removal constants.

These summer cooling effects were incorporated into the regression model through a variable named SDCH which was calculated as follows:

$$SCDH = P_{installed}\ * P_{on}\ * 5hCDH \qquad \text{Eq. (7)}$$

This variable incorporates the percentage of portable AC devices installed (based on weekly average temperature), the percentage of those installed which are on (based on daily average temperature), and the magnitude of response (based on past five-hour average temperature). Finally, the effect of humidity was incorporated similarly with the variable HumSDCH and using the past five-hour average humidex:

$$HumSDCH = P_{installed}\ * P_{on}\ * 5hHumidex \qquad \text{Eq. (8)}$$

2.2.2 ADDITIONAL PARAMETERS

Several non-climate variables were also included in the regression model. The sunset and sunrise times were incorporated into the model using a variable indicating whether there was daylight in a given hour (1 for sunlight, 0 for not). If the sunrise/sunset occurred part way through the hour, the variable was set to the proportion of time with sunlight. For example, if sunset occurred at 8:30 PM, the value for hour 9:00 PM would be 0.5 because half of the time period 8:00-9:00 has sunlight. Finally, although the response to weather change was assumed to be consistent within the groups of weekdays and weekends, the baseline demand may vary. For this reason, a set of dummy variables were included to indicate the day of the week. These dummy variables replaced the need for an intercept as they essentially represented a different intercept for each day type.

2.3 DISAGGREGATION

One benefit of using a changepoint model is that once the model had been fitted, the demand can easily be disaggregated. It was assumed that the demand is composed of a baseline demand which does not vary significantly throughout the year, and two temperature-dependant portions, space heating and space cooling. Although previous analysis of various non-space-conditioning appliances included in base demand has demonstrated variations of demand in devices such as refrigerators and water heaters with weather, these variations are much less significant. Thus the assumption here that all demand associated with temperature variables is space conditioning demand should provide a reasonable estimate. In order to reflect any systematic error on seasonal basis, the error from the regression model was added to the base demand. Based on this assumption the demand can be disaggregated as follows:

$$BD_{d,w,t} = \sum_{i=B1}^{i=B6} \beta_{i,w,t}\, x_{i,d,t} + \epsilon_{d,t} \qquad \text{Eq. (9)}$$

where $BD_{d,w,t}$ is the baseline demand, $\epsilon_{d,t}$ is the error from the regression model in Eq. (1) and *B1* to *B6* is the subset of non-climate parameters,

$$HD_{d,w,t} = \sum_{H1}^{H2} \beta_{i,w,t}\, x_{i,d,t} \qquad \text{Eq. (10)}$$

where $HD_{d,w,t}$ is the heating demand and *H1* to *H2* is the subset of parameters for heating (DH variables), and

$$CD_{d,w,t} = \sum_{C1}^{C6} \beta_{i,w,t}\, x_{i,d,t} \qquad \text{Eq. (11)}$$

where $CD_{d,w,t}$ is the cooling demand, and *C1* to *C6* is the subset of parameters related to cooling (DC variables). In this method, the error term is assumed to be daily variation in the baseline demand. The disaggregated demand is compared to similar data from relevant literature in 3.2.2. This model could also be applied for prediction of future demand based on predicted weather data and these predictions could be similarly disaggregated. The only difference there would be that there is no known error term for the baseline demand in Eq. (9), but this could be replaced by a random variable.

3 RESULTS & DISCUSSION

The following sections detail the regression (Section 3.1) and disaggregation (Section 3.2) results obtained for both the residential sectors.

3.1 REGRESSION RESULTS

The regression results are first presented for the residential sector since this was the data used to develop the model. The results are then compared to those obtained using fixed changepoint models. These are followed by the results obtained by applying the same method to the commercial sector.

3.1.1 RESIDENTIAL SECTOR

The regression results showed a good fit with the actual data, with the predictions explaining over 97% of the variance within the complete dataset (R^2 = 0.9710). This was comparable to the R^2 of 0.99 found by Kipping and Trømburg, despite the challenge of having both a significant heating and cooling effect. The mean absolute percent error (MAPE) for all hourly predictions was 4.57%. This is comparable to the range of 3.5-5.0% shown by the models studied by Hong, Wilson, and Xie, which had the disadvantage of not allowing for simple disaggregation [11]. When using regression, it is possible to produce a model which is very well fit to the specific data used in calibration, but which performs poorly when applied to new datasets. This phenomenon of excess specificity is known as overfitting, whereas the ability of a model to be applied to new data is called generalizability. To ensure the model was not overfitting the data and was sufficiently generalizable that it could be applied for demand predictions with future weather datasets, cross validation was performed. In cross validation, a dataset is split into two portions, training and testing. The model is fit using the training data, then applied to predict the testing data. The model performance is compared in both portions of the dataset, and if it performs significantly worse with the testing data this indicates it was overfitted. For this application, the cross validation was repeated 1000 times with a training set composed of a randomly selected 70% of the data, and the remaining 30% used for testing. The results for each sub-model can be seen in Table II-3. Stratification was used when selecting the datasets to ensure each day type was represented in the training set. There was only one holiday on a Tuesday and Friday, so these instances were always included in the training set. The average coefficient of determination for the training sets was 0.9423 while the value for the test set was only slightly lower at 0.9223. The models for weekends/holidays performed significantly worse with the testing set. This is due to the smaller quantity of data for this day type, but the training and testing coefficients of determination were still reasonably comparable at 0.9419 and 0.9129 respectively. It is notable that the worst fit was obtained around the time when customers are getting up in the morning and getting ready for the day (8:00AM on weekdays and 9:00-10:00 AM on weekends/holidays). This could be because this would be a time of high activity not dependant on temperature, leading to a larger proportion of unexplainable variability. It should be noted that the cross-validation results provide an idealized measure of model accuracy when it comes to projecting future demand. In reality, model inputs such as predicted future weather data will contain uncertainty and thus the error of future projected electricity demands could be much higher. For projections, the model accuracy will partially depend on the accuracy of the data input into it.

Table II-3: Residential Cross Validation Coefficients of Determination

Model Time / Day Type	Training		Testing	
	Weekdays	Weekends / Holidays	Weekdays	Weekends / Holidays
12 AM	0.9528	0.9503	0.9373	0.9178
1 AM	0.9475	0.9447	0.9281	0.9033
2 AM	0.9421	0.9398	0.9189	0.8938
3 AM	0.9368	0.9362	0.9140	0.8900
4 AM	0.9367	0.9345	0.9146	0.8786
5 AM	0.9344	0.9330	0.9140	0.8779
6 AM	0.9319	0.9315	0.9093	0.8663
7 AM	0.9244	0.9359	0.9032	0.8821
8 AM	0.8932	0.9214	0.8669	0.8568
9 AM	0.9330	0.9032	0.9161	0.8101
10 AM	0.9401	0.9110	0.9225	0.8453
11 AM	0.9431	0.9264	0.9265	0.8719
12 PM	0.9433	0.9492	0.9244	0.9178
1 PM	0.9516	0.9570	0.9386	0.9289
2 PM	0.9580	0.9555	0.9474	0.9271
3 PM	0.9624	0.9601	0.9525	0.9371
4 PM	0.9617	0.9602	0.9524	0.9373
5 PM	0.9596	0.9597	0.9496	0.9372
6 PM	0.9574	0.9596	0.9469	0.9362
7 PM	0.9567	0.9578	0.9466	0.9293
8 PM	0.9532	0.9586	0.9423	0.9243
9 PM	0.9569	0.9645	0.9462	0.9375
10 PM	0.9555	0.9643	0.9415	0.9284
11 PM	0.9527	0.9498	0.9390	0.9008
Average	**0.9452**	**0.9443**	**0.9291**	**0.9015**
Total Average	**0.9448**		**0.9153**	

Figure II-5 displays the residuals (model error) plotted against temperature. When the residual has a negative value, this indicates demand was overpredicted by the model, while conversely a positive residual indicates an underprediction. The residuals are approximately normally distributed, however Figure II-5 shows that the variance of the error is not constant across the entire temperature range. At temperatures higher than about 15 °C, error variance appears to increase, suggesting that the model was not as accurate in modeling cooling demand. This indicates that the error term in the model was not, as hypothesized, entirely due to fluctuations in base demand caused by unmodeled behavioural variations. Therefore, the disaggregation method likely provides less accurate estimates of air conditioning demand compared to heating. Initial models notably over estimated cooling demand in April, May and June, while underestimating the effects in July, August and September. For this reason, the Probit analysis components were added to model the installation and use of portable air conditioning units. While the Probit analysis improved results, it still did not perfectly model the air conditioning use. This is further supported by Figure II-6 which shows the average actual and modeled demand for each month. The same months were on average over and under projected, although to a lesser degree than in initial models.

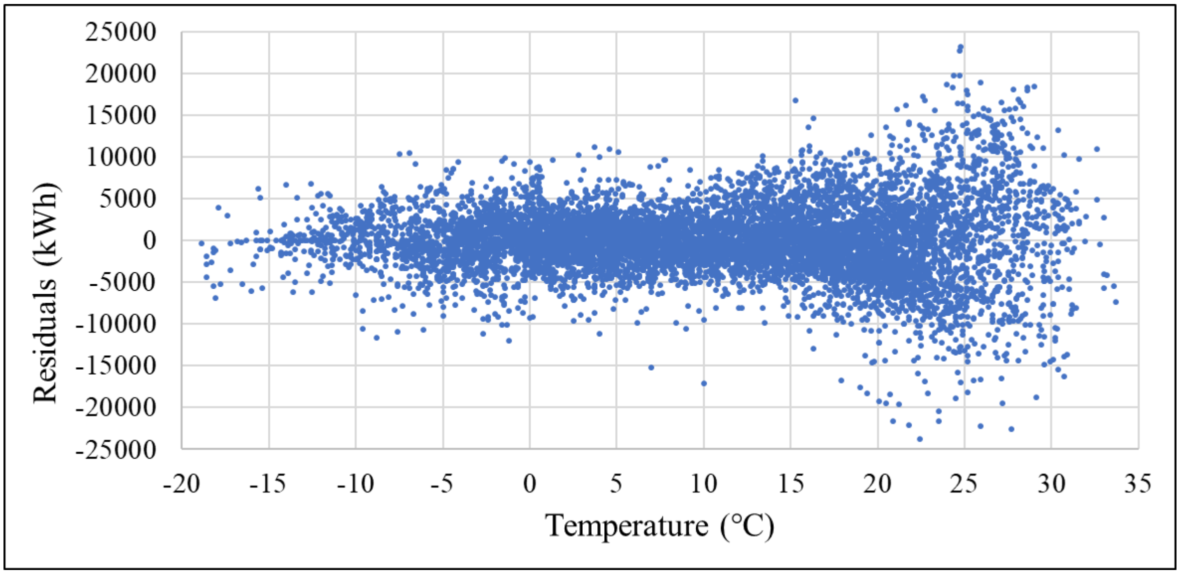

Figure II-5: Residuals Plot vs. Temperature

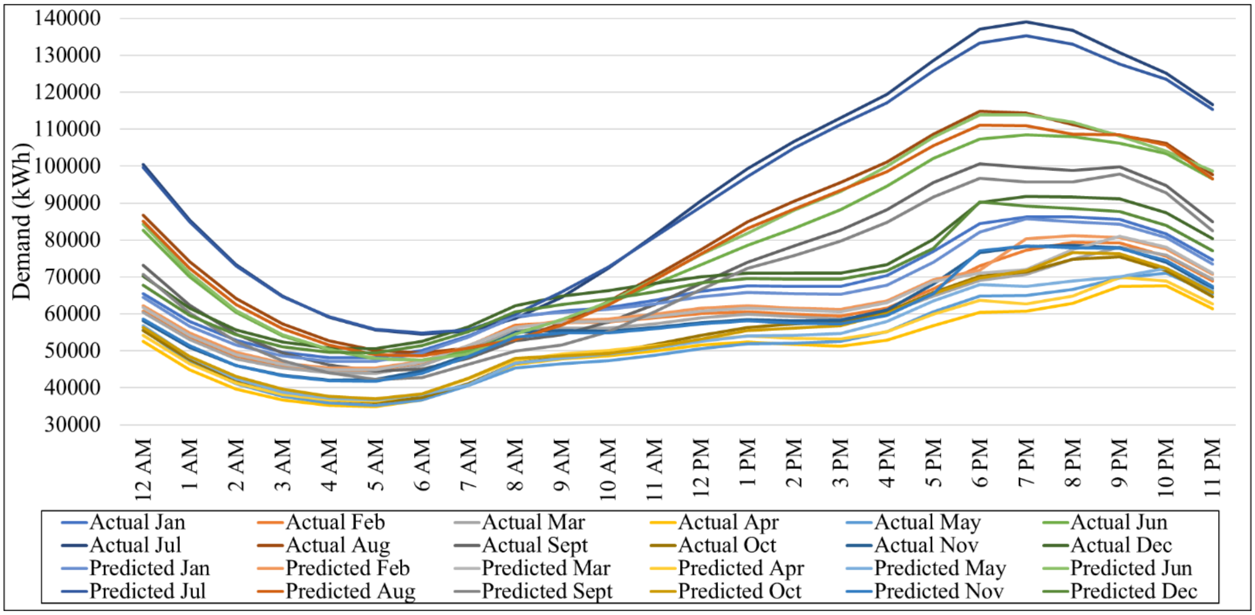

Figure II-6: Actual and Predicted Avg. Monthly Residential Demand

3.1.2 COMPARISON TO COMBINED DAY TYPE & FIXED CHANGEPOINT MODELS

It was proposed that the use of a variable changepoint for each time of day and day type would result in a more accurate model and disaggregation of the demand. In order to test this hypothesis, models were also produced where day types were not differentiated (24 hourly sub-models) as well as with a range of fixed changepoints. Typically, the base temperature for the computation of CDDs and HDDs is between 15 °C and 18 °C, however the variable changepoint method found changepoints as low as 9 °C at some hours. Therefore, the range considered spanned from as low as 9 °C to a slightly higher than typical 20 °C. Table II-4 shows several metrics and statistics for each of the resulting models. The use of separate sub-models for weekdays and weekends/holidays resulted in an improved fit but only by 0.10% and 0.0015. This slight improvement may not be sufficient to justify the additional computation required. Using a variable changepoint temperature produced both the smallest MAPE and largest coefficient of determination, however only by 0.08% and 0.0013 compared to the most accurate fixed changepoint models (12-13°C). This suggests that although a variable changepoint increased the accuracy of the predicted demand, the effect was only marginal. The data also shows that the percentage of demand predicted as base demand, cooling demand and heating demand varied depending on the changepoint selected. While these differences appear minor from the average values included in Table II-4, the shifts within the day at finer temporal resolution are much more significant. For example, the 18 °C fixed changepoint model predicted 43% more heating demand between 12 AM and 8AM than the varying changepoint model. Evidently this has implications for the accuracy of disaggregation on an hourly timescale, however without actual data to compare the results to it cannot be determined with certainty which method was more accurate. It is worth noting that all the models produced with the typical range of fixed changepoint temperatures predicted a significantly lower proportion of base demand (~2.5%), a slightly higher proportion of cooling demand (~0.5%) and significantly higher proportion of heating demand (~2%).

Table II-4: Model Results with Combined Day Types and Various Changepoints

Day Types	Changepoint Temperature	MAPE	Overall R^2	% Base	% Cool	% Heat
Separate	**Multiple**	4.57%	0.9710	72.4%	17.9%	9.7%
Combined	**Multiple**	4.67%	0.9695	72.4%	17.9%	9.7%
Separate	**9**	4.85%	0.9686	76.4%	16.3%	7.3%
Separate	**10**	4.76%	0.9691	75.3%	16.8%	7.9%
Separate	**11**	4.69%	0.9695	74.1%	17.3%	8.6%
Separate	**12**	4.65%	0.9697	72.9%	17.8%	9.3%
Separate	**13**	4.66%	0.9697	71.8%	18.2%	10.0%
Separate	**14**	4.70%	0.9694	70.8%	18.5%	10.7%
Separate	**15**	4.79%	0.9688	70.1%	18.7%	11.2%
Separate	**16**	4.92%	0.9678	69.7%	18.7%	11.6%
Separate	**17**	5.07%	0.9666	69.7%	18.4%	11.9%
Separate	**18**	5.20%	0.9656	69.6%	18.2%	12.2%
Separate	**19**	5.26%	0.9650	69.2%	18.0%	12.7%
Separate	**20**	5.32%	0.9644	68.9%	17.8%	13.2%

3.1.3 COMMERCIAL SECTOR APPLICATION

The model was also calibrated with commercial data from the same utility to test the cross applicability between sectors. The resulting commercial model explained an even higher proportion of the variance than the residential model (R^2 = 0.9790), with a significantly lower MAPE (1.85%). The cross-validation results shown in Table II-5 demonstrate that the models were not overfitted. One sub-model (7 AM) showed both poor average training and testing fit, despite having a good fit when applying the model to all of the data (0.9100). However, of the 1000 repetitions almost 50% showed similarly high cross-validation results to the other sub-models, while the others had very poor fits bringing down the average. When the training fit was high, the testing fit was also high and visa versa. This suggests that portions of this sub-model dataset are less dependant on weather (resulting in lower fits when selected as training data), but not that the model is overfitting. Despite the high accuracy of the overall model, the table shows that the fit for each given sub-model at a given hour and day-type was lower than in the residential results. This is likely because a lower proportion of the variation in commercial demand is due to weather (leading to worse sub-model fits), but a higher proportion is explained by time of day and day type (leading to a good overall model fit).

Table II-5: Commercial Cross Validation Coefficients of Determination

Model Time / Day Type	**Training**		**Testing**	
	Weekdays	**Weekends / Holidays**	**Weekdays**	**Weekends / Holidays**
12 AM	0.8920	0.9084	0.8688	0.8614
1 AM	0.8871	0.9185	0.8609	0.8715
2 AM	0.8885	0.9164	0.8589	0.8628
3 AM	0.8811	0.9190	0.8508	0.8697
4 AM	0.8870	0.9096	0.8604	0.8389
5 AM	0.8746	0.9043	0.8397	0.8068
6 AM	0.8793	0.9012	0.8433	0.8108
7 AM	0.8815	0.6688	0.8471	0.5302
8 AM	0.8688	0.9172	0.8337	0.8648
9 AM	0.8386	0.8950	0.7978	0.8027
10 AM	0.8715	0.8973	0.8411	0.8324
11 AM	0.9125	0.9098	0.8936	0.8479
12 PM	0.9330	0.9174	0.9177	0.8643
1 PM	0.9406	0.9200	0.9276	0.8671
2 PM	0.9419	0.9226	0.9275	0.8742
3 PM	0.9496	0.9269	0.9385	0.8779
4 PM	0.9508	0.9293	0.9370	0.8851
5 PM	0.9521	0.9159	0.9411	0.8668
6 PM	0.9454	0.9170	0.9326	0.8654
7 PM	0.9385	0.9227	0.9257	0.8732
8 PM	0.9304	0.9185	0.9151	0.8609
9 PM	0.9169	0.9150	0.8976	0.8593
10 PM	0.9087	0.9183	0.8860	0.8579
11 PM	0.8909	0.9182	0.8649	0.8714
Average	**0.9067**	**0.9045**	**0.8836**	**0.8426**
Total Average	**0.9056**		**0.8631**	

Figure II-7 shows the model produced an accurate average prediction for each month, suggesting that all seasonal effects are well represented in the model. However, the larger errors in the overprediction of August demand and underprediction of September show that the cooling effect was once again not as well modeled. Overall, the model produced for the commercial data showed better results than the residential, likely in large part due to the lower overall variability in this sector.

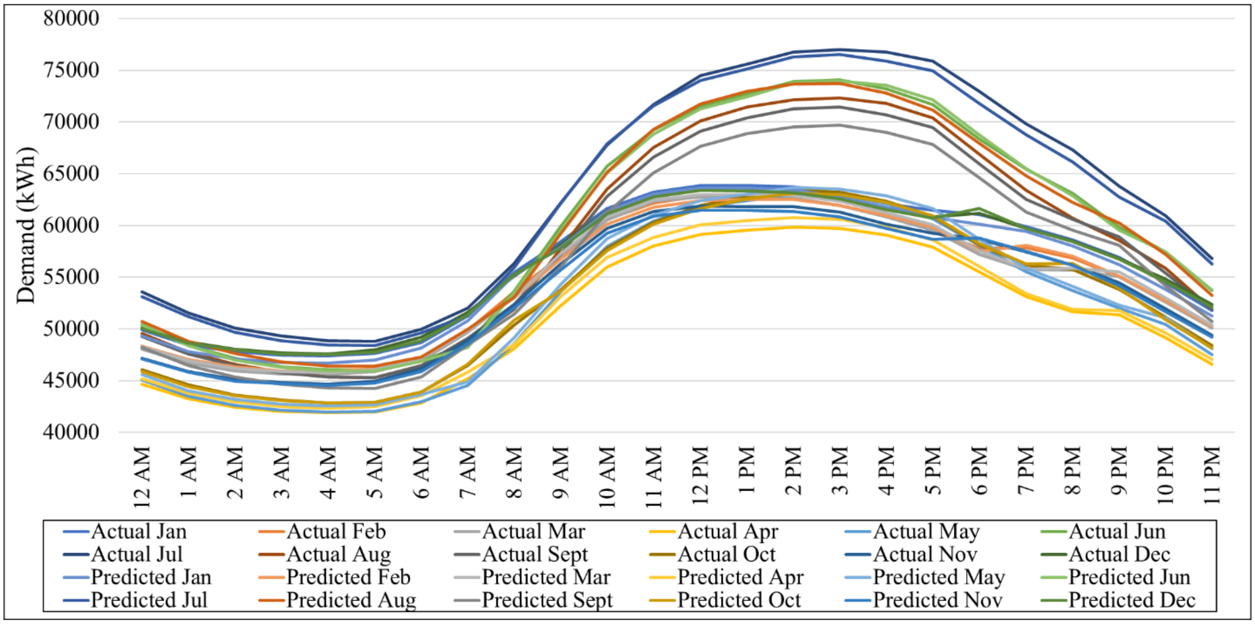

Figure II-7: Actual and Predicted Avg. Monthly Commercial Demand

3.2 DISAGGREGATION RESULTS

Based on the regression model and results present previously, the data was then disaggregated into base, cooling and heating demands. These disaggregation results are first presented for the residential sector, then compared to submeter data from another city in Ontario. Lastly, the commercial sector disaggregation is presented.

3.2.1 RESIDENTIAL DISAGGREGATION

Based on the model produced for the residential demand, the demand was disaggregated into the three main components of base demand, heating demand and cooling demand. Figure II-8 shows the average disaggregated demand for each season. As expected, base demand stays relatively constant through the year, and the summer and winter show large proportions of cooling and heating demand respectively. The spring and fall show a smaller mix of both heating and cooling.

Based on the assumptions of the model, if the heating and cooling demands are disaggregated accurately, the base demand should remain fairly constant, only varying due to fluctuation in behaviour and appliance use. To test this assumption, the base demand of each month is compared in Figure II-9. Each month shows similar base demand with a few notable exceptions. As previously mentioned, it seems the cooling demand in the late spring and early summer months was consistently overpredicted and as a result, these months can be seen to have lower predicted base demands. Similarly, the cooling demand in the later summer months was underpredicted and therefore the base demand is slightly higher. The month of December also was predicted to have higher base demand through the day compared to most months. This can be partially explained by the fact that weekends and holidays had higher base demands and that there were 12 such days in

December, compared to an average of about nine in the other months. Finally, the most significant variation can be seen between hours 5:00 PM to 9:00 PM. This is caused by variation in lighting requirements in the evening due to changing sunset times and is accounted for in the model by the 'daylight' variable. Likewise, sunrise times would explain a portion of the morning variation, although the differences are less obvious when examining Figure II-9.

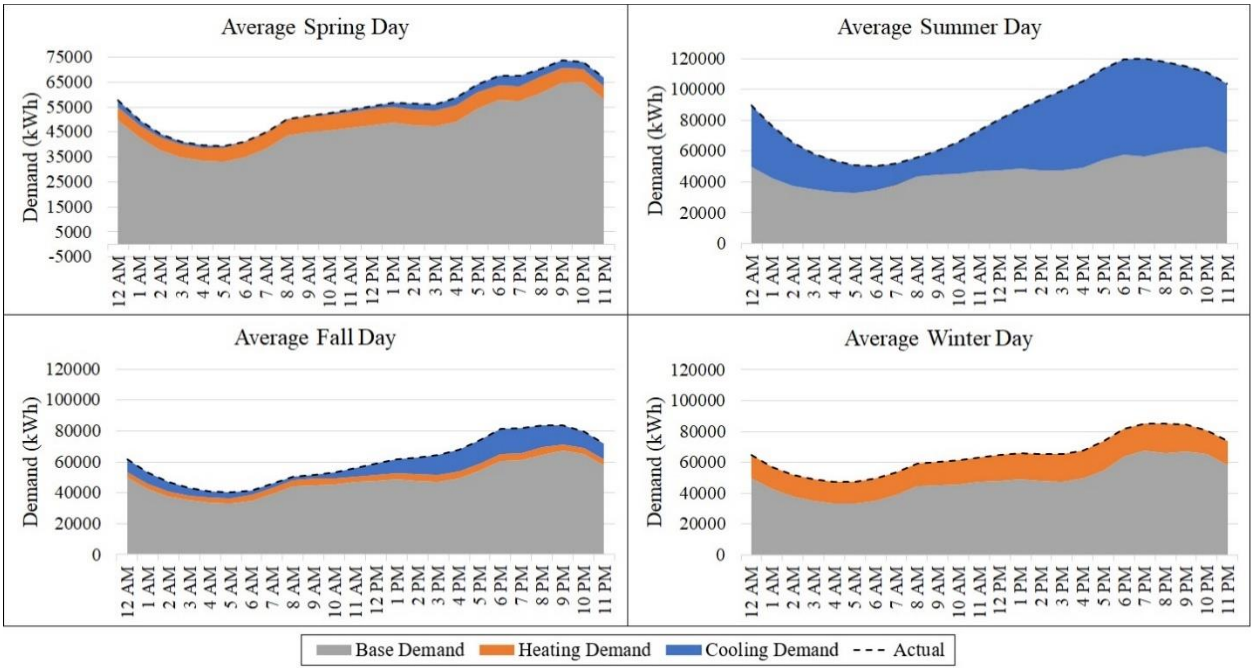

Figure II-8: Average Seasonal Disaggregated Residential Demand

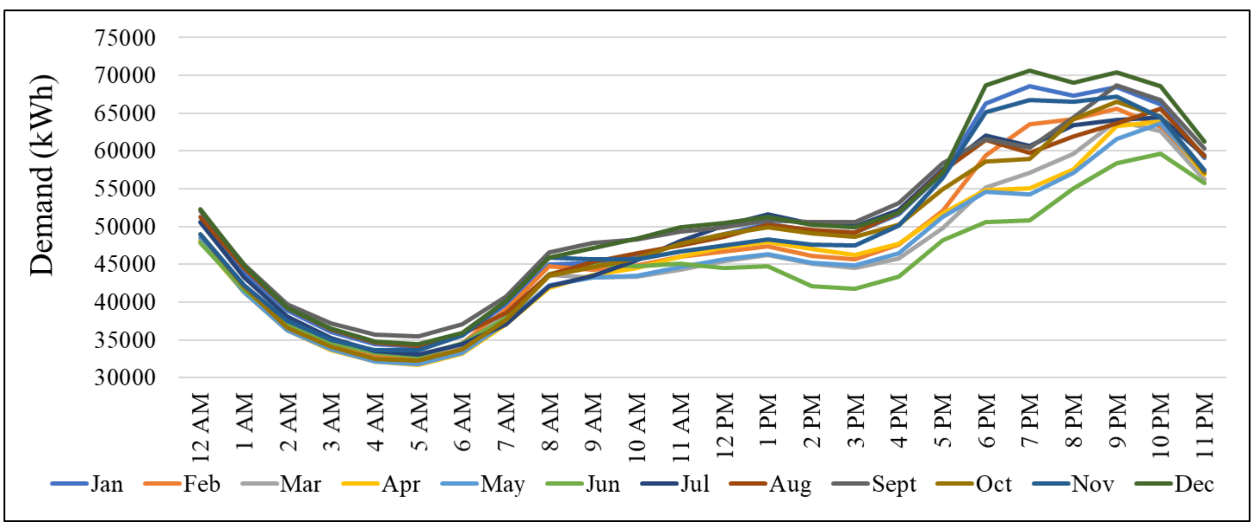

Figure II-9: Disaggregated Base Residential Demand by Month

3.2.2 RESIDENTIAL VALIDATION

The data modeled in this study did not have any accompanying submeter data with which the disaggregation could be evaluated, thus in this section it will be compared to submeter data from another study. Koskal, Rowlands and Parker [26] monitored several end-uses in 25 homes in the town of Milton, Ontario from 2011 to 2013. Since this study is also in Southern Ontario, only four to six years earlier, it would be expected that the behaviours and technologies driving demand, while not identical, should be similar. Therefore, the measured data from this submetering study was adapted to determine the approximate base, heating and cooling demands. It should be noted that in the Milton study, the furnace was used all year round for ventilation during both space heating and cooling periods. Therefore, when adapting the data from this study, furnace demand was considered heating demand in the winter and cooling demand in the summer. The average daily residential base demand during summer and winter weekdays, as modeled in this study and adapted from the Milton data, can be seen in Figure II-10. Demand was converted into a percentage basis to facilitate comparison between the different sample sizes (n = 80156 vs. Milton, n = 25).

Overall the distribution of base demand is notably similar between the modeled and actual results. It is notable that the differences between the summer and winter modeled base demand (less pronounced morning and evening peaks in the summer) can also seen in the Milton data. However, the modeled demand is more evenly distributed than the actual measured data. This could be explained by the smaller sample size in the Milton data which is less likely to include extreme outliers and therefore result in more pronounced peaks. Additionally, the study recognized that the results may not be representative as the homes monitored were on average larger and had a higher annual income and electricity usage than the Ontario average [26]. Another potential explanation is improving appliance efficiency since 2013, which would decrease the magnitude of peaks.

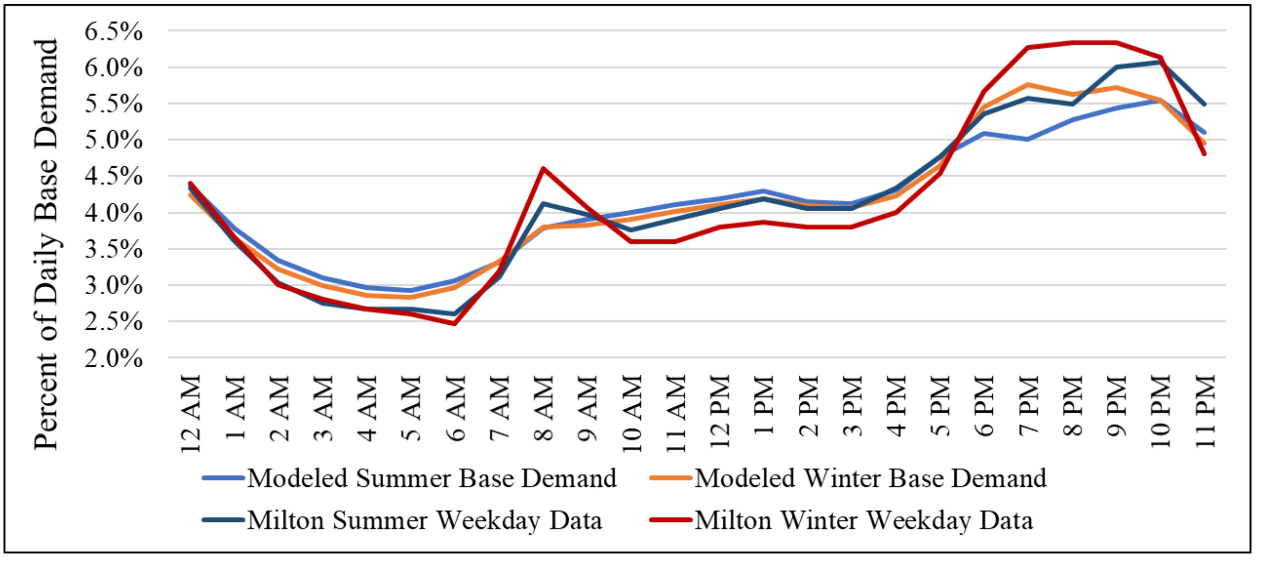

Figure II-10: Modeled and Adapted Base Demands [26]

The distributions of heating and cooling demands modeled in this study and adapted from the Milton submeter data can be seen in Figure II-11. The cooling demands show generally similar distributions, however the heating demands are quite different. Specifically, the adapted Milton data shows a significant peak in heating demand in the morning and a lesser one in the evening. This could be explained by certain customers using setback temperatures at night. In this case, the thermostats are programmed to let the house decrease in temperature through the night while occupants are asleep, then return to normal temperature settings in the morning. This would result in a significant morning peak. As noted, the Milton study was in an area with larger houses and higher incomes, thus having programmable thermostats is likely. Furthermore, since this morning peak would be similar through the majority of the heating season, the model presented in this paper may not identify the peak as temperature dependant and thus not disaggregate it. This possibility was supported by examination of the data which showed that compared to the rest of the day, the demand in the morning had a less defined changepoint for the 3-day average temperature. In other words, there was wider range of values over which morning demand showed little temperature dependence.

Another potential explanation for the difference in morning demands is the fact that the Milton heating data is adapted from furnace demand, which in some cases is used for both space conditioning and water heating. The morning and evening peaks could be explained by occupants showering in the morning before leaving for work or showering upon returning home from work and using hot water for chores such as washing dishes. These demands were not intended to be included in the disaggregated heating demand modeled in this paper. Since the adapted Milton data from the summer includes both air-conditioning and furnace demands, hot water use could also explain the higher morning demand seen in the summer. In order for a definitive conclusion to be drawn, more representative submeter data is required.

It should also be noted that the seasonal variation of water heating demand represents a potential source of error in the model presented. Although much of the water heating demand does not depend on weather, some portions do. For example, if the water entered the house at a colder temperature and thus required the furnace to run longer to heat it, this impact may be reflected. This is another potential explanation for the less defined 3-day average changepoint temperature in the morning, when households would be consuming hot water for morning showers. The morning period of lower temperature dependence resulted in the model finding higher 3-day average changepoint temperatures, with a peak occurring at around 8:00 AM. This would either result in the model disaggregating increased hot water demand during cold periods as space heating, or identifying lower levels of cooling demand during hot periods because of this being offset by the decreased demand for hot water. Given the lack of a morning heating demand peak and low morning cooling demands, the second possibility appears likely. Once again submeter data is required to validate the cause of the 3-day average changepoint temperature peaking at 8:00 AM and how it is impacting the results.

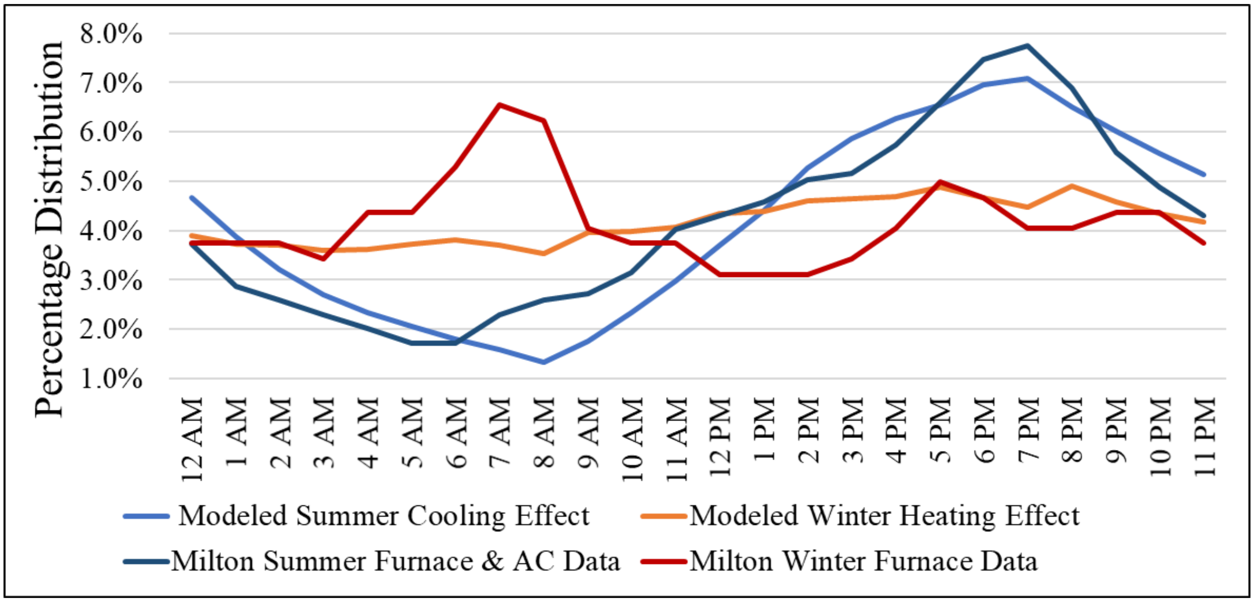

Figure II-11: Modeled and Adapted Heating and Cooling Demands

3.2.3 COMMERCIAL DISAGGREGATION

The disaggregation method was also applied to the commercial model and the average seasonal results are shown in Figure II-12. Once again, the base demand is quite consistent with some noticeable variation due to changing in lighting demands in the evening. It is notable that the heating and cooling demands represent much lower proportions of the total demand (3.55% and 6.62% respectively) compared to residential demand. This is to be expected, however these values are lower than the average Ontario values of 8% and 9% respectively, published by the IESO for 2015 [27]. This could be due to a different mix of commercial building types, or different energy sources for heating and cooling purposes. For example, the local University has an onsite energy conversion centre which controls the campus heating and cooling systems [28]. Once again to properly validate this disaggregation, sample sub-metered data would be required.

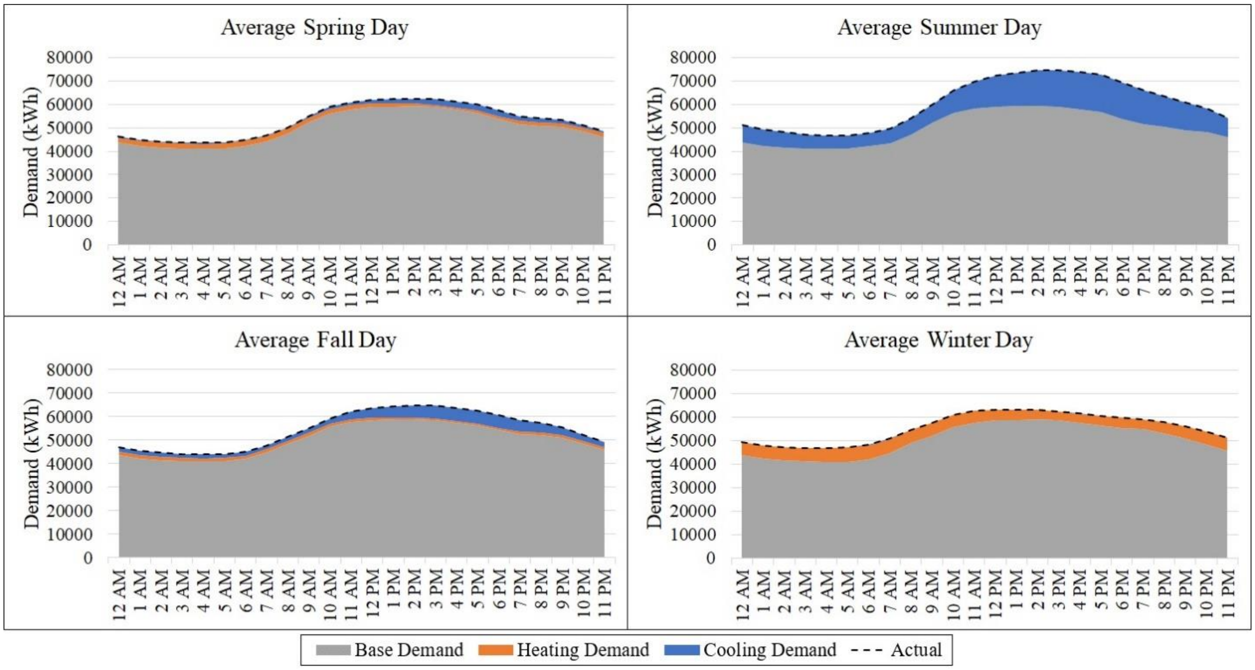

Figure II-12: Average Seasonal Disaggregated Commercial Demand

4 CONCLUSION

This paper presents a regression model for predicting aggregate hourly electricity demand based on weather. The model also disaggregates the demand into base, heating and cooling demands to facilitate additional modeling and analysis. The model requires minimal data inputs (only historical demand, weather, and daylength data) and can be applied in regions where submetering data is not available. A unique method of processing the temperature data into various temporal resolutions allowed the model to better capture both short and long-term weather impacts. The model provided comparably accurate predictions for aggregate residential demand and explained even high proportions of variance when applied to the commercial sector. However, it was less accurate during periods of high temperature (high cooling demand). This was partially mitigated through the unique implementation of 3 Probit models to better reflect AC usage. Future work will require additional analysis to further improve modeling of the behaviour that drives space cooling as the transition between heating and cooling seasons occurs.

The results of the disaggregation method appeared to be limited by the accuracy the model. For months in which demand was consistently overestimated, the heating or cooling demands were also overestimated, while the base demand was projected to be low (and visa versa). The results showed similarities to sub-meter data from another study in a similar region. This suggests that the model may provide accurate estimates of heating and cooling demand on average. The novel use of a variable changepoint only slightly improved the accuracy of the model. However, it had significant impacts on the disaggregation, and therefore the predicted quantity and temporal distribution of hourly heating and cooling demands. Additional data is required to validate the disaggregation results and confirm whether these differences constitute an increased disaggregation accuracy.

In conclusion, this method creates an opportunity to generate valuable data for future analyses from simple high resolution submeter data available at most utilities. Once the model is developed for a specific region it could be applied to project future demand under various climate change scenarios and assess the effect on the system. Future work will focus on validating the extrapolation of this model by comparing predictions of historical demand with actual data, and then applying the model to analyses of future scenarios. Furthermore, by changing the magnitude and distribution of the disaggregated space conditioning demands, the impact of changing technologies and penetration rates can also be assessed.

ACKNOWLEDGEMENTS

This research was conducted with funding support from The Natural Sciences and Engineering Research Council of Canada (NSERC), however they were not involved in the research or preparation of the manuscript. There are no conflicts of interest or competing interests to disclose.

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CHAPTER III: A SIMPLE PARAMETERIZED MODEL TO ADVANCE VISUALIZATION OF UTILITY LOAD CURVES FOR STRATEGIC SYSTEMS PLANNING

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Under review for publication in the journal "Utilities Policy"

1 INTRODUCTION

For the last two decades, the Canadian province of Ontario has had a focus on the development of a cleaner, more sustainable electricity sector. This began with the removal of coal, then shifted to the development of renewable energy supplies, energy conservation and efficiency through the implementation of the Green Energy and Green Economy Act in 2009 [1], [2]. This drove a major shift in the electricity supply mosaic of the province. The Independent Electricity System Operator (IESO) now reports 36% of total generation capacity is renewable, while an additional 35% is powered by nuclear [3]. While these technologies have reduced the carbon footprint of the electricity sector, they also have some disadvantages [4]. Nuclear is not quickly ramped up or down, thus is mostly limited to covering base load. Solar and wind are variable and non-dispatchable, which compounds the challenging balance of supply and demand. The transition towards renewable systems also moves globally, as worldwide wind energy capacity almost doubled and solar photovoltaic (PV) capacity more than quadrupled between 2012 and 2017 [5].

Concerns surrounding balancing supply and demand are amplified by load curves that change in both shape and magnitude. For example, the Canadian National Energy Board (NEB) discussed the changes from 2002 to 2016 in Ontario's average daily energy demand, presenting an overall decrease in demand accompanied by a now more pronounced evening peak [6]. This was attributed to efficiency improvements and embedded PV capacity. There are also more extreme changes like the now well-known duck curve in California. This is produced by a large drop in demand throughout the midday due to embedded PV generation capacity, followed by an extreme ramp in demand towards the final evening peak as the sun begins to set [7]. Further, as electricity systems have become cleaner, focus has shifted to transitioning historically fossil markets towards electrification. Increasing efficiency of electric heat pumps doubled sales between 2012 and 2017 [8]. The International Energy Association (IEA) projects the use of electricity for heating to continue to grow significantly in buildings as well as the industrial sector. Likewise, the demand from electrical vehicles (EVs) is expected to triple between 2018 and 2023.

As demand becomes more volatile throughout the day, it becomes more difficult for utilities and system operators to match supply and demand, plan future capacity requirements, and ensure consistent grid frequency [9]. This may eventually limit the penetration of intermittent generators [10]. Furthermore, the temporal distribution of demand will have a significant impact on the costs for the system operators, utilities and consumers. Increased variability and demand peaking could require oversizing of distribution assets, resulting in lower utilization and higher energy prices to recover the capital costs of the facilities. An investigation on the impact to utility revenues under various residential rate structures showed current volumetric tariffs did not reflect the impacts of PVs and EVs on the distribution grid [11]. In a 2019 survey of utility workers in the U.S. and Canada by Utility Dive, 96% and 91% of respondents expected significant or moderate increases in EV and PV penetration respectively [12]. Further, two of the three most commonly cited challenges with their regulatory models were justifying emerging investments and managing distributed resources. The major theme of the survey was uncertainty. This seems justified given that recent studies estimating future trends show wide variation in the ranges of predicted scenarios, let alone the effects these will each have on the load curve [13]–[17].

Historically many system operator and utility forecasting efforts have focused on short term predictions at high temporal resolution for operations planning, and long-term predictions of bulk and peak demands for capacity planning and informing policy decisions [18]. These can be complimented by medium term forecasts of moderate resolution focused on system reliability in the immediate future. A wide range of forecasting methods have been applied as summarized in several reviews [19], [20]. However, with the aforementioned changes and challenges looming, it is essential that long-term projections also consider the changing shape of the daily load. A review of current and future forecasting trends stressed the importance of not only macro drivers, but also sectoral decomposition and detailed temporal granularity describing consumption in peak hours, as well as those surrounding them [21]. One technique is to identify representative load curves for specific energy demanding sectors, scale them by the projected future total demand in each sector, and then recombine them to produce the total future load curve. Hainoun used this method in a study of future Syrian demand, deriving weekly and hourly coefficients for different day types to describe the temporal distribution of various sector demands [22]. Similarly, some of the long-term forecasting and optimization models like the popular TIMES model discussed by Suganthi and Samuel [19] includes the option to input load curves for varying sub-annual lengths of time, but the model itself does not predict the distribution [23]. For example Pina, Silva and Ferrão used several 24 hourly segments in each of the four seasons as inputs into the TIMES model to assess a case study of investing in renewable energy on the island of São Miguel in Azores, Portugal [10]. While this method accounts for changes in hourly demand due to growth or decline in sectors, it does not account for new technologies or policies, as also recommended by Lindberg et al. [21]. A variety of studies have examined specific scenarios of higher technology penetration (embedded photovoltaics [24], heat pumps [25], and/or electric vehicles [26]), demonstrating significant impacts on the total or sectoral demand or load duration curves. In order to fully encompass the technological changes, both the U.S. Energy Information Administration (EIA) [27] and National Renewable Energy Laboratory (NREL) [16], [28] have developed detailed national scale bottom up models which construct the total load curves from many specific end-use curves. However, these are extremely complex and data intensive.

Another subset of publications finds a balance between these intensive bottom up methods and the more simplified ones detailed previously. Koreneff et al. used seasonal indexes and hourly coefficients for three types of days to identify sector load curves [29]. The approach also accounted for specific technologies (heat pumps and EVs) that could significantly affect the future shape of the load curve but may not be reflected in the base model. Similarly, in other studies, consumption profiles for Danish customer segments were identified using monthly, hourly and day-type coefficients. Andersen, Larsen, and Boomsma used scaled sector load curves while adding additional EV and heat pump load [30]. This same model was then used to project demands regionally based on local sector loads [31] and as an input to EnergyPLAN to assess the Danish energy system [32]. Meanwhile, Boßmann and Staffell used two different models to project future load curves in Germany and the UK for the year 2050 [33]. One model, DESSTinEE, uses a similar sector load curve methodology, however breaks them down further to include transportation, and building space heating, water heating, cooling, and all other appliances. The other, eLOAD, uses a similar method, dividing each sector into 'relevant applications' which represent significant shares of demand and leaving the 'remaining load' as its own category [33]. In both cases these are scaled based on total demand projections. Finally, the Lawrence Berkeley National Laboratory's LBLN-Load model uses partially disaggregated load curves for representative customer clusters [34]. Weather effects are disaggregated and predicted with a temperature changepoint model, while other disaggregated loads are estimated from end-use datasets or assumed to represent a constant percentage of unassigned loads. All of these studies and models provide significant insight into the projected changes that will occur to the future load curves. However, most of the detailed model studies which could account for all relevant factors were focused on a national scale, and in some cases still required high volumes of end-use data. Notable differences exist between regions, including the supply and distribution infrastructure, customer sectors and characteristics, and end use technologies: all of which make it important to perform analyses on a regional scale [35]. As seen in the work by Andersen et al., extreme local values were not as accurately reflected when using national scale data [31]. Given the recent abundance of smart meter data being collected by utilities, this paper aims to address this research gap. Here we present a partially disaggregated load curve model which can be calibrated with local utility data to project their future electricity demands under a wide range of scenarios.

This paper will present a model predicting the average and peak shape of daily load curves in each season in the year 2040. A combined methodology will be used, implementing sector load curves identified based on historical data, with only the most important end uses disaggregated and specific new technology load curves identified. One of the most useful features of the model is its interface that enables users to adjust a variety of existing and new influencers, see the results in real time, and quickly investigate a wide range of demand scenarios.

2 MATERIALS AND METHODS

The following sections detail a daily electricity demand curve model based on Visual Basic for Applications coding. The model integrates principal parameters into sliding and button controls. This allows modifiers to be adjusted to generate a range of demand scenarios in real time. A sample visual of the interface side is shown in Figure III-1, displaying some of the controls on the left-hand. Some metrics are shown below the graphical display, as well as a toggle box where the user can choose to display any individual season, a summary of all seasons, or the validation results.

The immediate and visual feedback of the model facilitates rapid risk and opportunity identification for utilities. Once a risk has been identified, other parameters can also be adjusted to assess how the situation might be avoided and inform future investment or policy choices. As a case study, we model a variety of load distribution scenarios based on literature to illustrate the non-trivial uncertainty in projected energy demands. The model has been calibrated with data from a utility in southern Ontario.

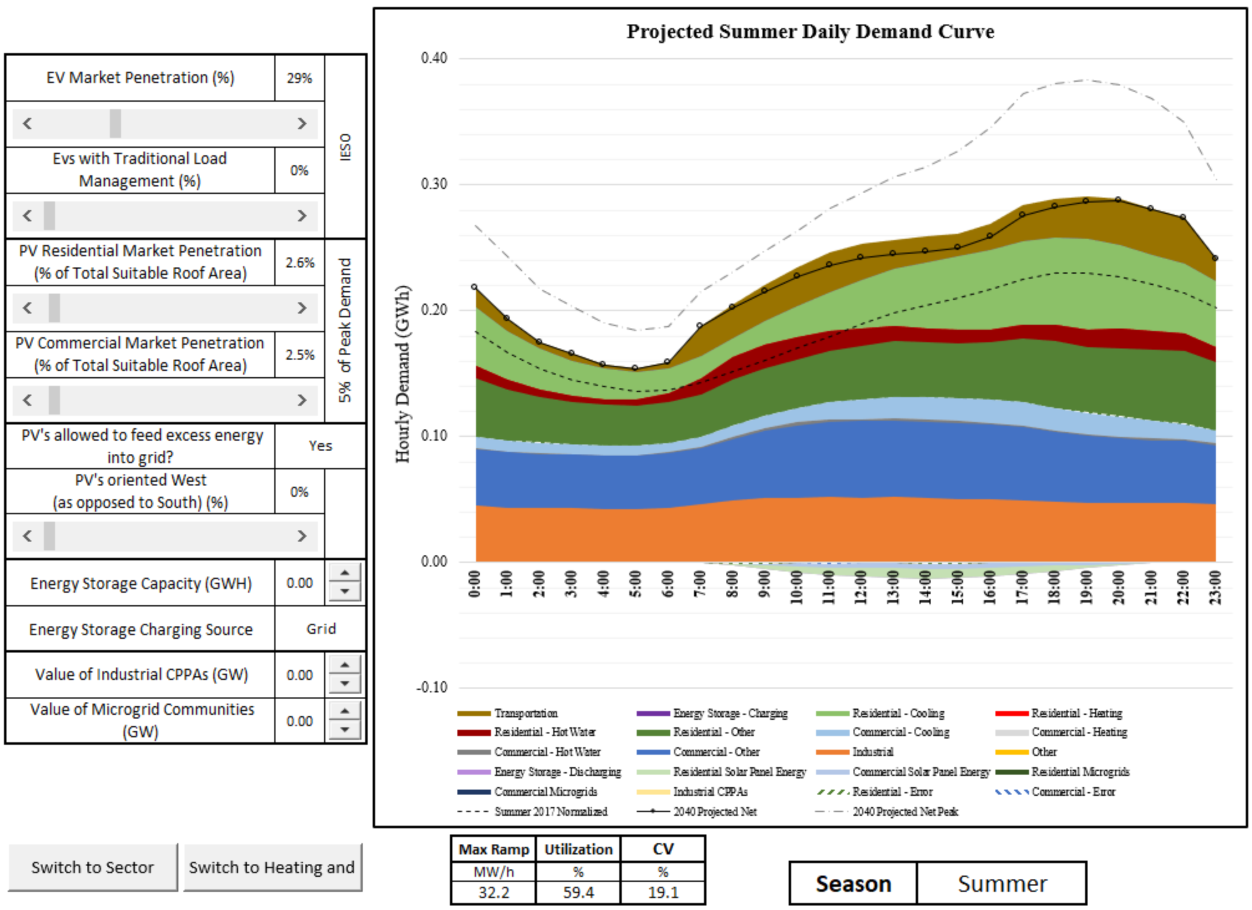

Figure III-1: Sample Interface and Projected Summer Demand Curve – IESO Outlook C

2.1 BASE MODEL

A fundamental assumption of this model is that specific sectors of the energy market have representative load curves based on behavioural patterns and end-uses that remain relatively constant through time but are significantly different between sectors. It was assumed that these load curves vary only in magnitude over time, except where influenced by disruptive technologies and policies. Thus, the total future load curve for each sector can be developed by scaling each sector load curve by the projected future demand, while additional supply and demand curves are introduced to reflect changing technology and policy. The sum of these curves will produce a projected daily average load curve. Since behavioural patterns and end uses vary between seasons, separate archetypical sector load curves and future demand shares were identified for each season. The sectors identified were Industrial, Residential, Commercial and Other. The 'Other' sector was intended to represent all load not encompassed in the Industrial, Commercial and Residential categories, however the data collected here did not include any such load and was therefore set to zero. The overall methodology is summarized in Figure III-2.

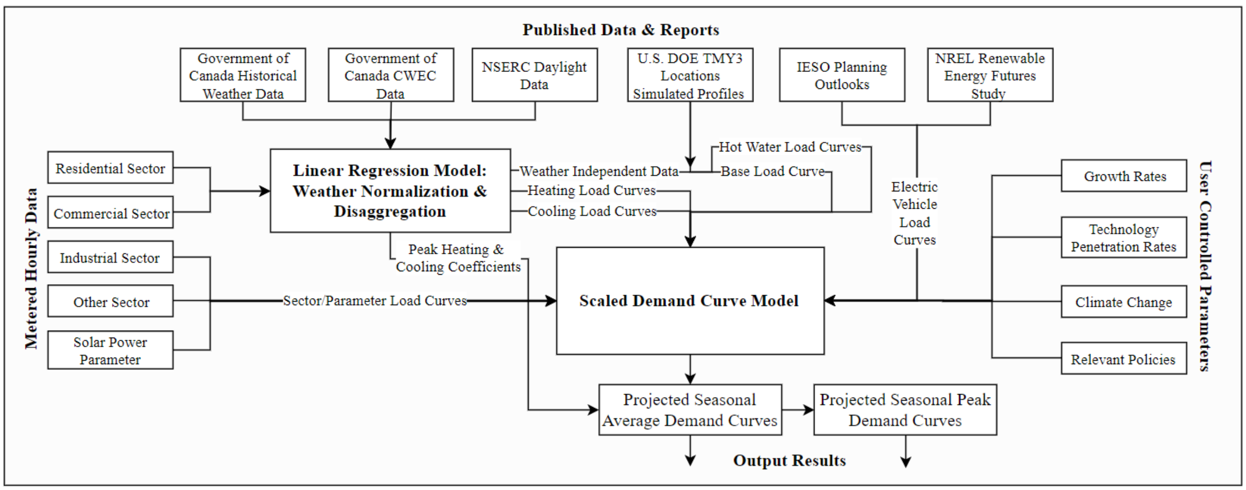

Figure III-2: Summary of Model Materials and Methods

The demand curve model was calibrated with data sourced from utility partners located in Southern Ontario. Load data for 80,156 residential, 8,278 commercial and 226 industrial customers containing one year of hourly demand from 2017 was used as the baseline year. The annual data was split into four approximate seasons of three months each: Spring (March, April and May), Summer (June, July and August), Fall (September, October and November), and Winter (January, February and December).The finishing hour was used to identify the electricity data, meaning demand from 7:00 to 8:00 was labeled as 8:00, etc. To best reflect the consistent behavioural patterns of customers, the data was adjusted from local standard time (LST) to daylight savings time (DST) between March 12th and November 5th. The commercial and industrial data showed significantly lower demand during ten days of the year where several customers suddenly dropped to almost zero demand. Measurement errors were suspected; thus, this data was omitted. The coefficients for the seasonal average daily curves for each sector can be calibrated based on the following formulas:

$$d_{m,s,t}^{\bar{y}} = \left(\frac{D_m^{\bar{y}}}{n_s}\right) * k_{m,s,t} * s_{m,s} \quad \text{Eq. (1)}$$

$$S_{m,s}^{\bar{y}} = D_m^{\bar{y}} * s_{m,s} \quad \text{Eq. (2)}$$

where:

$d_{m,s,t}^{\bar{y}}$ = average energy demand for the customers in a given sector (m = 1 to 4), during a given season (s = 1 to 4) at a given hour of the day (t = 1 to 24) in base year $\bar{y}$

$D_m^{\bar{y}}$ = total annual demand of the customers in sector m in base year $\bar{y}$,

n_s = number of days in season s,

$k_{m,s,t}$ = a coefficient which represents the percentage of daily demand in sector m during season s which occurs during hour t

$s_{m,s}$ = a coefficient which represents the percentage of annual demand in sector m occurring in season s

$S_m^{\bar{y}}$ = the total demand in season s of the customers in sector m in base year $\bar{y}$

Thus, four seasonal and 96 hourly coefficients were identified for each sector, representing an average scaled load curve. Prior to fitting these coefficients, the Residential and Commercial data was weather normalized, and the heating, cooling and hot water demands were disaggregated to be included separately as modifying parameters. This is discussed in section 2.2.1. The industrial demand did not require this as it showed little dependence on weather. The calibrated hourly coefficients ($k_{m,s,t}$), which form the normalized base load curves for each sector, are displayed in Figure III-3. With the main weather dependant technologies disaggregated, the seasonal curves are notably similar, and the evening variations can be explained by increased lighting demands with shorter day lengths.

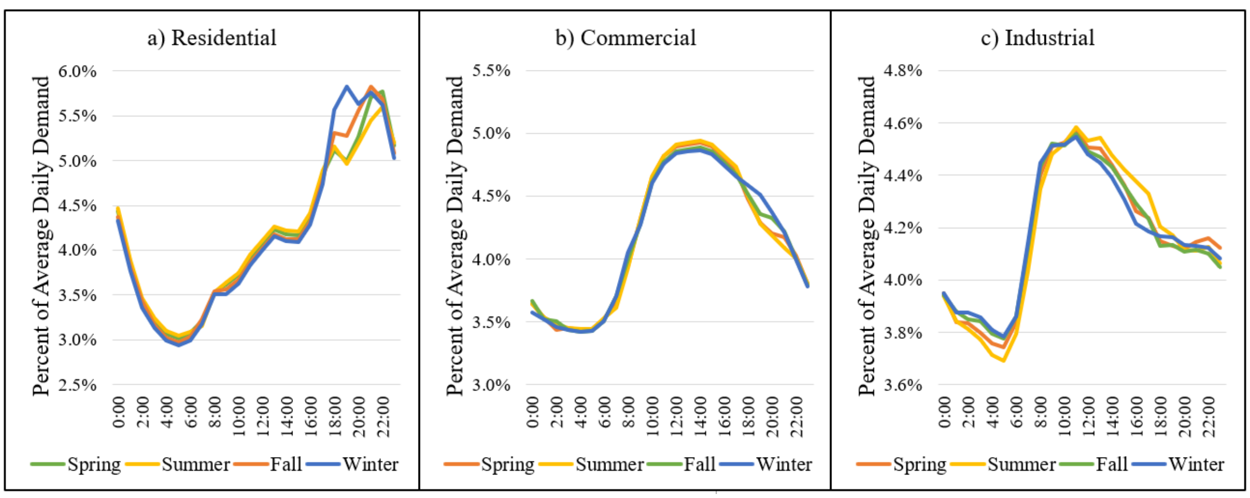

Figure III-3: Scaled Seasonal Daily Base Load Curves by Sector

As with each sector, any specific technologies or policies identified as influencing parameters must have daily load curves. Each specific parameter varied slightly in formulation and how their respective load curves and total demands were determined is detailed in section 2.2. Once determined, the coefficients for sectors and parameters can be used to predict future demand curves for a given year *y*, using the following:

$$d_{s,t}^{y} = \sum_m \left(\frac{D_m^{\bar{y}}}{n_s}\right) * (1 + i_m)^{(y-\bar{y})} * k_{m,s,t} * s_{m,s} + \sum_p d_{p,s,t}^{y} \quad \text{Eq. (3)}$$

where i_m represents the average projected annual growth rate (user-controlled parameter) for energy sector *m*, and $d_{p,s,t}^{y}$ is the total demand for parameter *p* in year *y*, season *s*, at time *t* as determined by equations (5)-(11) in section 2.2.

It was assumed that peak demands occur due to extreme weather events (either warm or cold), thus peak load can be estimated with average load curves for all sectors and parameters except those which are weather-related. The model makes a peak demand projection by additionally scaling each weather-related parameter by peaking coefficients, which represent the ratio between the average seasonal weather-related demands, and the peak demands. The coefficients are calibrated using the following formula:

$$P_{p,s,t,T}^{\bar{y}} = d_{p,s,t}^{\bar{y}} * m_{p,s,t,T} \quad \text{Eq. (4)}$$

where $P_{p,s,t,T}^{\bar{y}}$ is the demand occurring on the peak day for weather related parameter *p*, in season *s*, during hour *t*, and $m_{p,s,t,T}$ is the corresponding coefficient. These coefficients can also vary depending on projected climate conditions *T*, as is detailed section 2.2.1.2.

2.2 INFLUENCING PARAMETERS

The influencing parameters are either new supply or demand from developing technologies which are not represented in historical sector curves, or are specific end-use demands expected to change significantly which have thus been disaggregated from the base sector demand. Each of these parameters has specific controls in the model interface and are detailed in the following subsections.

2.2.1 ELECTRIFIED HEATING, COOLING AND HOT WATER

Heating, cooling and hot water (HW) represented over 85% and 70 % of 2015 energy demands in Ontario's residential and commercial sectors respectively [36]. The electric portion of these demands is likely to increase significantly in coming years due to heating equipment switching from traditional fossil fuel combustion, to electric sources such as heat-pumps. Meanwhile, rising temperatures due to climate change increase the magnitude of the already largely electric cooling demands. As detailed in 2.2.1.1, within both the residential and commercial sectors electrified heating, cooling and HW were disaggregated and identified as separate parameter-based load curves. This allows these end-uses to be adjusted based on the penetration of electrified technology and the effects of climate change, rather than assuming they will only scale proportionally with the growth or decline of the overall sectors. Once the demands are disaggregated, their demand curve coefficients can be calibrated like sector demands using equations (1)-(2).

As discussed further in section 2.3.1, the total potential demand (if there were 100% penetration) for each end-use and sector can be estimated using base year penetration rates and total demands. Similar to other sectors, they can then be projected forward to 2040 with estimated average annual growth rates. These total potential demands can then be scaled by the projected 2040 penetration rates for each electrical technology (from 0 to 100%) and sector to determine the projected electrical demand. Thus, future demands can be calculated by the following formula:

$$d_{p,s,t}^{y} = \left(\frac{D_p^{\bar{y}}}{n_s}\right)\left(\frac{Pen_p^{y}}{Pen_p^{\bar{y}}}\right) * (1 + i_p)^{(y-\bar{y})} * k_{p,s,t} * s_{p,s} * c_{p,s,t,T} \qquad \text{Eq. (5)}$$

where:

$D_p^{\bar{y}}$ = total annual demand of parameter p (ex. residential heating) in base year $\bar{y}$

Pen_p^{y} = the penetration (user-controlled) of parameter p in year y

i_p = projected average annual growth rate for parameter p

$k_{p,s,t}$ = coefficient found with Eq. (1) for parameter p in season s during hour t

$s_{p,s}$ = coefficient found with Eq. (2) for parameter p in season s

$c_{p,s,t,T}$ = coefficient found with Eq. (8) for parameter p in season s during hour t with climate conditions T (detailed in Section 2.2.1.2)

Each of parameter penetration and growth rates has a dynamic control in the model. Note the growth rate accounts for the expected growth of the sector (ex. for residential electrified heating, growth in number of households) and change in relative demand intensity (ex. changes in appliance efficiency). Changes due to increased or decreased technology penetration are controlled separately. For example, the growth rate for a technology could be negative due to increasing efficiency, but the total projected demand might be increased due to a higher penetration rate. The base penetration rates used for the utility are summarized in Table III-1. Recent commercial data could not be found for space cooling, and a trend of slightly increasing penetration was shown, so the upper limit of the values estimated for 2009 was used.

Table III-1: Baseline Technology Penetration Rates

	Electrified Heating	Electrified HW	Electrified Cooling
Residential	15 % [37]	17% [37]	93% [37]
Commercial	10 % [17]	19% [17]	75% [38]–[40]

2.2.1.1 DISAGGREGATION

To disaggregate the residential and commercial demand a regression model was developed. Many previous studies have used temperature to predict electricity demand as well as identify demand of specific end uses [41]–[44]. The concept of heating degree days (HDDs) and cooling degree days (CDDs) has been used by several papers to investigate the impacts of climate change on demand at a range of temporal resolutions [35], [45], [46]. Furthermore, a series of studies by Kipping and Trømburg used the same concept to model and disaggregate heating and cooling demand in residential and commercial buildings [47]–[50]. This method assumes that there is a changepoint temperature at which customers transition from heating to cooling demand. Thus, HDDs represent the number of degrees which the average daily temperature is less than this changepoint and CDDs represent the number of degrees higher. This same concept can be applied to different spans of time, for example with heating or cooling degree hours (HDH or CDH). Heating degrees (HD) and cooling degrees (CD) can be calculated by equations (6) and (7) where t is the length of time considered, T_t is the average temperature across the length of time and Tc_t is the changepoint temperature for the length of time considered.

$$DH_t = Max(\,Tc_t - \,T_t, 0) \qquad \text{Eq. (6)}$$

$$DC_{t,} = Max(\,T_t - Tc_t\,, 0) \qquad \text{Eq. (7)}$$

This technique was implemented using a regression method detailed in prior work [51]. The method used multiple time spans to capture short and longer term weather impacts, a varying changepoint temperature depending on time and type of day, and Probit analysis to estimate seasonal installation of portable air conditioning units.

The regression model was fit to the utility's data with climate data from Government of Canada historical records [52] and sunrise/sunset times from the National Research Council of Canada calculator [53]. It could then be used to predict future weather normalized demand and disaggregate it. Predictions were made for future years using the Canadian Weather Year for Energy Calculation (CWEC) dataset, which contains one year of climate data created by combining twelve "Typical Meteorological Months" from the past 30 years based on statistical comparison [54]. The predicted demand associated with HD and CD variables at each hour was allocated as heating and cooling demand respectively, while the remainder was considered 'base' demand. The errors in the original model predictions were assumed to represent variability in base loads and thus seasonal average errors were carried forward and incorporated as a component of the base demand in the normalized projections. The weather normalized results with these additional error terms were used to calibrate the model in equations (1)-(2) & (4).

The electricity demand for HW cannot as easily be disaggregated with climate data because most of the demand is not weather sensitive. Various sources have studied and modeled different influences on hot water demand, including seasonal variations [55], household size [56], day types [57], and potential for direct load control [58]. Although there are changes in consumer demand throughout the year, as well as variations in the incoming temperature of water, these effects were assumed to be negligible and therefore, water heating demand was assumed to be constant throughout the year at summer demand levels.

Knight, et al. showed hot water usage in Canada has a similar pattern to other countries with some cultural variations [59]. Therefore the U.S. Department of Energy (DOE) dataset containing archetypal simulated energy load curves for residential and commercial buildings was selected due to cultural similarity, geographic proximity, and availability of data for both sectors [60]. The model predicted natural gas demand as opposed to electricity, but it was assumed that the temporal distribution would be consistent regardless of the energy source. This assumption was used due to the limited availability of data, and it is recognized that this may need to be refined in the future.

For residential demand a group of American cities in the same region (Buffalo, Cleveland, Chicago, Detroit-City, Detroit-Metro, and Rochester) were selected and found to all have notably similar simulation results [60]. The average of these locations was used as the final residential HW load curve. This was also validated against an hourly profile of typical HW consumption from the California Energy Commission, showing a similar pattern [57]. The commercial simulations were performed for one city in the region (Chicago) and included a sampling of 16 commercial building types. A weighted average HW load curve was used based on the percentage of demand seen from each industry in Ontario according to the IESO outlook data [17]. Notably, the residential and commercial simulations showed the same hourly distribution of HW demand in all seasons, however they predicted an average 26% and 39% increase respectively between the summer and winter. This suggests disaggregated heating demand may include crossover from HW demand.

Using these HW load curves, the 'base' sector curves determined through the regression model, and the proportion of HW demand detailed in the IESO data, the HW demand was disaggregated to produce the 'Residential - other' and 'Commercial - other' load curves. These represent the distribution of all sectoral demand excluding heating, cooling and HW and were the demands used to determine the sector load curve as described in Eq. (1). The final annual average coefficients (not differentiated by season) for each sector can be seen in Figure III-4.

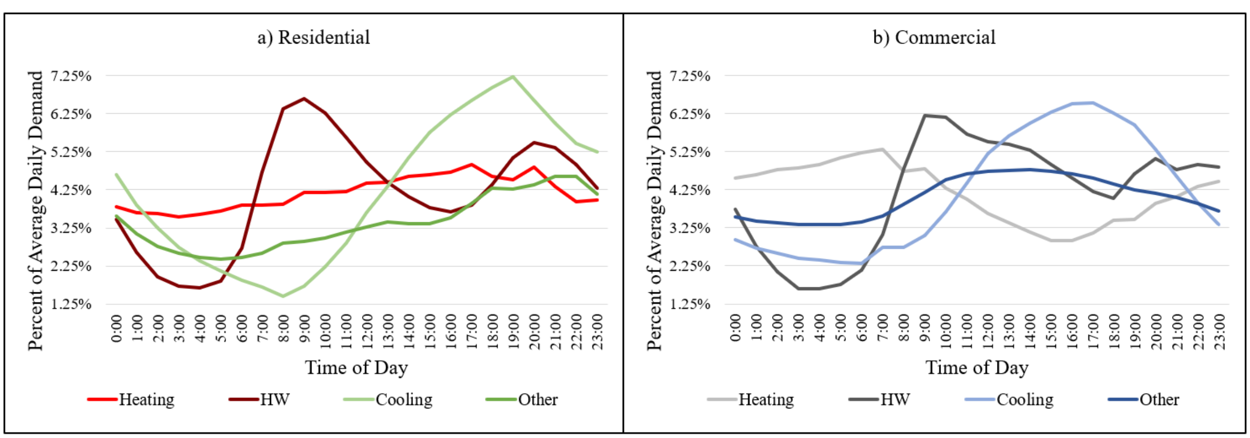

Figure III-4: Disaggregated Heating, Cooling and HW Scaled Demand Curves

2.2.1.2 CLIMATE CHANGE

The regression model [51] used to produce weather-normalized projections can also be applied to project the impacts of different weather conditions due to the changing climate. In order to examine the effect of increasing average temperatures, projections were made using the same CWEC dataset, but with all temperature values increased in increments of 0.5 °C. This was performed for temperature increases ranging from 0.5 °C up to 2.0 °C. For each increment, the projected weather-related demands were compared to those of the base weather data and a scaling coefficient was determined for both the average and peak seasonal demands, using Eq. (4) and the following:

$$d_{p,s,t,T}^{\bar{y}} = d_{p,s,t}^{\bar{y}} * c_{p,s,t,T} \qquad \text{Eq. (8)}$$

where $d_{p,s,t,T}^{\bar{y}}$ is the average projected demand for weather-related parameter *p*, in season *s*, on hour *t*, with average temperature increase *T*, and $c_{p,s,t,T}$ is the corresponding scaling coefficient. The average increase in temperature is dynamically controlled by the user.

2.2.2 ELECTRICAL VEHICLES

The integration of electrical vehicles (EVs) has the potential to markedly impact the demand curve. The impact of a variety of technical, spatial and behavioural/economic factors on the magnitude and distribution of demand has been modelled, including vehicle size, charging infrastructure capacity and location, consumer occupation, and charging preference [61]. Studies have also identified the opportunity for EVs to be a controlled demand source, and modelled the potential for significant load shifting to balance daily demand fluctuations [62], [63].

In this preliminary model, the characteristics of this parameter have been simplified to illustrate the baseline impact anticipated with increasing penetration. The projected number of personal vehicles can be determined as the product of estimated future population in the region and the estimated future quantity of vehicles per capita in the region. The quantity of personal vehicles per capita was estimated based the historical data for a series of similarly sized cities in Southern Ontario from Transportation Tomorrow surveys from 1986-2016 [64]. Based on the average values and slowly increasing trend, a 2040 value of 0.735 personal vehicles per capita was extrapolated. The total number of EVs can then be determined through the EV penetration which is the first of three EV related controls in the model. This can be then be multiplied by the estimated demand (9.22 kWh [17]) per vehicle to generate the total daily demand.

The next two controls affect the distribution of EV demand throughout the day. There are a variety of sources that suggest significantly different distributions. One interface control determines whether the daily distribution is based on IESO [17] or NREL [16] projections. Each of these resources includes multiple potential load curves, thus the final control allows adjustment of the mix of the distributions from a given source. The IESO has a projected load profile for a convenience dominated charging pattern with minimal load management, and one for a charging pattern with effective load management (based on the current load curve). The third control defines the percent of vehicles (or demand) following the load management curve. Thus, when this control is set to 0%, the load curve is the projection without load management, and when at 100% it is with optimal load management. When set to any value in between the curve is a weighted mix of both projections. Similarly, NREL has two potential hourly load shapes which are mixed depending on the control settings. The default is a scenario where the utility has no control. In this case, all charging occurs when consumers return home and continues until complete or until a new trip is started. The alternate curve is predicated based on the condition that charging infrastructure is abundant and the consumer will have the opportunity to plug in their EV whenever parked. The adapted potential load curves from each of these sources as well as a sample of the mixed results are shown in Figure III-5.

The projected future demand can be determined using Eq. (5), where the hourly coefficients are determined based on the dynamic controls discussed. No seasonal effects were considered so all seasonal coefficients were set to 0.25. Since the penetration and demand in the base year may be zero, these values are replaced with placeholders indicating the total potential penetration and demand as estimated previously.

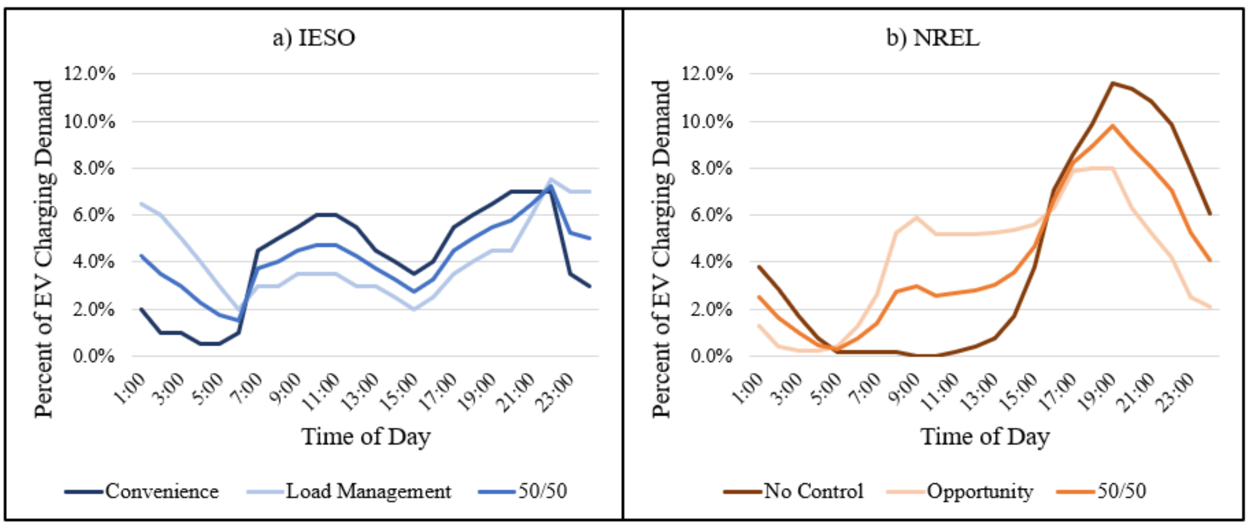

Figure III-5: Projected EV Load Curves for a) IESO and b) NREL

2.2.3 PHOTOVOLTAICS

Photovoltaics in the form of rooftop panels are reaching significant penetration in residential and commercial markets; in Q1 2018 IESO reported just over 2GW of embedded solar capacity [65]. This represents approximately 5% of the total capacity currently installed on the transmission grid and already has started to impact the shape of daily demand curves [3], [6].

The potential production capacity available from rooftop solar panels was estimated to be approximately 3.01 kW per capita in a large region of South Eastern Ontario, assuming a future average efficiency of 22.9% [66]. This covered a variety of population densities and landscapes and was thus assumed to be representative of Ontario. The total potential capacity can then be estimated and scaled by the projected population and percent penetration according to prescribed scenarios.

Along with customer demand data, many utilities meter embedded generation separately (particularly if a feed in tariff is present). The utility partner with which this model was calibrated also provided metered production from 765 customers with solar assets in the region. This can be used to establish average seasonal coefficients for the PV parameter, as can be seen in Figure III-6 a). The coefficient at each hour determined with Eq. (9) is the percentage of the average day's peak hourly production in that season. Seasonal coefficients are determined from Eq. (10), using a regional capacity factor from Natural Resources Canada [67] to relate peak hourly production on the average day of each season with estimated installed capacity. Note all demands in this case are negative since PVs provide supply.

$$k_{p,s,t} = \left(\frac{D^{\bar{y}}_{p,s,t}}{min_t(D^{\bar{y}}_{p,s,t})}\right) \qquad \text{Eq. (9)}$$

$$s_{p,s} = \left(\frac{min_t(D^{\bar{y}}_{p,s,t})}{C^{\bar{y}}_{p}}\right) \qquad \text{Eq. (10)}$$

where:

$D^{\bar{y}}_{p,s,t}$ = total demand of parameter *p*, at time *t*, in season *s*, of base year $\bar{y}$
$min_t(X)$ = is a function that finds the minimum value of X for all *t*
$C^{\bar{y}}_{p}$ = the installed capacity of parameter *p* in year $\bar{y}$

The shape of production curves will also vary depending on the orientation of a solar panel. A variety of sources have examined the possibility of shifting PV alignment to optimally match production with demand [68]–[70]. Two representative sets of coefficients were established in the model for south and west facing panels. The seasonal curves produced previously from the utility data were assumed to be for traditional south facing panels and thus used in the model for the baseline scenario. An additional parameter which allows the user to specify a mix of West facing panels was also included, with the load curve responding accordingly and producing a weighted combination of the two curves. The sample west facing distribution from Richardson and Harvey's work was adapted and assumed to be a representative curve for the summer [70]. The other seasons were estimated by scaling this curve by the relative hourly production compared to the summer (this was assumed to be proportional to solar radiation). The resulting hourly coefficients are shown Figure III-6 b).

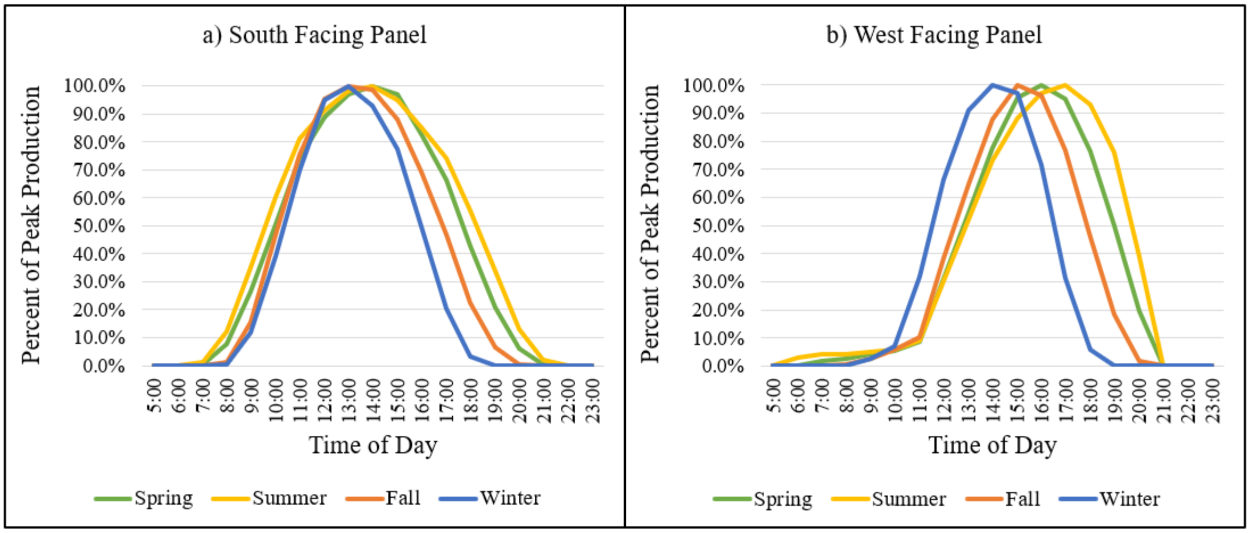

Figure III-6: Photovoltaic Scaled Load Curves a) South, b) West

Although the curves have the same shape, the model includes two parameters which differentiate between residential and commercial photovoltaic penetration so that these can be adjusted individually. Based on the formulas in [66] used to calculate total roof area per capita, it was estimated that 40% of the total potential solar capacity per capita is commercial, whereas 60% is residential. It should also be noted that for the baseline curve, both parameters were set to 2.5% based on current estimated capacity and projected potential capacity. The model also displays the total penetration from both sectors in a metric commonly used by utilities, percent of peak demand.

Projections of future production are made using the following equation, where C_p is the estimated total potential capacity:

$$d_{p,s,t}^{y} = C_p * Pen_p^y * k_{p,s,t} * s_{p,s} \qquad \text{Eq. (11)}$$

2.2.4 NON-UTILITY PROCUREMENT

Another trend in energy markets is customers leaving traditional utility models in pursuit of independent energy procurement either through community microgrids or corporate power purchase agreements (CPPAs).

As an approximation, in this model it is assumed that a microgrid community will have a combination of commercial and residential demand at a ratio consistent with the overall utility demand. The total capacity of microgrids can be adjusted dynamically. Since this essentially represents residential and commercial customers leaving, a supply curve with the same coefficients (but negative) as the total projected residential and commercial demands for the current scenario will be applied. The magnitude of supply is constrained such that the peak of this total microgrid supply curve will be equal to the selected capacity of the grid, owing to the assumption that each microgrid is designed to meet the average daily peak demand of all connected consumers.

To illustrate the effect of large industrial customers leaving, it was assumed in this model that all CPPAs would be signed with corporations in the industrial sector. A dynamic control allows the user to set the total capacity of all CPPAs which produces a negative supply curve with the same distribution as the industrial sector. It will be assumed that the CPPA is able to meet average daily peak demand and thus the highest point on the negative supply curve will be equal to the established total capacity.

2.2.5 ENERGY STORAGE

The implementation of utility scale energy storage is unique from the other parameters in that the shape of the load curve produced depends completely on the demand of each of the other load curves. As such any time another parameter is adjusted, the energy storage is redistributed. This model parameter is adjusted based on the total projected energy storage in GWh and can be changed by increments of 0.1 GWh. A round-trip efficiency of 70% was assumed based on the assumption that a combination of batteries and bulk energy storage such as pumped hydro storage or compressed air energy storage would be used [71]. It is assumed the storage is fully charged and discharged once per day.

An algorithm was developed so that when energy storage capacity is added by the user, additional 'charging' demand is added to the times of lowest demand on the daily demand curves, while negative 'discharging' supply is added during the peak hours. This is done iteratively, adding 0.01GWh of demand and 0.007 GWh of supply at a time (ten steps per 0.1 GWh added by the control) until the total value is reached. While this may not result in perfectly smoothed demand curve the limited steps reduce computation requirements to ensure smooth model operation. Furthermore, real energy storage operation is unlikely to be perfectly optimized since future demands are uncertain. The model also includes an option to control whether energy storage is charged through the "Grid" or "Solar Only." In grid charging the energy storage charging demand can be allocated during any hours, whereas with solar charging it can only occur at times when solar panels are producing power. Therefore, during solar charging, the total energy storage is also effectively limited by the total solar production.

2.3 SCENARIOS

To validate the accuracy of the model, it was first tasked with matching historical demand data from the base year in 2017. The model automatically generates an estimated baseline curve from the load curves and annual demand data entered. This was compared to the utility partner's data in Section 3.1.

In addition, to demonstrate the capabilities of the model and assess the range of potential outcomes for demand distributions, a variety of scenarios were developed as a case study. In 2016 the IESO produced the "Ontario Planning Outlook" (OPO) report which includes a range of economic and technological scenarios (Outlooks A – D) for the next 20 years [17]. This includes projections of the future energy demand in a variety of sectors as well as the penetration of specific technologies. These were used to generate one set of scenarios. Furthermore, to examine the potential effects of more extreme sector disruption, an additional set of scenarios were projected.

2.3.1 IESO OUTLOOKS

Outlook A considers a scenario where adoption of new disruptive technology such as electrical heating and EVs is low. A lower overall growth and continued focus on conservation and efficiency measures results in a slight decline in demand across almost all energy sectors. Outlook B is similar except in this scenario economic and population growth remain higher, matching the conservation and efficiency gains to result in a marginal growth in total demand across most sectors. Outlooks C & D use similar growth projections to scenario B, but also consider additional electrification. Both project higher electrical heating and EV penetration rates, as well as a significant portion of industrial demand, which is currently met through onsite fossil fuel combustion, transitioning to electricity from the grid. The difference between the two is that Outlook D has slightly higher projections for each of these categories. The main characteristics of each outlook are summarized in Table III-2.

To determine the model inputs for each outlook, a series of calculations and estimations were performed using the outlook data; the full results can be seen in the supplemental material. Each outlook includes baseline demand for each sector in Ontario from 2015, as well as projections for the year 2035. Using these values, the average annual growth rates for each sector can be calculated and projected forward to 2040 (see Table S1). Demand data is also provided for specific end uses in both the commercial and residential sectors, including heating, cooling and hot water. By subtracting these demands from the total, this data can be used to determine the projected growth rate of the weather-independent end uses, or ‘other’ commercial and residential sectors. Furthermore, the current and projected penetration rates of electrical heating and hot water are provided. Using this information, the estimated total potential demand for these end uses can be determined in each scenario (see Table S2). With these theoretical total potential demands the growth rate for these parameters can then be calculated for each scenario to reflect the projected effects of changing consumer choices or technological efficiencies independently from the change in market penetration. Finally, the outlooks include projections of the average characteristics of electric vehicles and the total demand of the transportation sector. This was extrapolated to 2040, along with historical Statistics Canada data on vehicle registrations [72]. The EV data was then converted into an approximate equivalent market penetration in each scenario (see Table S3) so that it could be applied to the model parameter.

Table III-2: IESO Outlook Characteristics [17]

Outlook	Years	Growth in Number of Households	Growth in Commercial Floor Space	Annual Growth in Industrial GDP	Electric Heating & HW Gain in Market Share	Electrification of Industrial Fossil Fuel Uses	Millions of EVs in Ontario
A	2015-2025	11%	10%	0%	0%	0%	0.6
	2025-2035	7%	8%	1%			
B	2015-2025	14%	15%	1%	0%	0%	1.0
	2025-2035	9%	11%	1%			
C	2015-2025	14%	15%	1%	25%	5%	2.4
	2025-2035	9%	11%	1%			
D	2015-2025	14%	15%	1%	50%	10%	2.4
	2025-2035	9%	11%	1%			

All IESO Outlook data is based on gross projections for the entire province, thus may not be strictly representative of the changes that are expected to be seen locally. However, they provide baseline scenarios for demonstration. Therefore, in each IESO scenario the projected sector growth rates for the respective Outlook were applied to the baseline sectoral demand seen in 2017. Likewise, the parameters controlling residential and commercial electrical heating and HW penetration rates were set to equivalent province-wide penetration projections. Since these projections were for 2035, the projected trends for penetration were extrapolated to 2040 in each scenario using fitted curves (Table S4). Likewise, the EV penetration parameter was set based on the extrapolated projected penetration rate. Since multiple parameter calculations require the future population, an estimate was made for each scenario by applying the household growth rates to the current population [73]. The resulting population projections were in close agreement to those estimated from the Ontario Ministry of Finance’s expected regional growth [74].

2.3.2 ADDITIONAL SCENARIOS

The additional scenarios were developed based on a variety of literature sources. Table III-3 summarizes the parameter values used in each scenario and the justification for their selection. The first two additional scenarios were developed to illustrate more extreme ranges in demand that could be realistically expected based on IESO Outlooks and additional sources. The next two scenarios were developed to demonstrate the sensitivity of Ontario’s electricity market to developing a ‘duck-curve.’ The first duck curve scenario uses values that fall well within the cited ranges, while the second ‘extreme duck curve’ scenario shows modifying factors at their extreme values.

Table III-3: Additional Scenario Characteristics

	High Scenario	Low Scenario	Duck Curve Scenario	Extreme Duck Curve Scenario
Sector & Population Growth Rates	IESO Outlook maximums [17]	IESO Outlook minimum [17]	IESO Outlook A [17]	IESO Outlook B [17]
EV Penetration	45% - NEB projected sales with Canadian Vehicle Survey age distribution [13], [75]	7% - IESO Outlook A [17]	35% - interpolated from Institut de l'énergie Trottier and e3 Hub 2030 and 2050 projections [14]	45% - NEB projected sales with Canadian Vehicle Survey age distribution [13], [75]
EV Charging Distribut	NREL 50% Home, 50% Work Charging [16]	NREL 50% Home, 50% Work Charging [16]	NREL 50% Home, 50% Work Charging [16]	NREL 75% Home, 25% Work Charging [16]
Electric Heating & HW Penetration	61% residential & commercial – NEB, Trottier, IESO Outlook D & Quebec data [13], [14], [17], [76]	2015 Ontario levels [17]	31% - midpoint value, close to IESO Outlook C [17]	61% residential & commercial – NEB, Trottier, IESO Outlook D & Quebec data [13], [14], [17], [76]
Embedded Rooftop PV Penetration	7% - NEB reference case [13]	25% - NEB technology case projections [13], [76] and high current penetration relative to other regions [65], [77]	20%- NEB technology case projections [13], [76]	30% - similar to high penetration neighbourhoods in California [78], [79]
Non-utility procurement		10% of total demand leaving for microgrids or CPPAs – double losses seen by NV Power [80]		10% of total demand leaving for microgrids or CPPAs – double losses seen by NV Power [80]

3 RESULTS & DISCUSSION

The following sections discuss the results of the model once calibrated with utility data. First it is validated through comparison with the actual data, then the eight case study scenarios are presented.

3.1 BASELINE VALIDATION

Figure III-7 compares the actual, modeled, and normalized seasonal demand curves. The modeled curve shown includes the error from weather disaggregation in the base demand, as described in section 2.2.1.1. Before the inclusion (not shown in figure), the mean absolute percent error (MAPE) between 2017 modeled and actual data was 0.80%, with the highest error being seen in the spring (1.54%). The incorporation of this error into the modeled demand improved the accuracy to only 0.04% MAPE. There was still a very small error, presumably due to the missing data in certain sectors which required some days to be discarded when calculating the actual total seasonal averages. The normalized curve is the demand predicted based on the CWEC dataset.

Similarly, Figure III-8 compares the actual, modeled and normalized peak seasonal demand curves. The fit between modeled and actual curves was not as consistent for the peak demand. While the spring and winter hourly MAPEs were between 1- 2%, the summer and fall were higher at 4.43% and 2.57% respectively. Although the modeled summer peak day did not directly follow the actual data, the error during evening peak hours was only 0.74%. In contrast, the modeled fall data showed a better fit in the night and morning (1.92%) but was significantly over predicted in the late evening (6.03%). This can be partially explained by the fact that the error terms included for the fall were positive due to a general underprediction of fall demand by the model. However, the extremely hot days were generally overpredicted, thus this intended correction actually increased the error. This could also explain to a lesser degree the error in the summer. It also suggests that in future work it may be beneficial to include a sperate error adjustment term for peak demands.

The weather normalized curves were significantly different in some seasons for both average and peak demands. The CWEC data had warmer summer and spring temperatures than seen in 2017, resulting in an increase in modeled cooling demands. In both cases the normalized average daily demand was 3.8% higher, while the peak day demands were over 7% and 14% higher respectively. In contrast, the temperatures in fall 2017 were lower than those in the CWEC dataset. Although this resulted in a projected increase in heating demands, this was offset by reduced cooling demands and resulted in a lower total demand (1.5% less average day and 12% less peak day demands).

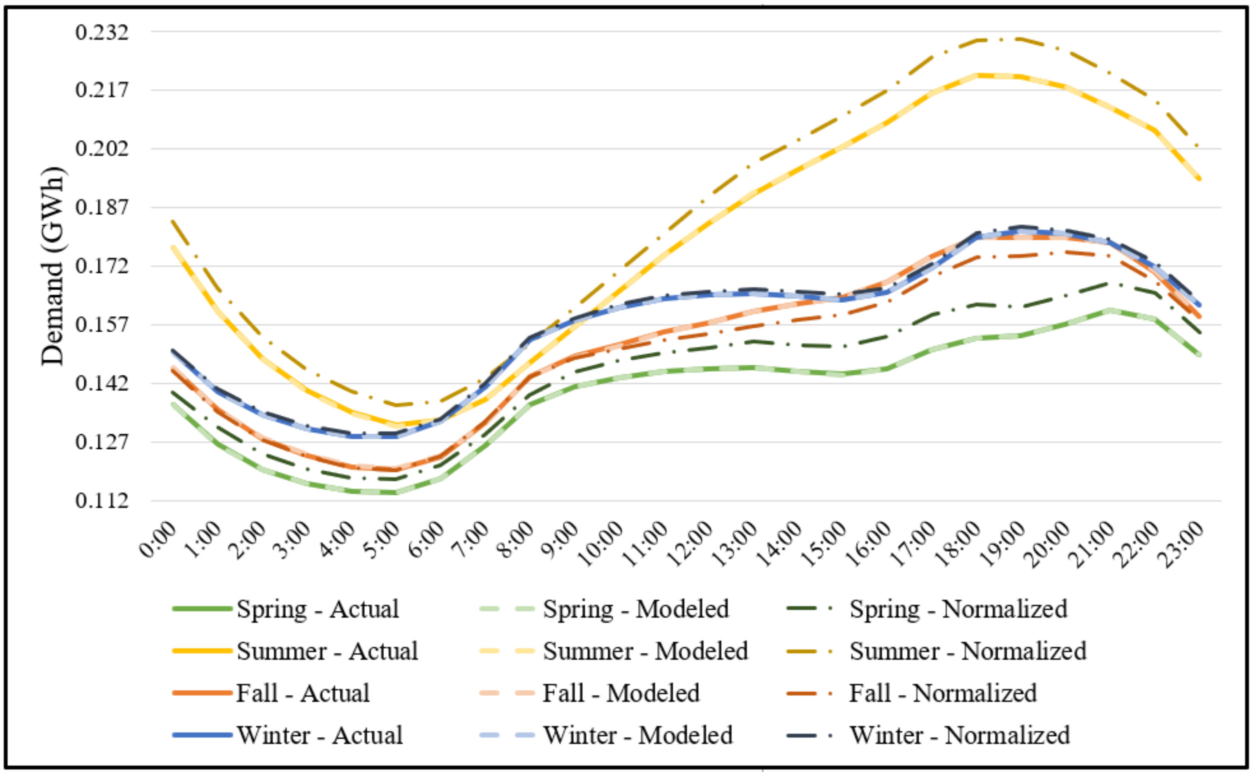

Figure III-7: Actual, Modeled and Normalized 2017 Seasonal Average Demand Curves

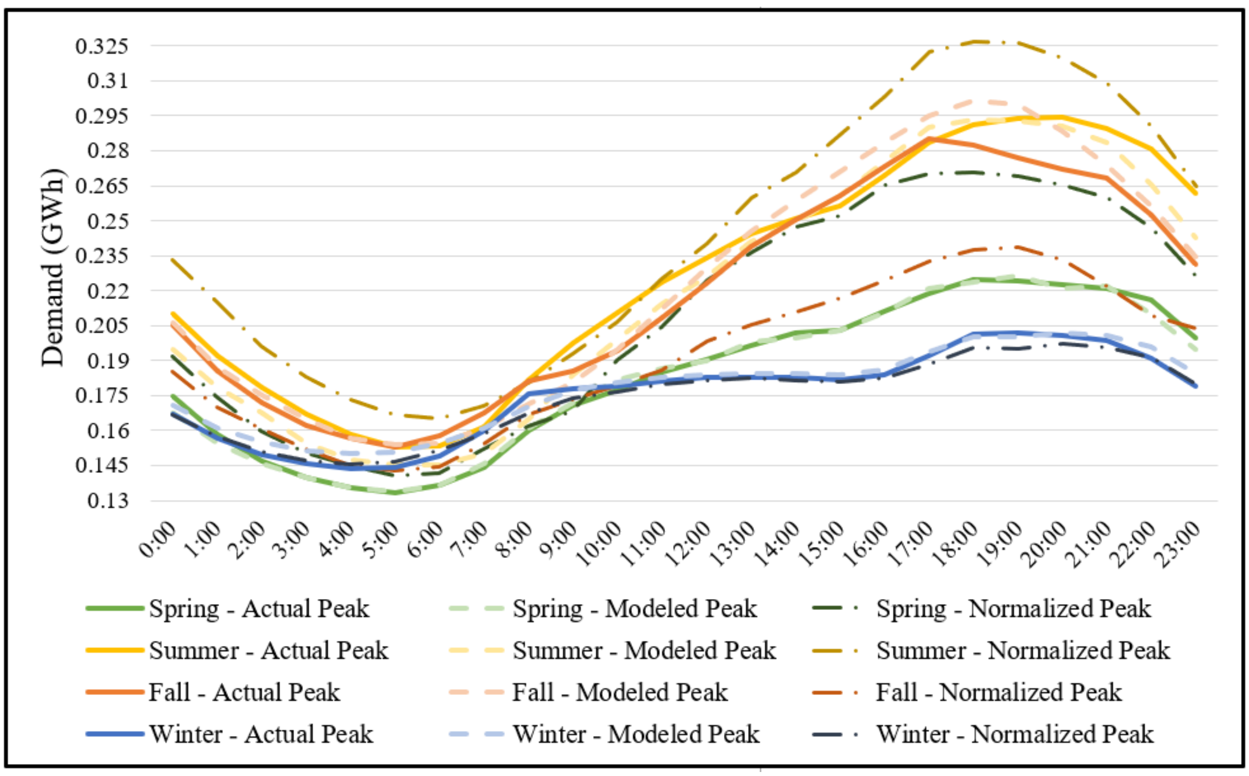

Figure III-8: Actual, Modeled and Normalized 2017 Peak Seasonal Demand Curves

3.2 IESO OUTLOOKS

For each outlook the model produced four seasonal demand curves broken into the various sectors and end uses. An example model output (summer demand curve for the IESO Outlook C) is shown in Figure III-1. To facilitate comparison between scenarios, the 2017 modeled, 2040 projected average and 2040 projected peak demands from each season were combined for each scenario and presented in Figure III-9. A similar combined curve can also be viewed by the user in the model. In addition, Table III-4 shows a variety of metrics which can be used to assess the changes to the demand curve in each scenario. The peak ramp rate is defined as the largest increase or decrease between successive hours in the future average seasonal demand curves. This is important as it indicates the level of flexibility required from supply assets to increase or decrease their generation to match demand. The ramp rates from peak demand curves were not considered in this metric as these represent outlier occurrences and the goal was to quantify the ramp rates which would be commonly experienced in day to day operations under the new scenarios (rather than perhaps only once or twice a year). Note, the 'Modeled 2017' data represents the weather normalized 2017 results, and the bolded values in the peak and daily demand columns represent the total base values. All other values in these columns represent the change from these base values in the given scenario.

Table III-4: IESO Outlook Metrics

IESO Outlook	Change in Peak Demand (MWh)	Change in Avg. Daily Demand (MWh)	Load Factor (Avg. demand / Peak demand)	Peak Ramp Rate of Seasonal Avg. Days (MWh/h)	Avg. Hourly CV of Seasonal Avg. Days
Modeled 2017	**327.0**	**3828.4**	0.488	18.6	12.9%
Actual 2017	-32.7	-66.2	0.533	17.8	12.9%
A	-16.0	-186.9	0.488	18.2	14.2%
B	17.3	321.9	0.502	20.3	14.4%
C	56.1	1367.9	0.565	32.2	15.4%
D	75.8	2009.4	0.604	35.7	14.7%

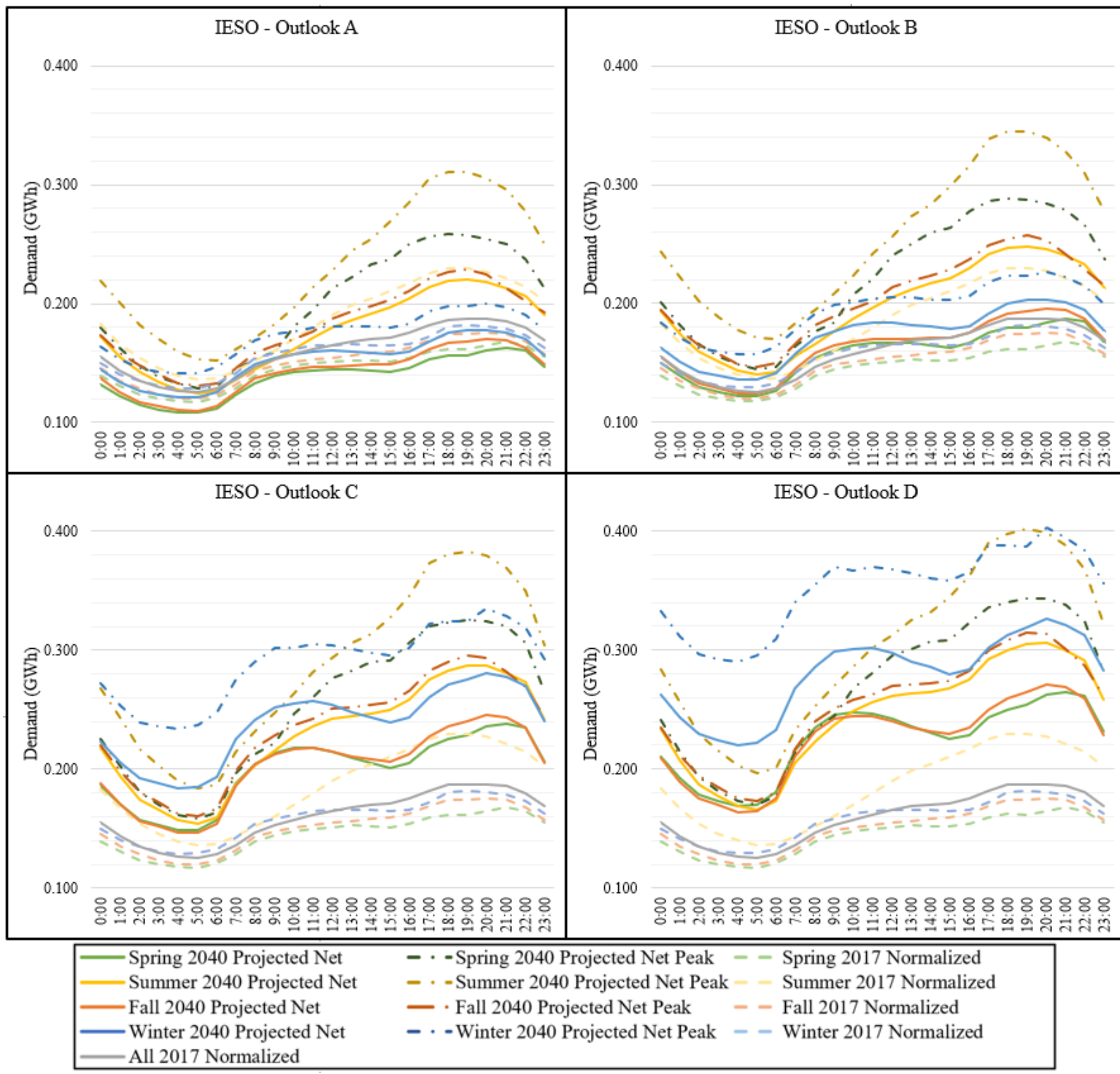

Figure III-9: Projected Seasonal Demand Curves – IESO Outlooks A (Top Left), B (Top Right), C (Bottom Left) & D (Bottom Right)

Table III-4 shows that the weather normalized demand had a significantly higher peak demand as well as a slightly increased average demand compared to the 2017 data. As mentioned previously, the CWEC dataset had higher summer temperatures, which resulted in the large increase in peak demand. These higher summer temperatures and those in the spring were also responsible for the increased average demand, partially offset by the lower fall temperatures. Since the peak load was projected to increase more significantly than average, the load factor decreased from 0.533 to 0.488. These increased weather effects also resulted in marginal increases in peak ramp rate, while the hourly coefficient of variation (CV) stayed constant.

Outlook A showed only a slight decrease in total and peak demand, as well as peak ramp rate, while in Outlook B there was a slight increase in all three. Neither scenario projected significant change in the modifying parameters and as a result Figure III-9 shows marginal change to the overall shape of the curves. Outlook B does show a slightly more pronounced morning peak due to the increased HW demand and electric vehicle charging upon arrival at work. This also explains the increased average seasonal CV of hourly demand curves in both scenarios. Outlook A has an identical load factor to the 2017 modeled data, while the load factor increases to 0.502 in Outlook B. The increase can be explained by the fact that the main differences in parameters (increased electrified heating, HW and EV penetration) add demand either to all seasons equally or in the non-peak seasons disproportionately. Therefore, the peak demand increased relatively less than total demand, resulting in a higher load factor.

Outlooks C and D showed increased electrified heating, HW and EV penetrations as well as high growth in the industrial sector. These resulted in a significant growth in the peak demand and total demand. The ramp-rate also showed a large increase in these scenarios, but as opposed to the peak and total demands, the difference between Outlooks C and D was not significant. In the modeled 2017 data as well as Outlooks A and B, the peak ramp-rate was ramping down as demand plummeted at the end of the day, whereas in D it was a ramp-up in the morning and in C both were almost equal. This is caused by the same factors which resulted in a more pronounced morning peak in Outlook B, but to a much greater degree (as can be seen in Figure III-9). Furthermore, industrial demand was projected to grow significantly due to electrification of fossil fuel end-uses. While overall the industrial sector has a more evenly distributed demand than the residential and commercial sectors, the daily peak ramps very quickly in the early morning. The two pronounced peaks seen in Outlooks C and D also resulted in increased CV values. It is noteworthy that the CV was significantly lower in Outlook D than Outlook C despite a visible increase in daily variability in Figure III-9. This is because CV is a measure of the variance relative to the mean. The higher electrification of heating and industry increased base demand, meaning the variance, represented a smaller proportion of mean demand. A similar trend was also seen with the increasing load factors from Outlooks A to D. Although the increasing peak demands would require a larger capacity not used through the night and non-peak seasons, this would represent an increasingly smaller proportion of the total system capacity.

The increasing load factor values can also be explained by another significant shift which occurred with Outlook D; the projected overall peak demand occurred in the winter instead of the summer. With significant peaks in both the winter and summer, the load is more evenly distributed throughout the year. The IESO projections suggested that the winter peak would surpass summer peaks as early as the late 2020’s in Outlook D and early 2030’s in Outlook C, with the winter peak continuing to increase and widening the gap in the following years [17]. In contrast, these results suggest that the peak demand would have just barely surpassed the summer peak in 2040, and only in Outlook D. This difference is rational since the utility being studied is one of the most southern in Ontario and thus would see much higher air conditioning and lower heating demands than the average Ontario utility.

These four outlooks illustrate the wide range in future scenarios being projected. The results demonstrated that increasing electrification of heating, transportation and industry would result in greater demand variability and increased ramp rates. However, this would also lead to a higher base demand, thus resulting in a higher load factor and potentially a lower relative variability. While the multiple peaks and high ramp rates pose a challenge, particularly in a system with increasing intermittent renewable penetration, if the new loads can become partially dispatchable, the lower relative variance (CV) could be smoothed.

3.3 ADDITIONAL SCENARIOS

The resulting impacts to the demand curves in the high demand, low demand and two duck curve scenarios are summarized in Table III-5, while Figure III-10 shows the projected load curves. Once again, bolded values in the peak and daily demand columns for the weather normalized 'Modeled 2017' scenario represent the total base values, while the remainder of the columns represent the change from these base values.

Table III-5: Additional Scenario Outlook Metrics

IESO Outlook	Change in Peak Demand (MWh)	Change in Avg. Daily Demand (MWh)	Load Factor (Avg. demand / Peak demand)	Peak Ramp Rate of Seasonal Avg. Days (MWh/h)	Avg. Hourly CV of Seasonal Avg. Days
Modeled 2017	**327.0**	**3828.4**	0.488	18.6	12.9%
Actual 2017	-32.7	-66.2	0.533	17.8	12.9%
High	151.6	2364.0	0.539	33.2	18.0%
Low	-48.9	-1142.0	0.403	25.4	27.6%
Duck Curve	47.1	639.3	0.498	31.0	21.9%
Extreme Duck	89.3	487.4	0.432	37.3	29.7%

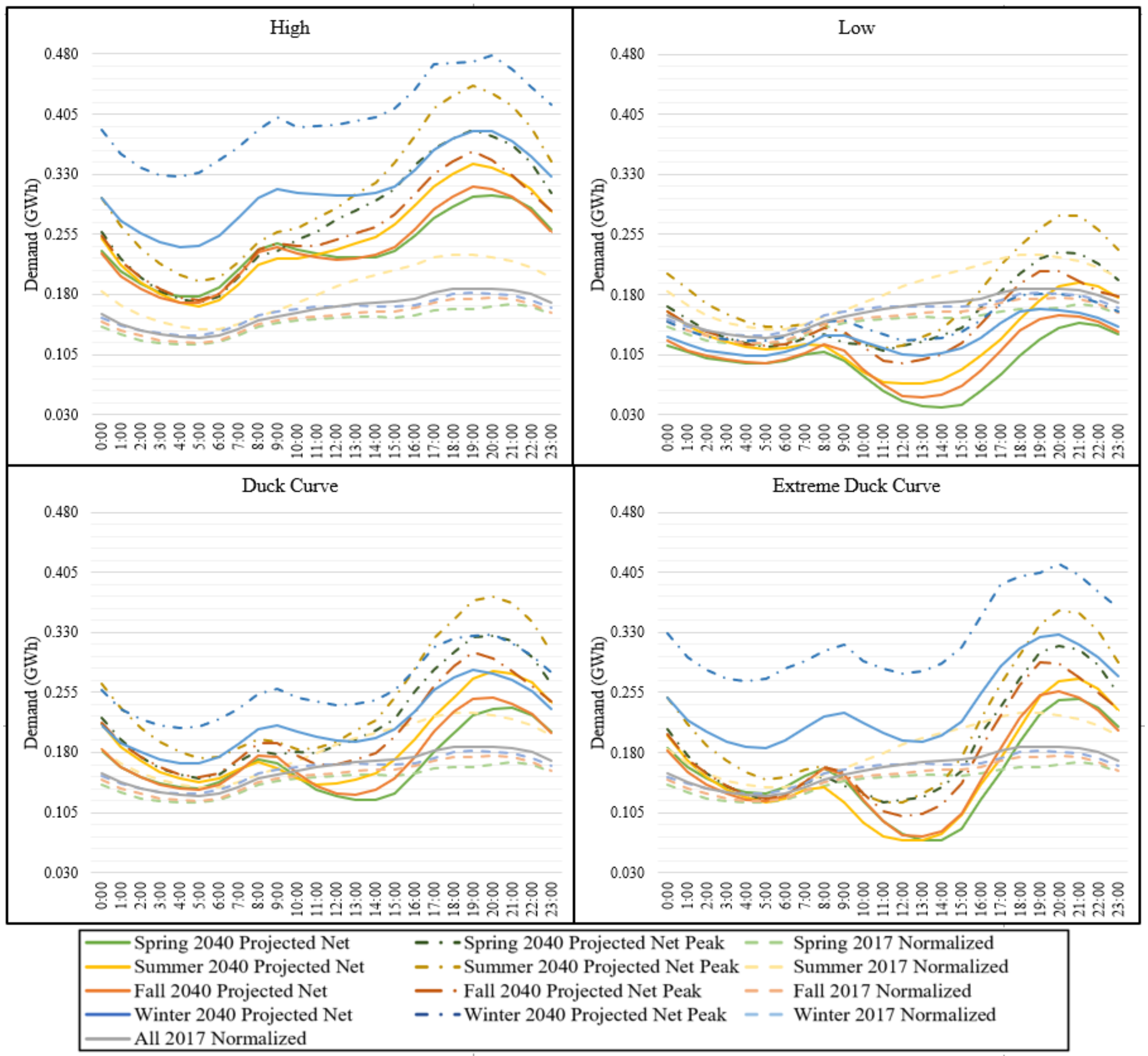

Figure III-10: Projected Seasonal Demand Curves – High Demand (Top Left), Low Demand (Top Right), Duck Curve (Bottom Left) & Extreme Duck Curve (Bottom Right)

The high and low demand scenarios demonstrate the extreme range in demand which could reasonably be expected. The high scenario projects an average of over 3.5 GWh more demand per day than the low scenario, and a peak hourly demand over 200 MW higher. As in the IESO Outlook D, the high demand scenario showed a winter peak due to the large growth in heating demands. Likewise, the increased electric heating, hot water and EV penetration added demand to non-peak seasons, resulting in a more evenly distributed demand throughout the year and generally more favourable metrics. Although there is a large growth in the average evening peak due to the electrical vehicle penetration, the high overall demand meant that the variation was relatively less significant, leading to a high load factor (0.539) and relatively low CV (18.0%). The CV was higher than the modeled 2017 data, but not compared to the low scenario where the CV rose to

27.6% and load factor dropped to 0.403, making the system less profitable and more challenging to manage. The high CV and low load factor were caused by the large quantity of solar supply in the afternoon. Since the PV capacity does not produce much electricity during the evening peak, the peak demand declined significantly less relative to the total demand. The result is a minor duck curve shape. The only factor which would make the high demand scenario more difficult to operate than the low scenario was the peak ramp rate. While the evening demand spike in the low scenario did produce a higher ramp rate than 2017 data, it was not as large as the evening drop-off of the high scenario (25.4 MWh/h compared to 33.2 MWh/h).

Figure III-10 shows that both duck curve scenarios produced a similarly shaped average demand curve to the low demand scenario. A prominent morning peak is followed by a significant decline in demand throughout the afternoon to values even lower than those seen at night. This is then followed by a very large, sustained growth in demand from noon into the evening. Comparing the first duck curve scenario to the low scenario, the lower PV penetration, results in a less significant drop in demand in the afternoon, but the high EV charging demand when consumers return home from work causes a larger evening peak. This scenario uses all parameter values well within the ranges found in literature and exemplifies the sensitivity utilities may have to developing this type of demand curve if not managed properly. While this scenario does have a slightly higher load factor than the modeled 2017 data due to the electric heating and EV penetration balancing seasonal variation, it also has much higher variability throughout the day as shown by the high ramp rate and CV.

The extreme duck curve scenario has even higher penetration of the disrupting technologies and demonstrates the worst-case scenario, with afternoon valleys almost as deep as the low scenario, and peak demands even higher than the previous duck curve. While the peak demand increased almost twice as much compared to first duck curve scenario, the total demand only increased by about half. This is because a large portion of the increased demand from electrification is met by embedded PV assets which, as previously mentioned, do not produce much electricity during the evening peak. Furthermore, the very high electric heating penetration in this scenario resulted in a winter peak, when PV generation is lowest. This combination makes this scenario particularly difficult to manage as there is a low load factor (0.432), and very high peak ramp rates (37.3 MWh/h) and CV (29.7%). The peak winter season has a much smaller range of daily demands and therefore could hypothetically use a relatively high proportion of cheap and clean base supply such as hydro or nuclear. However the other seasons, despite having less total demand, have a much larger daily range and more significant late afternoon to eventing ramp. Assuming base demand generators have limited dispatchability to meet this ramp, it would be necessary to maintain a large quantity of responsive assets to meet these huge demand fluctuations in the other seasons. As a result, there would either need to be redundant idle capacity, or a large proportion of the supply mix composed of quickly dispatchable generators such as those powered by fossil fuels.

These results once again illustrate the extreme range of possible outcomes and the challenging balance of multiple interacting parameters. Electrified heating can balance seasonal demand and create higher proportions of base demand in some scenarios, but it can also cause imbalances if other parameters such as PVs reach high penetration levels. Likewise, EVs may represent an opportunity to replace demand being met by embedded capacity, but this may not be beneficial if they are disproportionately increasing peak demand. Both sets of scenarios highlight the necessity of a tool which allows the user to quickly assess all potential outcomes and balance the risks and rewards with proactive policies and investments.

4 CONCLUSION

This paper presents a model designed to project the shape of the 2040 average and peak seasonal demand curves for a utility based on a wide range of parameters. The model was developed so that the modifying parameters can be adjusted to illustrate their effects and interactions in real time. The changing shape of the daily load curve has non-trivial implications for the operation and profitability of a utility. Thus, this tool enables utilities to examine the range of potential outcomes, assess risk and evaluate mitigation techniques.

The model was calibrated with data from an Ontario utility. The linear model used for weather normalization and disaggregation had a very good fit with 2017 data and the errors were included in the base demand component to reflect any systematic seasonal errors. This could potentially be improved with more specific data about customer appliances to further disaggregate demands into specific end uses, such as heat pumps vs. baseboard heaters, or central vs. portable air-conditioning. The results of the average load curve model were validated against the actual 2017 data showing a very good fit. The peak demands predicted by the scaled load curve model showed adequate fit, but could be improved for extremely hot days, particularly those occurring outside of the hot season (summer). In the future, additional error terms will be considered to improve this fit. Another option for further study would be to use larger quantities of weather data and develop a peak curve based on an upper percentile range, rather than a single peak datapoint. The main limitation of the scaled load curve model is that it assumes sector distributions will remain constant except for the identified disruptive parameters. This may not be valid if relevant factors are overlooked and thus not disaggregated. Future studies could break down each sector further into specific industries and end uses to help further refine the model.

Some additional features will also be added in future versions of the model. This includes the non-trivial quantification of relevant capital costs and revenues for each projected scenario. Additionally, in future work a climate change parameter will scale heating and cooling parameters based on the projections of the Canadian Centre for Climate Modelling and Analysis.

Eight scenarios based on IESO Outlooks and other literature were presented as a case study and to illustrate the significant range in potential demand distributions for a future utility. The resulting notable variations demonstrate the complexity of the system and multitude of scenarios which could be considered. Of those presented, the low load factors and high ramp rates illustrated in the duck curve scenarios showed the potential negative impacts of increasing technology penetration without proper policy and planning. Given the uncertainty of future predictions an immediately illustrative tool of this nature that enables stakeholders to quickly assess a range of projections and identify the impacts and interactions of various technologies or policies can be very valuable. Beyond projecting the impacts of challenging scenarios, the model could also be used to assess how various technologies and policies may be used to mitigate or offset negative impacts.

ACKNOWLEDGEMENTS

This research was conducted with funding support from The Natural Sciences and Engineering Research Council of Canada (NSERC). There are no declarations of interest to be made.

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CONNECTION OF CHAPTER III AND CHAPTER IV

The utility load curve model detailed in Chapter III was the result of several iterations on previous versions of a similar model. The goal was to develop an initial baseline proof of concept and then continually refine it to include more parameters and provide more accurate projections. This presented version will be the first to be published (once accepted), however it has since been continually refined based on additional research and stakeholder feedback. One of the main objectives of this research was to provide tools and analysis for utilities at a finer resolution than the national scale models typically seen in previous literature. Therefore, the next step in this research was to model even lower levels in the distributions system. Chapter IV investigates local technology and customer variability within a utility’s service area at the transformer level, with the goal in mind being to use this information to develop a more refined version of the load curve model. While some modeling and scenario analysis was performed in Chapter IV, this was done outside of the framework detailed in Chapter III. Then, upon conclusion of this research, the utility load curve model from Chapter III was updated to incorporate the finer resolution data, as well as a few additional parameters. These modifications are detailed in Appendix C.

CHAPTER IV: INVESTIGATING DISTRIBUTION SYSTEMS IMPACTS WITH CLUSTERED TECHNOLOGY PENETRATION AND CUSTOMER LOAD PATTERNS

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Under review for publication in the journal "International Journal of Electrical Power & Energy Systems"

1 INTRODUCTION

With the global focus on climate change, there has been increased efforts to transition energy systems from fossil fuels to more sustainable sources. This emphasis has led to significant development in renewable systems such as photovoltaic solar panels (PVs) which are often installed on rooftops and connected directly to local distribution systems. However renewable generation can present challenges as it is intermittent and does not necessarily match demands temporally. Furthermore, the magnitude and timing of demand is changing quickly as sectors traditionally based on fossil fuels such as heating, and transport are transitioning to electric heating (EH) often in the form of heat pumps (HPs) and electrical vehicles (EVs). All of these factors are leading to a large degree of uncertainty in the sector, as evidenced by Utility Dive's 2019 survey of utility workers [1]. With the vast majority of respondents expecting growth in EV and PV penetrations in their region, they described significant forthcoming challenges in terms of justifying emerging investments and managing distributed energy resources. These issues will challenge the energy system as operators struggle to maintain balance with less flexible supply and more volatile demand, while local utilities are required to invest in larger capacity to meet peak demands despite significant portions of their total demand being met by local generation.

Researchers have investigated the potential impacts of these technologies on distribution grid demands. Muratori used a Markov process to construct load profiles for 200 households and 348 EVs, examining the impact of various penetration and charging levels on individual residential customer profiles, as well as on an aggregated transformer profile [2]. Another study modeled the demand of plug-in hybrid EVs on a residential transformer using ten representative weekdays from a metered household and ten generated profiles from representative drivers in the National Household Travel Survey (NHTS) 2009 [3]. The resulting demand curve was used to calculate the estimated transformer hotspot and life loss. Similarly, Gray and Morsi estimated hot spot temperature and resulting transformer loss of life using the NHTS and the 2015 Canadian Plug-in Electric Vehicle Survey to generate EV demand profiles [4]. They also examined the addition of rooftop solar panels, demonstrating that they significantly improved the life of the transformer by decreasing demand and allowing it to cool, even if generation was not concurrent with peak demand. Beaufils and Pineau investigated the impact of these two technologies on utility revenues and concluded common volumetric tariffs would likely not be sufficient to balance revenues with costs [5]. While these studies investigated a variety of charging patterns, they assumed a single representative aggregate base demand for the transformer. This may not be representative of the diversity found within the system.

Another set of literature performed in depth load flow or expansion planning analysis of real, representative, or model distribution systems with new technology penetration. One study used models of a real urban network with 6000 customers, a rural one with 189 residential customers and a ‘generic’ one with 386, combined with real EV data from the SwitchEV project [6]. They found that the distribution system was not homogeneous, with some regions having much higher capacity to handle EV penetration than others (the urban network in their study). Mao, Gao and Wang used Monte Carlo simulation of EV loads and time series analysis to simulate load flow in urban, suburban and rural areas of Columbus Ohio, assessing the loss of life on both continuous loading equipment such as transformers and discrete operation equipment such as voltage regulators [7]. They also found differences in impact between regions, with the suburban area being most prone to depreciated asset value. Another paper examined the impact of PV generation on network losses and congestion in a real distribution system in Barcelona, finding that excessive penetration actually increases these issues (particularly in semi-urban areas) and concluding analysis should be done on a local basis [8]. Other studies used statistical databases on representative residential customer groups in order to generate various representative consumer and network load curves. McKenna et al. modeled demand for seven UK household types and found the optimal PV, HP, or PV and HP capacities to serve each household [9]. Neighborhood characteristics were then clustered into three groups and representative networks developed for each using the household types. Load flow analysis was applied to each network under various penetration rates of PV and HP, finding that infrastructure upgrade costs were lower in urban areas [9]. Another study examined three potential future scenarios considering EV, PV, HP, and micro combined heat and power, as well as demand flexibility [10]. Load profiles were modeled for old and new residential developments in 10 population densities. Finally, an expansion planning model formulated as an MILP problem was also used to investigate the optimal configuration of technology penetration, considering EV, PV, Wind and energy storage (ES) [11]. The results showed that implementation of ES along with EVs delayed investment in infrastructure. These studies provide valuable insight, however, focus exclusively on residential transformers. While the main impact from EVs is expected to be on residential transformers, one proposed method for shifting the load and impact from EVs is through diverse charging opportunities such as at workplaces or public charging stations [6], [12]. Likewise, other technologies such as HP and PVs will be present with all customer types.

The representative clusters of customers or neighborhoods used in many of the previous studies are based on detailed statistical and demographic data which may not be available to utilities or system operators for refined regions within their service areas. They could instead simulate the entire system with actual data and additional load added for various scenarios, as Neaimeh et al. did for specific regions [6], but this requires significant computing resources. Instead, this paper proposes that representative transformer load profiles could be determined through clustering, allowing a much lower volume of analysis to identify potential risks, opportunities and strategies for mitigation in diverse regions across the service area. Clustering of demand curves has already been performed in a number of studies for the targeting of customers in demand response initiatives [13]–[15]. However, as far as the authors are aware the only such clustered analysis applied to transformer level loads on the distribution system was by Wamburu, et al. [16]. This study used transformer load data from a small city and clustered the average daily load curves, illustrating significantly different distributions and hypothesizing about the reasons and impacts. However, they did not use these clusters as the basis for their investigation and instead performed a detailed analysis on all of the transformer load curves, examining how heavily each transformer was loaded compared to its capacity, before adding EV demand and presenting the change in loading. Additionally, this paper postulated that technology penetration will not be uniform and thus investigated scenarios of disproportionate penetration across transformers [16]. This assumption is supported by studies such as Javid and Nejat's which developed a multiple logistic regression model to predict EV penetration in different counties based on demographic, economic and infrastructure characteristics [17]. Another study recognized this potential as well and suggested these clustering effects could result in significant local impacts even at low overall penetration [2]. In fact, similar clustering effects in terms of customer behaviors and end-uses can explain the variations and patterns of baseline load currently observed across transformers.

Based off these observations, this paper presents an investigation into the impacts of technology clustering and penetration on distribution transformers. The first contribution of this paper is an assessment of the current technology clustering effects, through examining localized penetration rates of PVs, and EH at the transformer level in a real utility service area. This can serve as a reflection of what range of distributions may be reasonably expected with new penetrating technologies in the future. Next, clustering analysis is performed on real transformer loads to find eight diverse representative load curves. Finally, a variety of EV, PV, EH and ES penetration scenarios are presented to illustrate how each transformer cluster is impacted by the technologies and their interactions. Based on these results, a variety of mitigation techniques can be assessed to develop policy recommendations. Additionally, the impacts in each scenario are aggregated up to the total demand curve because the local distribution system is not the only factor impacted and this must be considered in order to make informed decisions. Specifically, this paper investigates the disconnect between local optimal operation of energy storage, and operation which is optimal for the overall system. The use of a small number of representative clusters simplifies the analysis, reducing computing needs and allowing for a wide variety of scenarios to be quickly assessed.

2 MATERIALS AND METHODS

This paper presents an investigation into the local variability of customer types and technology penetration within the distribution system of an electricity utility and the potential future impacts of new technology penetration. The current penetration of PV and EH across different transformers was assessed as an indication of the relative differences which could also be expected from new technology. Clustering was then performed to identify a set of representative typical load curves for transformers within the city. Finally, a set of scenarios for increased EV, PV and EH technology penetration was assessed for each transformer cluster, to examine the potential system impacts and policy implications.

Clustering was used to identify customer characteristics as well as to group transformers into representative clusters based on similar load curve patterns. The k-means method was selected for all clustering performed in this analysis due to its simplicity and certainty of convergence. Furthermore, comparison of different clustering methods has shown that k-means performs well when the goal is to identify a range of unique and representative load patterns [18]. It was implemented in Python with scikit-learn, using the optimized 'k-means ++' seeding method to improve convergence speed [19]. In all cases the goal was to group similarly distributed curves regardless of magnitude. Thus, prior to clustering all load curves were normalized by dividing all data points by the mean demand for that customer. Using this method, the normalized data still represents daily and seasonal fluctuations, but on a relative basis (as a percentage of average demand).

Customer demand data from a southwestern Ontario utility was used in this investigation. The data was filtered to remove any customers with more than 30 days of missing data. After filtering, the data included hourly meter data for 79497 residential, 7669 commercial, and 201 industrial customers, as well as 761 distribution connected solar panel installations. This data is mapped to the 6272 distribution transformers; however, no additional customer description was available, nor the capacity ratings of each transformer. The following sections will detail the methodology used to assess the local variability and establish representative clusters for the case study scenarios. First the technique used to assess local technology penetration is detailed in Section 2.1 followed by the method for clustering transformer load curves in Section 2.2, and lastly the methods by which future scenarios were generated are presented in Section 2.3.

2.1 LOCALIZED PENETRATION

Each solar installation was identified as a unique customer and thus the customer penetration at any given location could be easily identified as the ratio between PV customers and other customers. In contrast, no data was available on which households contained electric heating, therefore this had to be determined from the load data. To achieve this, residential and commercial customers were grouped into clusters and those belonging to clusters where the demand showed a strong correlation to cooler temperatures (increasing demand) were assumed to have electric heating. As mentioned previously, clustering of customer load profiles is common and despite not specifically focusing specifically on electric heating, several works have identified clusters with different space conditioning characteristics in a similar manner [20], [21]. The method used in this paper is tailored specifically to the objective of identifying heating and cooling characteristics.

The clustering was performed with demand data at both daily and monthly resolutions. The use of daily demand eliminated hourly variance due to customer behaviour differences, while providing many data points to establish the relationship with temperature. Meanwhile, the monthly resolution provided a clear display of seasonal patterns and provided validation. Cluster membership is not definitive in the k-means algorithm as the clusters identified may vary with repetition, thus using two resolutions facilitated comparison and confirmation of memberships. A customer was assumed to have a significant portion of EH if included in the strongly temperature dependant cluster at either resolution, or if at both resolutions it was included in either the moderate temperature dependence cluster or the cluster which transitioned to high temperature dependence (added EH during the year). The number of clusters was determined through the elbow method, as well as examining the results to ensure appropriate differentiation between the groups with regards to their relationship with temperature. Both residential and commercial customers were grouped into 12 clusters.

2.2 REPRESENTATIVE TRANSFORMERS

Clustering was also applied to group transformers with similar demand distributions and identify a representative set. The total net demand (sum of all customer demand and local PV production) in each hour was used as the basis for clustering. Several outliers were identified where certain transformers had extreme changes in demand for a portion of the year (presumably due to new development or system restructuring), or significant capacities of solar panels were installed part way through the year. Thus, to avoid clusters converging to these extreme outliers, the normalized net data was filtered to remove any transformer with a peak or minimum value higher/lower than a factor of 10 or -10. This method assumes that no transformer would see demand (or production) in any hour ten times that of the overall average, unless there was a significant compositional change through the year. Since the goal is to identify representative clusters, these unique cases are not relevant and thus the total number of transformers clustered was reduced from 6272 to 6123.

When selecting the number of clusters to use in this case it was essential to balance the need for a large enough set to represent the full range of variations, while not so large to require excessive modeling efforts when assessing scenarios. Once again using the elbow method and examination of the resulting clusters, eight was selected as the final number.

2.3 TECHNOLOGY PENETRATION SCENARIOS

In order to assess the impact of future technology penetration on each of the representative transformer clusters a variety of scenarios were modeled. One load curve was estimated for each cluster using the average characteristics of the cluster along with the normalized profile. The baseline demand for each cluster was first estimated by multiplying the normalized profile by the average hourly net demand for the transformers in the cluster. Several additional loads or supplies were then calculated for each scenario to account for the impact of increased EV, PV, EH, and ES penetration. The same method was also applied with the total utility demand to illustrate how these factors may also impact operation of the larger scale electricity system.

The total potential EV demand was calculated based on the Independent Electricity System Operator's (IESO) estimates in their planning outlook (9.22 kWh/vehicle/day [22]), as well the estimated future number of light duty vehicles in the city. This value was estimated based on historical growth in vehicles per capita in similar Southern Ontario cities [23] and the population in the region [24]. The demand can then be scaled by the estimated penetration rate. A constant average daily distribution and demand was assumed for each day of the year, however the shape of the distribution depended on whether vehicles were determined to be only charged at home, or at work as well. Fischer, Harbrecht, Surmann and McKenna, as well as Shepero and Munkhammar modeled EV demands with stochastic Markov chains and showed how the distribution of EV demand would differ between charger locations, presenting distributions with notably similar shapes [25], [26]. Therefore, the distribution used for scenarios with only home charging was a weighted average of the profiles adapted from Fischer et al. for different types of occupations. This was weighted by the relative quantity of demand expected for each occupation, the percentage of workers falling into each category and the estimated proportion of people who use their vehicle each day in each category [25], [27], [28]. When charging both at home and at work were assumed, the profiles for each location were adapted from those produced by Fisher et al. under the assumption the driver charged their vehicle whenever possible (regardless of current state of charge). In this case approximately 56.4% of demand was met at home, with the remainder occurring at work [25]. With either distribution, whichever portion of demand occurred at home was allocated to each representative transformer based on the proportion of the total number of residential customers located in that cluster. Meanwhile, the proportion of workplace demand on transformers was allocated to the commercial and industrial customers based on current employment statistics (60% and 40% respectively) and assumed to be proportional to the demand [29]. This method assumes that bigger workplaces with a higher electricity demand will likely have more employees, and as a result more EVs charging there.

In order to simulate the impacts of increased PV penetration it is necessary to estimate the potential for growth. Total theoretical capacity was calculated based on Wiginton, Nguyen and Pearce's estimation of approximately 3.01 kW of potential rooftop capacity per person in a comparable region of Southern Ontario [30], and the population in the region [24]. Based on the formulas provided by [30], it was also estimated that approximately 60% of viable roof area is residential, with the remainder being flat rooved commercial or industrial buildings. These total potential capacities were then allocated to each transformer cluster similarly to the EVs: residential potential based upon the proportion of total customers in the cluster, and commercial/industrial based on the proportion of total sector demands. The current installed PV capacity in each cluster was also estimated from the local generation data and a regional capacity factor from Natural Resources Canada [31]. These localized current and potential capacities could then be used to determine approximate capacity penetration rates for each transformer (as opposed to the previously mentioned customer penetration rates from section 2.1). The historical cluster generation curves can then be scaled and subtracted from the baseline demands using the baseline capacity penetration and the penetration specified in the scenario. The exception to this process was cluster 6 where there was insufficient current PV capacity and instead the total generation load curve and penetrations were used as proxy.

Similarly to the PVs, the estimated electric heating demand was calculated using the historical data and scaled based on projected penetration increases. Only the data from cluster 5 was used to determine historical heating demand as this transformer group had very high heating penetration and thus was assumed to demonstrate the best representation of high penetration demands. It was assumed that the aggregate residential heating demand distribution would be similar across different clusters, however this may not be the case for commercial demand since different customer types may have significantly different demand distributions. Furthermore, many of the transformer clusters had low numbers of electrically heated commercial customers, making it difficult to disaggregate a heating distribution which could be reliably scaled. For these reasons, only residential heating penetration was considered as a factor in the scenarios. The data from cluster 5 was scaled to fit each transformer cluster based on the proportion of residential customers and projected penetration. Furthermore, the impact of air source HPs was also assessed by scaling heating demands by the estimated coefficient of performance based on temperature data. It was assumed the HPs would be sized to meet all heating demands and the performance follows the average relationship to temperature detailed by Szekeres and Jeswiet [32]. The variable speed centrally ducted HP was selected due to the capacity to meet all demands even at low temperatures, and the fact that most Ontario households already have central heating and/or cooling [33], [34].

Since only total demands were known, the estimated heating demands from the cluster 5 residential customers had to be disaggregated using a model based on previous work [35]. Several adjustments were made to account for the significantly higher heating penetration in this data. Firstly, several additional variables were added for the sun angle, and civil/nautical dawn and dusk times, to account for the period before/after complete sunset/sunrise where additional lighting may also be required. Furthermore, it was found that in the presence of both significant cooling and heating, the algorithm disaggregated too much demand into both categories, resulting in extremely low base demands. Placing a buffer of 3 degrees on either side of the determined changepoint temperatures for calculating heating and cooling degrees improved model fit and produced base demands closer to expected values. This was confirmed through the concept of the 'locus of minimum load,' which suggests that the days of minimum load in the transition months between heating and cooling seasons will show similar demand distributions and be representative of the total load without heating or cooling (baseload) [36]. Examining the Tuesdays, Wednesdays and Thursdays (which have the most consistent demand distributions) in April, May, September and October (transition months with days of minimum load), the average hourly base demand produced by the modified model had a mean absolute percent error of only 0.9% when compared to the locus of minimum load. Further details on the updated disaggregation model can be found in Appendix C, Section 2.2.

The use of ES at each transformer was simulated using an algorithm. When applied, it was assumed that a battery system with the same specifications of a Tesla Powerwall would be implemented: 13.5 kWh of energy, 5kW maximum continuous real power and 90% round trip efficiency [37]. For the purpose of this algorithm it is assumed that the battery charges and discharges fully once per day. Thus, for each day of the year, 1 kWh of 'charging demand' and 'discharging supply' are allocated to the hours with the lowest and highest net demand respectively. This is repeated until the total demand and supply capacity has been allocated for each day. Note that on the last repetition of this algorithm one full kWh hour is not allocated, only the remaining portion of charging and discharging capacity. The max power capacity is respected by ensuring that the total charging or discharging in a given hour is at most 5kWh. In order to demonstrate how optimizing ES for the local transformer vs. total aggregate demand can result in differences, the same algorithm was also applied to the total demand curve, allocating 6272 times as much supply and demand (1 ES unit/transformer). This can then be compared to the distribution formed by aggregating the individual transformer cluster results.

In order to assess the impacts of each of these technologies on each transformer cluster, a wide variety of scenarios were assessed. The median transformer has 12 customers, while the average has 14, meaning that the lowest possible penetration above 0% for some technologies on a typical transformer is ~7-8%. For transformers with residential customers, the customer numbers increase to 14 and 16, meaning a minimum penetration of 6-7% for technologies which are one unit per household, and 3.5-4% for EVs (an estimated 1.8 vehicles per household). These values represent the minimum penetrations examined, while the others are based off of projections from the literature and the localized clustering effects demonstrated in Section 3.1. Scenarios investigating penetration of multiple technologies were also considered to determine the impacts of their interaction and examine specific policy implications. All of the scenarios assessed are described in Table IV-3 to Table IV-7 of section 3.3.

3 RESULTS & DISCUSSION

The following sections detail the results, including variations in localized penetration (Section 3.1), the representative transformer clusters (Section 3.2) and implications of future penetration scenarios (Section 3.3).

3.1 LOCALIZED PENETRATION

Based on the total number of PV installations and other customers, the overall customer penetration rate can be estimated at under 0.9%. However, when looking at the ratio on a transformer level, this can be seen to vary significantly. Given that when there are low customer numbers, penetration rates become insignificant (for example one of two customers equals 50% penetration) the following analysis focuses on transformers with a larger number of customers. Not including transformers with less than ten non-PV customers, the penetration ranges from 0-25% and more than 100 transformers had over ten times the average penetration. Figure IV-1 shows the full distribution of PV penetration rates across transformers with at least 10 non-PV customers. There are also 3643 transformers fitting this criterion which have no PV installations (0% penetration) and are not included in the figure to avoid stretching the vertical axis and allow easier visualization of the distribution. Although also excluded from the figure, it is also worth noting that one transformer with 9 residential customers had an extremely high 67% penetration, demonstrating how even more extreme outliers can occasionally be observed in small areas.

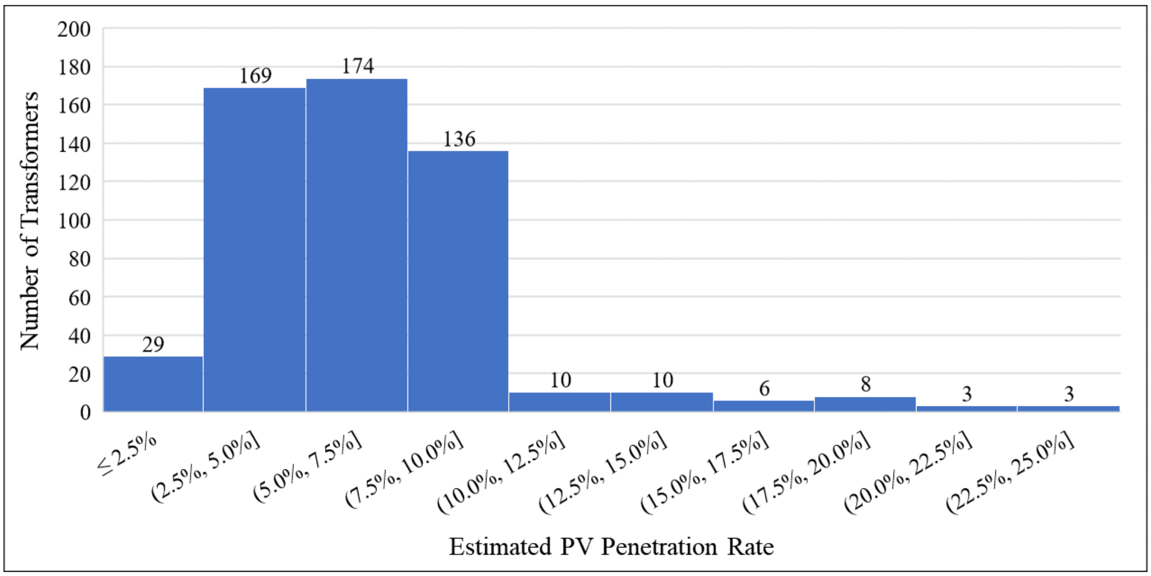

Figure IV-1:PV Customer Penetration Across Transformers

In order to identify the customers with EH, all customers were clustered into twelves groups and the relationship between demand and temperature was examined. This large number of clusters allowed for the differentiation of a customer group with very significant temperature dependence (full EH), as well as one with less significant relationships (combined systems or supplemental electric heating). Furthermore, smaller outlier clusters were identified, such as customers which transitioned from high temperature dependence at the beginning of the year to low dependence at the end of the year (~1% of residential and 2.5% of commercial customers), and visa versa (~1% of residential and commercial customers). These were assumed to represent customers which changed heating systems or occupancy during the year.

Based off the method established it was estimated that approximately 10.7% and 14.4% of residential and commercial customers respectively have EH. These values are close to the provincial averages estimated in previous studies: 10.6-19.3% for residential [22], [38], [39] and 10-17% for commercial [22], [40]. As with PV installations, the penetration rates showed significant localized variation. Of the 3944 transformers which had at least 10 residential customers with complete data, 2420 had at least one customer with electric heating, while 231 had more than triple the average penetration rate. In fact, 32 transformers showed 100% penetration of residential EH. A histogram displaying the full distribution of residential EH penetration rates across transformers with at least 10 customers can be seen in Figure IV-2.

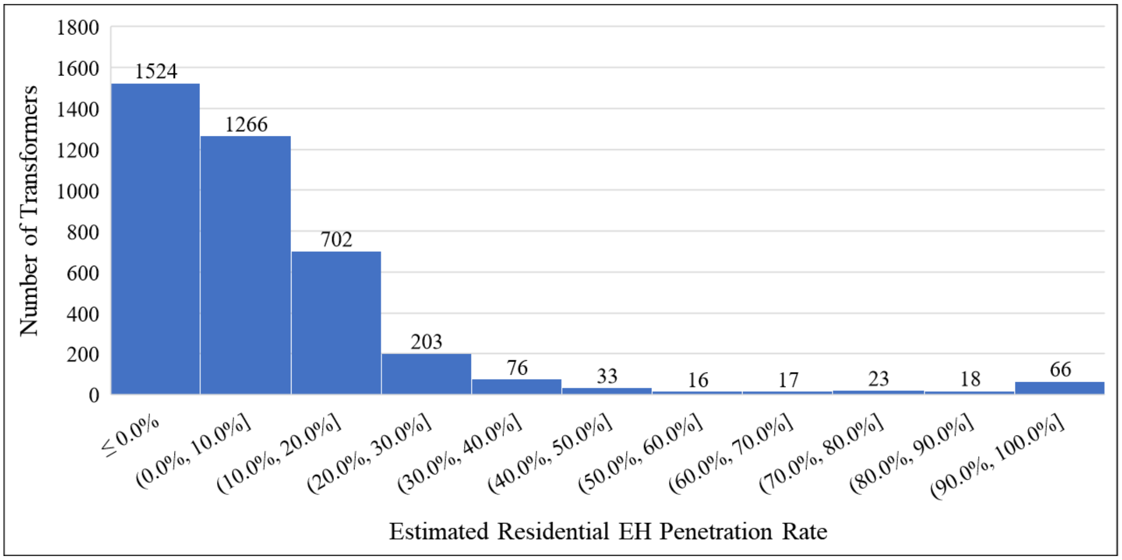

Figure IV-2: Residential EH Penetration Across Transformers

Most transformers with commercial customers had much lower numbers of customers, making the local penetration rates in many cases not relevant (ex. 100% if there is only one commercial customer). Of the 2361 transformers with commercial customers without missing data, only 446 had at least 5. The penetration rates in these cases ranged from 0-67%, with 63 transformers having double the average penetration rate. Figure IV-3 shows the full distribution of commercial EH penetration rates across transformers with at least 5 commercial customers.

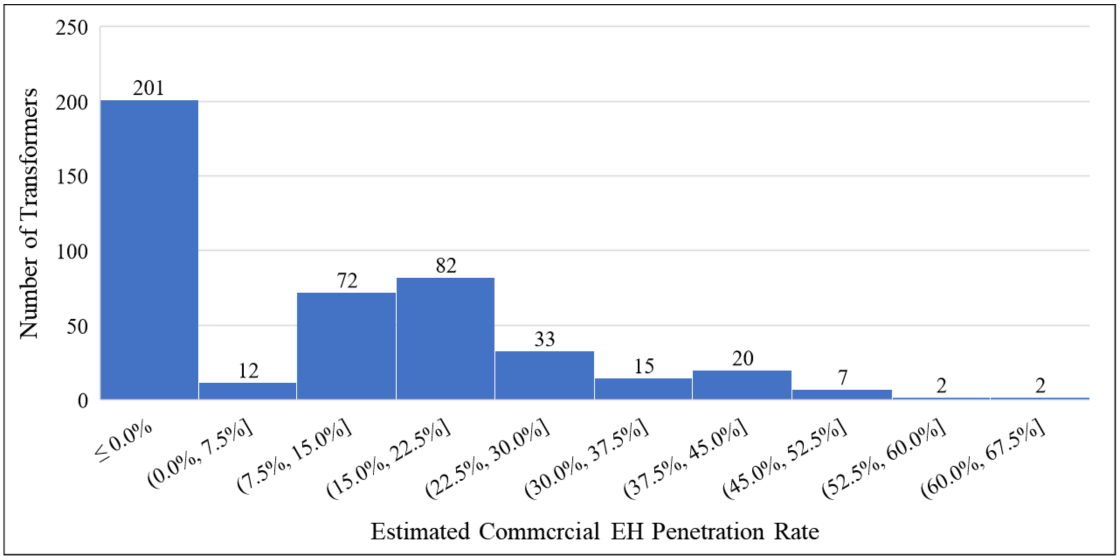

Figure IV-3: Commercial EH Penetration Across Transformers

The localized penetration rates vary significantly across different parts of the distribution system. This was shown for both new developing technology (PVs), as well as older ones (EH) and demonstrates the need for the analysis performed in this paper. Firstly, the concentrated grouping of these different technologies will result in vastly different local load profiles which must be considered when modeling future impacts on the distribution system. Furthermore, when assessing and planning for the growth of new technologies and their impacts, it is essential to consider this clustering effect and model higher penetration scenarios than what might be expected on average. For example, although it may be many years before EV penetration reaches 25% on average, PVs have already reached 25% penetration in a few neighbourhoods despite an average penetration of only 0.9%. Examining the impacts of higher penetrations will help to prepare for these occurrences and allow for informed policy development to minimize negative impacts.

3.2 REPRESENTATIVE TRANSFORMER LOAD PROFILES

The clustering of distribution system transformer load profiles produced eight representative distributions. The seasonal averages of these curves can be seen in Figure IV-4 and the extreme variation between clusters demonstrates the need for more detailed analysis than just sector averages when modelling potential impacts on the distribution system and making policy decisions. Through examining these results and the customers connected to the transformers in each cluster, it was possible to draw some generalizations about what each cluster represents. This information is summarized in Table IV-1, along with the number of transformers belonging to each cluster. To illustrate how the localized clustering of technology can have an impact on and correlate with different load profiles, Table IV-2 describes the estimated penetration rates for PV and EH in each cluster. Data removed as outliers is also included in the tables labeled as cluster 99, to provide transparency in regard to the type size and proportion of customers which were removed.

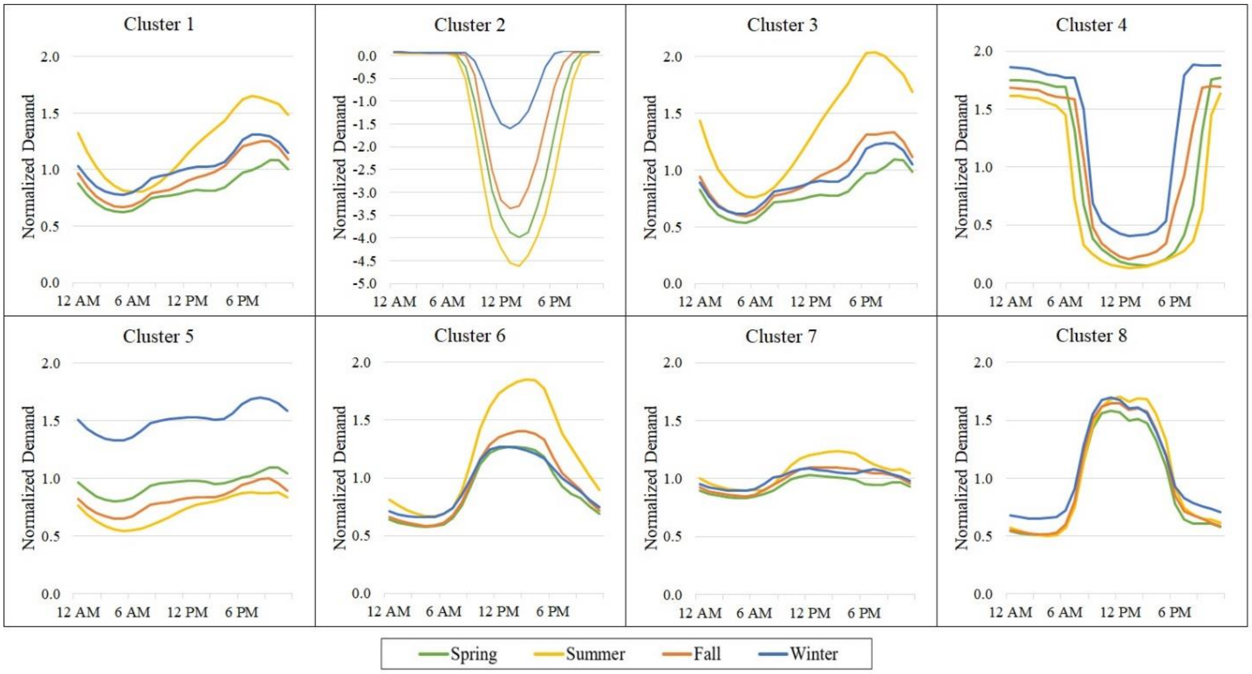

Figure IV-4:Transformer Cluster Average Seasonal Load Curves

It can be seen that clusters 1 and 3, which represent over 70% of all the transformers in the city, contain the vast majority of residential customers (93%) and thus are likely located in residential neighbourhoods. In addition, there is a significant quantity of small businesses: commercial customers with average annual demand significantly less than the overall average. Similarly, the large number of PV installations (85% of total) show relatively small average productions, as might be expected from residential or small business rooftop installations. The main difference between these clusters is that Cluster 3 has a higher proportion of residential customers and also shows a much more pronounced increase of demand in the summer, suggesting higher cooling demands. Without further customer information it is difficult to determine if this is due to larger housing, or older housing with lower insulation and less efficient cooling systems. Cluster 3 also has a below average proportion of EH and thus a lower winter demand which further accentuates the relative peaking in the summer.

Meanwhile, Cluster 5 represents a significantly smaller number of neighborhood transformers where there is a very high EH penetration, resulting in a significant winter peak. This cluster contains a large number of residential customers as well as 600 moderately sized commercial customers (close to average annual demand). However, upon investigation it was noticed that both sets showed almost identical average load distributions, suggesting that these commercial customers may simply be apartment buildings which do not have unit submetering and thus are registered as larger commercial customers. This suggests that cluster 5 may be representative of more urban neighborhoods, as is also supported by the higher number of larger industrial customers compared to clusters 1 and 3.

Clusters 6 to 8 are representative of transformers located in business areas, mostly containing commercial and industrial customers. As evidenced by the average annual demand in Table IV-2, the majority of customers in Cluster 6 are medium sized businesses, which can be seen in Figure IV-4 to have significant cooling demands in the summer. Cluster 8 has a similar average demand for commercial customers, but also includes some bigger industrial ones and PV installations. The load curve shows a similar shape, but has significantly less seasonality, partially due to PV generation matching the seasonal demand variance. Continuing this trend, Cluster 7 contains a bigger proportion of even larger commercial, industrial and PV customers. The load curve shows little variation between seasons or even within the day and therefore likely represents transformers for large shift-based facilities which operate 24/7 such as hospitals, factories, etc.

Finally, clusters 2 and 4 both represent unique situations seen by only a small number of transformers (23 and 88) which are unlikely to be useful for modeling, but nonetheless should be separated from the other clusters. Cluster 2 represents transformers with extremely large, likely ground mounted, PV installations which mostly have their own dedicated transformers. Meanwhile, cluster 4 contains many commercial customers with high demand at night and minimal during the day, which have been assumed to be street lighting. Another small subset which was fit into this cluster due to the load curve similarity, is transformers with mixed customer demands and very large PV installations which drop net demand to near, or below, zero during the day.

Table IV-1: Transformer Cluster Descriptions, Counts and Demands

Cluster	Description	Transformer Count	Total Number of Customers				Average Annual Customer Demand (MWh)			
			Res.	Com.	Ind.	PV	Res.	Com.	Ind.	PV
1	Moderate space conditioning demand - residential	1,597	30,943	1,832	1	292	6.8	18.4	223.7	-11.9
2	Mostly large ground mounted PVs	23	0	17	3	25	0.0	13.1	2.6	-227.1
3	High cooling demand - residential	2,891	42,975	496	0	357	7.5	14.9	0.0	-6.4
4	Streetlights & large commercial / industrial rooftop PVs	88	33	209	4	7	5.0	19.8	674.5	-294.4
5	High heating demand commercial & residential	484	3,731	600	17	22	10.3	60.0	968.0	-29.1
6	High cooling demand - commercial	364	475	2,117	32	5	6.0	35.4	187.7	-1.7
7	Low variability industrial & commercial customers	517	1,026	1,759	78	9	5.6	164.6	3,439.7	-220.4
8	Low space conditioning commercial	159	23	407	52	19	5.9	40.9	519.1	-120.0
99	Outliers	149	291	232	14	25	2.6	29.1	51.3	-214.3
All		**6,272**	**79,497**	**7,669**	**201**	**761**	**7.3**	**61.2**	**1,599.0**	**-271.2**

Generally, Table IV-2 shows that the technology penetration rates were relatively consistent across clusters, except in extreme cases where the technology became one of the defining characteristics of the cluster. Both residential and commercial EH ranged between 10-18% except for cluster 5 where penetration was extremely high, and clusters 3 and 6 which were defined by particularly large cooling peaks and low heating demands in their respective dominant sectors.

The PV penetration was not included for cluster 2 as there were more PVs than non-PV customers and as mentioned previously it is believed to include multiple large ground mounted facilities. When comparing the customer penetration rates (percentage of customers with PVs) previously discussed in section 3.1 to the capacity penetration rates (current capacity as a percentage of estimated regional potential capacity) estimated with the method detailed in section 2.3, they are significantly lower (total values of 0.9% vs. 2.5%). However, a large portion of this difference can be explained by some very large installations including the assumed ground mounted ones in cluster 2. Since the factor used to estimate total potential capacity only considered rooftop potential, ground mounted facilities should not be considered in the penetration rates. Furthermore, it is worth noting that if only residential customers are considered and it is assumed all PV installations under the IESO's microFIT contract structure (<10kW capacity [41]) are residential installations, then the gap disappears. With these assumptions the estimated customer and capacity penetrations are 0.9% and 1.0% respectively. This may be an over estimation of both penetration rates as some microFIT contracts are with commercial customers, however it shows that including only smaller installations which would be expected to have less variance in capacity from customer to customer, the approximations using both methods are similar. This implies that current penetration is higher among large commercial and industrial customers compared to smaller businesses, resulting in the higher overall estimated capacity penetration rate compared to the customer value.

Table IV-2: Transformer Cluster Technology Penetration Rates

Cluster	Estimated Technology Penetration			
	Residential EH	Commercial EH	PV (Customer)	PV (Capacity)
1	13.4%	16.2%	0.9%	1.8%
2	NA	18.8%	NA	NA
3	4.0%	11.8%	0.8%	0.9%
4	18.5%	15.7%	2.8%	71.8%
5	66.7%	51.0%	0.5%	1.5%
6	15.1%	7.1%	0.2%	0.0%
7	16.5%	10.3%	0.7%	1.9%
8	13.6%	10.4%	1.9%	6.3%
99	15.6%	17.1%	4.7%	68.8%
All	**10.7%**	**14.4%**	**0.9%**	**2.5%**

3.3 SCENARIO IMPACTS

Clusters 2 and 4 were not considered in these scenarios since they represent a small number of outlier transformers for which the investigated technologies are for the most part not relevant. The results and analysis focus on the three mainly residential clusters (1, 3 and 5) and three predominately commercial and industrial ones (6, 7 and 8). The results of all scenarios are summarized in Table IV-3 to Table IV-7, showing the relative scenario peak demand compared to the baseline peak demand (Rel. Peak), the number of hours in the scenario where the demand is over 115% of the baseline peak demand (Hrs > 115%) and the ratio of average demand to peak demand, or load factor (LF). While the impact of the load curve on transformer life is not specifically modeled, previous work has used the guideline that an increase in peak hourly load of 15% over the nominal transformer capacity decreases its life by a factor of ten, and another factor of 10 for a 50% increase [2]. The capacity of the transformers in this study are unknown and the current peak loading can vary significantly even within one utility service area [42], however comparing the change in peak load still provides a sense of the potential impact on distribution infrastructure, particularly in any areas which already are close to capacity. As transformer peaks increase utilities may need to invest in new capacity, meaning increased capital costs; however, if the total demands increase as well, this also will lead to increased revenues. Therefore changes in the LF metric, as the ratio between peak and average loads, provide an approximate ratio between changes in utility revenues and capital costs. The 'utility death spiral' mentioned in the literature review would occur when peak loads increase significantly while LF declines.

The results for scenarios with increasing EV penetration can be seen in Table IV-3. Regardless of charging pattern, the minimum penetration of 4% has insignificant impact on the peak load and load factor. At penetrations of 25% or higher, significant effects are observed. With home charging only, two of the mainly residential clusters (1 and 3 which representing over 70% of all transformers) show increases in peak demand of more than 15%. This result is aligned with previous literature. Muratori projected a growth in transformer peak hourly load factor of 25-65% for 50% penetration depending on charging infrastructure, while 100% penetration led to 54-88% growth [2]. The adapted data used in this study considers mixed infrastructure and most residential transformers showed 28-34% peak growth for 45% penetration and 62-76% for 100% penetration. These corresponded to 51-114 and 430-1383 hours over the 115% threshold in each scenario. Notably, the smaller number of transformers with a winter peak (cluster 5) had much less significant impacts. Overall, the increased peaks were found to be mitigated when both home and work charging are used as the load is then spread across all transformers, and the commercial/industrial clusters show less significant impacts. This suggests that EV charging load does not coincide as significantly with baseline peak load hours in these sectors. This is also beneficial for the aggregate demand curve, reducing the evening peak and more evenly distributing EV demand throughout the day. However, even with mixed charging locations, at penetrations of 45% or higher, the two residential clusters as well as cluster 7 show over 15% peak growth once again. At 100% penetration all clusters have exceed this threshold and cluster 7 shows 77%

increase in peak demand with over 1000 hours above the 115% threshold. Clusters 6 and 8 which generally represent smaller commercial and industrial customers were least impacted by EV penetration, with minimal increases in peak demand until higher than 45% penetration.

While such high penetration rates may seem to be problems of the distant future, the analysis of localized clustering showed that at a technology penetration rate as low as 1% (projected for EVs by 2025 based on National Energy Board (NEB) sales estimates and historical vehicle age distributions [43], [44]), individual transformers can show up to 25% penetration. Furthermore, based on the NEB's technology case projections, penetration is expected to reach 27% by 2035 and 45% by 2040. If distributed at all similarly to current EH, by this point one could expect many transformers to reach 100% penetration. These results suggest that EV penetration could begin to significantly impact individual transformer lifespans in the near future.

Table IV-3: EV Penetration Scenarios by Transformer Cluster

EV Pen. & Charging	**Cluster**	**1**	**3**	**5**	**6**	**7**	**8**	**Total**
	Baseline LF	41.6%	33.2%	43.0%	38.4%	64.1%	36.4%	52.9%
4% - Home Charging	Rel. Peak	103%	102%	101%	100%	100%	100%	102%
	Hrs > 115%	0	0	0	0	0	0	0
	LF	41.8%	33.4%	43.0%	38.4%	64.1%	36.4%	52.8%
4% - Home & Work Charg-ing	Rel. Peak	101%	101%	101%	100%	100%	100%	101%
	Hrs > 115%	0	0	0	0	0	0	0
	LF	41.8%	33.3%	43.3%	38.8%	64.6%	36.7%	53.1%
25% - Home Charging	Rel. Peak	119%	116%	106%	101%	100%	100%	111%
	Hrs > 115%	7	1	0	0	0	0	0
	LF	41.9%	34.4%	43.0%	38.5%	64.1%	36.4%	51.9%
25% - Home & Work Charging	Rel. Peak	111%	109%	104%	101%	101%	101%	106%
	Hrs > 115%	0	0	0	0	0	0	0
	LF	42.0%	33.8%	44.6%	41.0%	67.5%	38.3%	54.2%
45% - Home Charging	Rel. Peak	134%	128%	111%	101%	101%	100%	120%
	Hrs > 115%	114	51	0	0	0	0	16
	LF	42.0%	35.2%	43.1%	38.6%	64.1%	36.4%	51.3%
45% - Home & Work Charging	Rel. Peak	120%	117%	107%	102%	120%	103%	112%
	Hrs > 115%	10	1	0	0	39	0	0
	LF	42.2%	34.3%	45.8%	43.0%	59.7%	39.5%	54.9%
100% - Home Charging	Rel. Peak	176%	162%	125%	102%	101%	100%	144%
	Hrs > 115%	1383	430	28	0	0	0	303
	LF	42.1%	36.8%	43.1%	38.9%	64.1%	36.5%	49.9%
100% - Home & Work Charging	Rel. Peak	146%	137%	130%	117%	177%	126%	127%
	Hrs > 115%	218	118	34	4	1216	117	69
	LF	42.5%	35.2%	43.3%	42.9%	45.9%	36.3%	56.5%

Increasing penetration of rooftop PV is a concern not only for the grid operators who are fearful of the operating challenges of a potential 'duck curve' [45], but also utilities whose profits may begin to erode from net metering [1], [46]. Satchwell, Mills and Barbrose found that the impacts of customer-based PV on revenue outpaced the reduced infrastructure costs but suggested that this impact could be minimized by targeting areas where the PV installations most effectively deferred capital costs [46]. This can be assessed by examining the effect on the peak demand and load factor for the scenarios in Table IV-4. All clusters showed reduced peak loads with increasing penetration, except cluster 5. This is because it is the only cluster with a significant winter peak, a season in which PV production is lowest and most limited in time due to shorter day lengths. Notably, the predominately commercial/industrial clusters showed more significant peak reduction than the residential ones. In fact, at low penetration the reduction in peak demand outpaces the overall reduction in demand causing the load factor of curves to increase. As penetration increases beyond 25% this effect is reversed because the new peaks become during hours of low or no production which thus cannot be reduced significantly by PVs. Additionally, PV generation begins to exceed demand in many hours. These results indicate that that commercial or industrial PV installations may be best poised to defer capital investments for utilities and could in fact improve their revenue faster than costs in certain areas expecting growth. However extreme penetration levels will significantly reduce revenues. Furthermore, since the total system peak coincides with residential peak demand, high PV penetration does little to reduce peak demand for the total system and would result in lower utilization for other generation assets. As with EVs, these high penetration rates can be expected in the near future on certain transformers due to unequal localized penetrations (currently 100 transformers with ten times average penetration). The NEB technology case projects a doubling of solar capacity by 2030 and five times as much by 2040.

Table IV-4: PV Penetration Scenarios by Transformer Cluster

PV Pen.	**Cluster**	**1**	**3**	**5**	**6**	**7**	**8**	**Total**
	Baseline LF	41.6%	33.2%	43.0%	38.4%	64.1%	36.4%	52.9%
7%	Rel. Peak	99%	98%	100%	96%	96%	99%	99%
	Hrs > 115%	0	0	0	0	0	0	0
	LF	40.3%	32.3%	42.0%	38.7%	65.5%	36.5%	52.0%
25%	Rel. Peak	98%	96%	100%	89%	90%	91%	98%
	Hrs > 115%	0	0	0	0	0	0	0
	LF	34.5%	28.0%	38.4%	38.5%	64.8%	37.2%	47.2%
50%	Rel. Peak	97%	95%	100%	84%	88%	84%	97%
	Hrs > 115%	0	0	0	0	0	0	0
	LF	26.3%	21.6%	33.4%	36.3%	58.9%	35.9%	39.9%

Increasing electrification of heating could prove to be a major source for increased revenues for electricity utilities in the coming years. Table IV-5 shows the results of scenarios with increasing

EH and demonstrates that at 40% penetration most transformers show little to no impact on peak demand. However, with higher penetration winter peaks grow significantly beyond the 115% threshold and even the 150% threshold with 100% penetration. Likewise, the total grid peak grows to 110% and 138% in each of these scenarios. This impact can be significantly mitigated if high efficiency HPs are used. These results suggest that with moderate EH penetration, or high HP penetration, utilities could benefit from increased revenues without capital investment in higher capacity infrastructure. Similarly, this would improve utilization of the current grid level generation assets, without requiring additional capacity investments. However, it should be noted that these results may not be indicative of the impacts in colder climates where a winter peak is currently seen, such as in more northern Ontario. Once again, while these high penetration rates on average are unlikely, they are already currently observed on some transformers and the IESO projects a doubling of penetration by 2035 in some scenarios [22]. It is also important to note the 40% and 67% scenarios presented in Table IV-5 represent reduced and baseline penetrations for cluster 5, explaining the different impacts compared to clusters 1 and 3.

Table IV-5: EH Penetration Scenarios by Transformer Cluster

EH Pen. & System	**Cluster**	**1**	**3**	**5**	**6**	**7**	**8**	**Total**
	Baseline LF	41.6%	33.2%	43.0%	38.4%	64.1%	36.4%	52.9%
40% - Standard	Rel. Peak	101%	100%	89%	100%	100%	100%	100%
	Hrs > 115%	0	0	0	0	0	0	0
	LF	48.9%	41.8%	45.3%	38.7%	64.2%	36.4%	57.9%
40% - HP	Rel. Peak	100%	100%	89%	100%	100%	100%	100%
	Hrs > 115%	0	0	0	0	0	0	0
	LF	44.3%	36.1%	45.3%	38.5%	64.1%	36.4%	54.6%
67% - Standard	Rel. Peak	139%	119%	100%	100%	100%	100%	110%
	Hrs > 115%	158	4	0	0	0	0	0
	LF	41.4%	40.5%	43.0%	39.0%	64.4%	36.5%	56.7%
67% - HP	Rel. Peak	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
	Hrs > 115%	0	0	0	0	0	0	0
	LF	46.9%	38.2%	43.0%	38.6%	64.2%	36.4%	56.1%
100% - Standard	Rel. Peak	186%	157%	114%	100%	100%	100%	138%
	Hrs > 115%	916	284	0	0	0	0	235
	LF	36.2%	35.7%	40.8%	39.4%	64.6%	36.5%	49.5%
100% - HP	Rel. Peak	104%	100%	105%	100%	100%	100%	100%
	Hrs > 115%	0	0	0	0	0	0	0
	LF	48.2%	40.8%	42.2%	38.8%	64.3%	36.4%	58.0%

The potential impacts and interactions of multiple technologies penetrating to high levels are presented through a set of scenario results in Table IV-6. In these scenarios EVs were assumed to always have access to home and work charging. The increased peak demand with high EV penetration can be partially offset when PV penetration is also high (45% and 25%). This is particularly effective in clusters 6 and 8 with small to medium sized business customers. However, as penetration increases still further (100% and 50%), this effect does not continue. The two scenarios including HP penetration demonstrate that even at significant penetration levels (67%) these will have no impact on the peak demands. Meanwhile, the additional demand due to electrified heating during non-peak seasons could serve to offset the reduced revenue due to net metered PV. However, with extreme penetration of all considered technologies the results are less promising: extreme peak load growth of 14-86% requiring investment in expensive capital, and lower load factors indicating less revenue relative to this capacity. It is also noteworthy that the extreme combination of EV and EH penetration results in overall system peaks being seen on winter mornings when heating demands are high and consumers begin charging their EVs at work.

Table IV-6: Technology Combination & Mitigation Scenarios by Transformer Cluster

Penetration	**Cluster**	**1**	**3**	**5**	**6**	**7**	**8**	**Total**
	Baseline LF	41.6%	33.2%	43.0%	38.4%	64.1%	36.4%	52.9%
45% EV 25% PV	Rel. Peak	114%	109%	107%	91%	120%	99%	106%
	Hrs > 115%	0	0	0	0	30	0	0
	LF	37.8%	31.1%	41.5%	43.7%	43.4%	55.0%	51.5%
100% EV 50% PV	Rel. Peak	134%	124%	130%	114%	176%	123%	116%
	Hrs > 115%	62	19	34	0	1062	81	1
	LF	34.3%	28.8%	35.9%	37.2%	39.2%	32.2%	49.8%
45% EV 25% PV 67% EH - HP	Rel. Peak	114%	109%	107%	91%	120%	99%	106%
	Hrs > 115%	0	0	0	0	32	0	0
	LF	42.4%	35.7%	41.5%	43.9%	55.1%	38.3%	54.5%
100% EV 50% PV 100% EH - HP	Rel. Peak	148%	124%	134%	114%	176%	123%	134%
	Hrs > 115%	305	29	56	0	1066	83	99
	LF	36.6%	35.0%	35.4%	37.5%	39.3%	32.2%	46.9%

To illustrate the effects of high technology penetration scenarios and help understand why certain technologies are impacting different transformer clusters each way, several resulting demand curves are presented in Figure IV-5. This shows the average summer and winter demand curves, as well as the peak demand curve for clusters 1, 6 and 8 when there is 45% EV (charged at work and home), 25% PV and 67% HP penetration. In the mainly residential cluster 1, the EV charging occurs in the evening, coinciding with current peak demand periods, and not when PV's are producing power. In contrast, the two predominantly business sector clusters show peak EV demand in the morning, just before demand begins to ramp up for the workday. Furthermore, the peak demands through the afternoon occur simultaneously to PV production, particularly in the summer when cooling demand and PV generation are highest. However, it can also be seen that most PV generation does not occur at the same time as EV charging, particularly at work. Thus if penetration levels increase still further, the peak morning EV demand quickly overtakes the baseline afternoon peak. This explains the reduced mitigating effect of PVs at high penetration observed previously from Table IV-6. This also demonstrates why the positive impacts of simultaneous EV and PV penetration are not produced with the larger customers in cluster 7, as Figure IV-4 shows they exhibit minimal afternoon peaking.

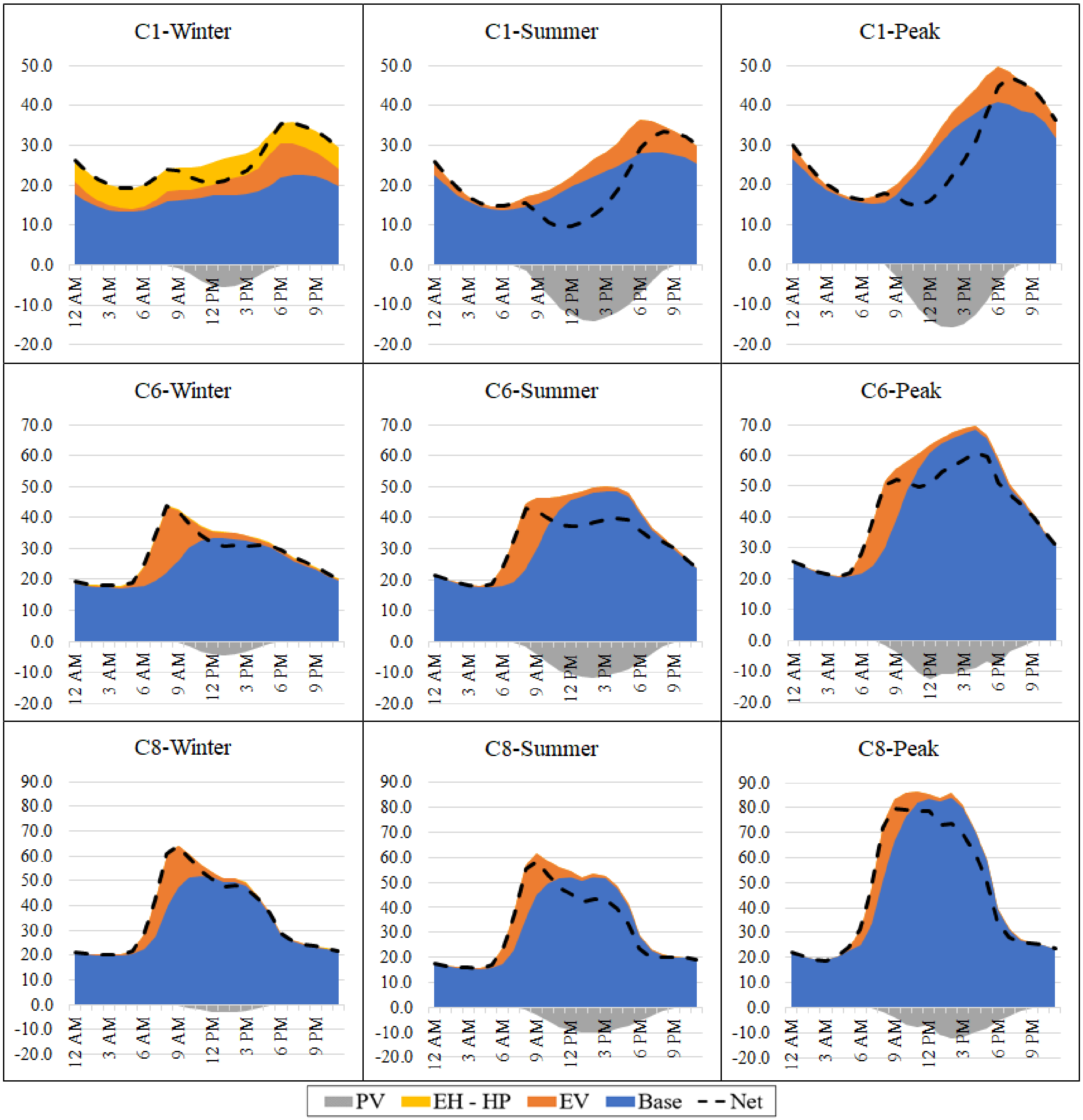

Figure IV-5: Transformer Clusters 1, 6 & 8 with 45% EV, 25% PV and 67% EH – HP Penetration

The last set of scenarios (shown in Table IV-7) investigates the use of ES to assess its ability to mitigate the negative impacts of technology penetration. Comparing these results to the baseline scenarios without ES in previous tables shows that, as expected, ES is able to reduce peak demands and increase LF for all transformers. However, the effectiveness varies by cluster, with the residential ones showing the most significant impact. This is because these are smaller transformers with less load, thus the ES capacity represents a larger proportion of total demand. Conversely the very large transformers in cluster 7 show very little effect from only 13.5 kWh of energy storage. On all residential clusters ES can be seen to more significantly reduce the peak demand in high EV penetration scenarios, than switching from home only charging, to both home and work charging, or implementing higher penetration of PVs. This is not the case in the small business clusters 6 and 8 where PV is more effective until both EV and PV reach very high penetration. In the extreme penetration scenarios, one Powerwall equivalent of ES is still effective at reducing peak demand, but in several cases not below the 115% threshold. With increasing capacity of ES the effectiveness at reducing peak demands decreases significantly on residential transformers but remains relatively constant on commercial/industrial ones. With three Powerwall equivalents, all transformer clusters can maintain peak demand at 111% or less except for cluster 7 where the extremely large transformer size would require much more significant storage to be effective.

The column labeled “Total” in Table IV-7 displays the aggregated effects on the total demand curve, assuming each transformer has one unit of ES and operates so as to optimize locally. The “Grid” column uses the same capacity but optimizes for the overall grid demand. While initially the difference is small, with increasing technology penetration and variability of demand a significant difference between local and regional optimality develops. This suggests that it is necessary to determine a balance between servicing overall grid peak, so as to avoid unnecessary investment in significant peaking assets, while also serving local needs to reduce capacity requirements and extend the life of distribution system components. Since in most scenarios residential transformer load profiles best match the total profile in terms of peak demand timing, energy storage units on these transformers show the best conformity to energy storage which is optimized to total grid. It is only once extreme EV and EH penetrations are reached (resulting in winter morning peaks) that commercial ES begins to better align.

Table IV-7: ES Mitigation Potential by Transformer Cluster

Scenario	Cluster	1	3	5	6	7	8	Total	Grid
	Baseline LF	41.6%	33.2%	43.0%	38.4%	64.1%	36.4%	52.9%	52.9%
25% EV - Home only ES	Rel. Peak	110%	106%	100%	94%	98%	95%	106%	104%
	Hrs > 115%	0	0	0	0	0	0	0	0
	LF	45.3%	37.8%	45.9%	41.2%	65.5%	38.3%	54.5%	55.4%
45% EV ES	Rel. Peak	110%	107%	101%	96%	117%	99%	108%	105%
	Hrs > 115%	0	0	0	0	1	0	0	0
	LF	46.4%	37.7%	48.4%	45.7%	61.1%	41.0%	57.1%	58.6%
45% EV 25% PV ES	Rel. Peak	103%	99%	101%	84%	117%	93%	100%	97%
	Hrs > 115%	0	0	0	0	8	0	0	0
	LF	41.7%	34.5%	43.9%	47.6%	56.2%	40.8%	55.0%	56.3%
100% EV 50% PV 67% HP ES	Rel. Peak	123%	111%	119%	107%	174%	117%	124%	116%
	Hrs > 115%	59	0	6	0	1048	1	29	1
	LF	41.6%	36.8%	39.0%	40.0%	39.9%	33.9%	49.4%	52.8%
100% EV 50% PV 67% HP 2 x ES	Rel. Peak	116%	103%	110%	100%	171%	111%	121%	105%
	Hrs > 115%	5	0	0	0	1011	0	15	0
	LF	44.2%	39.9%	42.3%	43.0%	40.5%	35.8%	50.6%	58.4%
100% EV 50% PV 67% EH - HP 3 x ES	Rel. Peak	111%	98%	108%	92%	168%	105%	121%	99%
	Hrs > 115%	0	0	0	0	982	0	15	0
	LF	46.5%	42.1%	43.5%	44.9%	41.1%	37.8%	49.3%	59.8%

3.3.1 ANALYSIS

While average penetration of EVs and PVs may not pose significant challenges in the near future, the current localized penetration of PVs showed over 100 transformers exhibiting ten times the average penetration. Thus, even at low levels which do not justify significant investments in diverse charging infrastructure, some residential transformers may begin to be impacted. The analysis showed that PVs were relatively ineffective at decreasing the growth in peak demand on such transformers, while ES proved more effective. Furthermore, on residential transformers the local optimal operation of ES generally aligned well with optimal operation for the grid, thus allowing deferral of investment in new transformers, while also potentially providing larger scale grid services. Residential EH demands were shown to have little impact on peak loads until extremely high penetrations if high efficiency HPs were implemented. These could be incentivised by utilities as an opportunity for increased revenues without exacerbating the need for capacity investments. As EV penetration increases further, it would be beneficial to diversify the charging demands across transformers by encouraging or establishing charging stations as workplaces, particularly smaller businesses. These transformers also proved to be a good fit for PVs since the times of high generation better match peak demands as well as a small portion of the expected new EV charging demands. However, commercial and industrial areas were not as well matched for ES as their higher loads per transformer would require larger storage capacity to be effective, and the local optimal operation does not align as well with the aggregate grid requirements.

4 CONCLUSION

This study investigated the localized clustering of technology penetration and demand curve shape across the distribution system of an electric utility. It was found that even at low overall technology penetration some transformers exhibited much higher localized levels. Furthermore, transformer load curves varied significantly throughout the distribution system, even within sector groups. With a set of representative load curve clusters an analysis was performed to assess the impact of increased EV, PV, EH and ES penetration on transformers. The EV load curves were estimated based on previous literature and the projected peak load growth for residential transformers produced similar results to other studies, showing that high penetration could significantly reduce transformer life or require additional capacity investments. The impacts of PV and EH penetration in this study were based on historical data and showed that these technologies have varying effects on the peak load across different transformer clusters. Finally, the simulation of energy storage at each transformer cluster, as well on the total grid, showed differences in optimal operation. One limitation of the method used in this study is that despite better accounting for variability in transformers baseline loads, it only considered average EV charging profiles. While this produced similar results to previous literature it could be improved by using multiple EV charging profiles to determine how effects may vary with clustered differences in local driving behaviours. Additionally, with more diverse charging profiles future work could assess the potential for smart charging of EVs and investigate the impacts of various capacities of charging infrastructure.

Based on the results obtained a series of recommendations can be made. Firstly, investment should be encouraged in diverse charging infrastructure to distribute load across transformers. ES is best implemented in residential neighbourhoods where it can effectively balance loads while simultaneously providing aggregate level grid services. In the region studied, residential EH if in the form of high efficiency HPs can provide increased revenues for utilities and will have little impact on transformer peak. Meanwhile, PVs are most effective at reducing peak demand on commercial and industrial transformers where baseline and projected EV charging demands are better aligned with the times of generation. These strategies could be implemented to defer infrastructure costs either through tailored customer incentives or direct investment by system operators and local distribution companies.

ACKNOWLEDGEMENTS

This research was conducted with funding support from The Natural Sciences and Engineering Research Council of Canada (NSERC), however they were not involved in the research or preparation of the manuscript. There are no conflicts of interest or competing interests to disclose.

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CHAPTER V: ENGINEERING CONTRIBUTIONS AND FUTURE RECOMMENDATIONS

1 SUMMARY AND CONCLUSIONS

Concerns over climate change and long-term sustainability are leading to significant changes in our energy systems. As such a wide range of studies have been undertaken to predict and project the future of energy systems. However, many of the most thorough of these efforts are performed on the national scale and require significant volumes of data. Processing on this level of analysis quickly becomes extremely computationally intensive if trying to increase resolution, and extreme local variations are often overlooked. Therefore, this work provides a significant research contribution by focusing on comprehensive models at a finer geographic resolution. These can be calibrated by regional authorities using mostly their own in-house data and leveraged to gain insights into potential extreme local impacts. Furthermore, many extensive national level studies still present a large degree of uncertainty around how extensively and how quickly these system transformations will occur. For these reasons, rather then predicting specific scenarios, this thesis focused on the development of parameterized models with interfaces which allow the user to quickly assess a wide range of parameters and scenarios. By limiting to a finer geographic scope, the models presented provide the capability for utilities to process the overwhelming volume of smart meter data increasingly available into simplified informative projections. The dynamic design facilitates assessment of the potential impacts, opportunities and challenges which might occur in their specific region, under a vast array of scenarios.

To begin, Chapter II focused on disaggregating total electricity data from smart meters into base, heating and cooling end-uses, to allow utilities to leverage this local data for future modeling analyses. The regression model developed built on previous changepoint models adding several new features and showed a good fit with both the aggregate residential and commercial sector data from the utility partner. It was found that extending the concept of degree days to different lengths of time allowed for short and long-term weather effects on demand to be better represented, while implementing variable changepoint temperatures depending on the time and type of day improved results still further. Peak cooling demands not seen in some of the previous study areas were further reflected in the model though inclusion of probit analysis to approximate gradually installed portable units. The developed method allows creation of valuable data for future analysis, facilitating weather normalization, projection of future climate change impacts, and assessment of changing technology for these services in future analyses.

The utility level load curve model presented in Chapter III contributes to the literature by establishing a parameterized dynamic framework allowing users to easily shift and scale sector and end-use load curves based on input scenario settings. The design facilitated visualization of how each of the factors and their interactions specifically impact local seasonal load curves. The tool could be used to quickly assess a range of scenarios and sensitivities, highlighting challenges and opportunities. A review of national and provincial literature allowed synthesis of a diverse set of potential scenarios which were implemented in the model using data from a utility in southern Ontario. These projections demonstrated significant changes to the local daily demand curve, highlighting similar and unique potential issues and opportunities to those discussed in previous literature, in the context of the specific utility studied. Most importantly, these scenarios illustrated the extreme range of outcomes being projected by different sources and the current uncertainty in the industry, demonstrating the need for such flexible modeling techniques at refined geographic levels. Overall the model advances techniques in scenario assessment for utility planning and risk mitigation.

In Chapter IV the level of analysis was further refined geographically to consider implications of new technology penetration within local utility distribution systems. Previous literature has suggested that technology penetration may vary within a service area, impacting different regions more significantly, however no studies were found quantifying these factors. This study investigated localized technology penetration rates for EH and PV across transformers and showed significant variance. This emphasizes that while overall penetration of new and developing technologies may remain low in the immediate future, distribution system models should also consider the impacts of much higher penetration levels to prepare for the smaller proportion of local extremes which will inevitably be produced. Transformer load curves were then clustered into a representative set of eight curves, showing that significant variation also occurs in baseline load throughout the utility service area and reinforcing the need for refined levels of modeling. In depth system load flow analysis was often performed in previous literature to assess impacts to the system however this has significant data and computational requirements. This study instead used the clustered representative transformer profiles and a similar parameterized, scenario-based modeling technique to that in Chapter III, to simplify the assessment of future transformer loads, while still reflecting system variability. Once again, the parameterized design eases examination of the impacts of moderate technology penetration as well as potential local extremes. As with other chapters, the method provides a way for utilities to process smart meter data into a fairly computationally simple model facilitating the assessment of future impacts and evaluation of policy decisions.

2 FUTURE RECOMMENDATIONS

The set of models presented in these studies and their application with smart meter data from a utility in southern Ontario provide an illustration of the uncertainty in the industry, and examples of the type of insights and value which can be gained through modeling. It was shown that the effect of technologies can vary significantly and can become impactful locally even when overall adoption is low. This reinforces the need to assess and prepare for extreme scenarios which may be seen in outlier examples, alongside more realistic ones likely to be broadly seen across the network. The model results serve as a recommendation of techniques utilities can use when considering their future business pathways and looking to make informed decisions.

The results also led to a few technology and sector specific recommendations to guide future policy development and investment. Firstly, it was shown that uncontrolled home EV charging can significantly increase total and local peak demands. Rooftop PV installations can partially offset these new peak demands and defer capacity investment. However, the majority of PV generation does not coincide with EV charging and thus total demand is decreased more significantly than the peak, which has implications for system operation and utility revenues. It was found that PVs were most effect at matching demands and deferring costs if installed with small businesses. In regions with summer peaks, such as the one studied, it was found that moderate penetration of EH could balance seasonal variances in total and local demand, allowing for higher capacity utilization and utility revenues, without increasing the peak. Lastly, energy storage was found to be the most effective tool for balancing demand. If installed within the distribution system this would be most beneficial with transformers in residential neighborhoods where local and system peak demands are best matched. These recommendations are based on results specific to the data used, however many may be also generally applicable to regions with similar characteristics.

When designing modeling initiatives, a balance must be found between the level of detail required to provide meaningful results, and the resources required with increased complexity. While this research aimed to provide techniques and insights which could be leveraged with minimal resource requirements, there are still a few recommendations for how these analyses could be refined, or how complimentary research could improve the results. Firstly, the disaggregation model presented in Chapter III could be improved through validation with actual measured data. This could be achieved through a submetering study collecting heating, cooling and total loads for a selection of households. It would not only relieve the uncertainty around disaggregation results but could also provide insights into how the model could be improved. Additionally, further research should be done to find a method of tailoring a buffer temperature for each hour and day type (as discussed in Appendix C, section 2.2). An area for potential improvement in the utility level demand model from Chapter III would be to further break down sectors. If sufficient customer information was known, the customers could be split into subsectors. Alternatively, this could be achieved through clustering customer in sectors into groups with similar load curves, as was done with transformers in Chapter IV. Even without customer information clustering might allow for identification of subsector groups based on archetypical load curves, allowing for further assessment of the impact of differential growth and economic development. Lastly, the optimal clustering technique to be used in this method, as well the one proposed in Chapter IV, should be investigated further. K-means was applied in this study due to its simplicity and guaranty of convergence, however research into the optimal clustering techniques for these specific applications could improve results and reduce the computing resources required.

The scenarios presented in these studies were far from exhaustive, therefore a series of future analyses should be performed with the presented model set in order to gain additional insight. For example, while the model presented in Chapter III included a parameter to demonstrate the impact on demand from an average change in temperature due to climate change, none of the presented scenarios delved into these impacts. Furthermore, the model was calibrated for future climate conditions by using the normalized weather data and increasing all temperature values by the proposed average increase. This may not be representative of the true impacts of climate change as they could also result in greater daily and seasonal weather variability. Future studies could use projected climate change data sets such as those produced by the Canadian Centre for Climate Modelling and Analysis and provide more detailed investigation into the seasonal impacts under different scenarios. Similarly, both Chapter III and Chapter IV included controls or scenarios for the implementation of energy storage, but general assumptions were made around the type and characteristics of the energy storage to be used. Future specific studies should investigate the impact of different forms of energy storage by changing the constraints placed on its operation in the allocation algorithms. This could be used to examine the optimal mix and application of different forms of energy storage under diverse scenarios.

Overall, in order for the modeling toolset presented to remain effective and provide valuable insight, it is essential that it be continually updated, and new investigations be performed to account for and assess the new technologies and policies arising every day.

3 ENGINEERING CONTRIBUTIONS

The engineering contributions of the research and the models presented in this thesis can be summarized by the following points:

1. An improved regression model for predicting and disaggregating space conditioning from aggregate sector loads, through the novel incorporation of variable changepoint temperatures, multiple resolutions of temperature data and probit analysis (Chapter II)
2. An adaptable model for long term utility level electricity demand at finer temporal resolution than standard utility models, and incorporating a wider set of modifying technologies and policies (Chapter III)
3. A dynamic, parameterized framework and modeling interface with real-time visualizations of scenario results to facilitate evaluation of multiple impacts and scenarios (Chapter III)
4. A literature review and summary of the range of future values projected by various sources for parameters influencing electricity demand in Canada (Chapter III)
5. Presentation of a diverse set of scenarios for future electricity demand for a utility in Southern Ontario, demonstrating the uncertainty in the industry and extreme range of potential local outcomes (Chapter III)
6. Quantification of the variability in local technology penetrations throughout a sample utility service area at the transformer level (Chapter IV)
7. A clustering method for identifying residential customer segments with and without electric heating (Chapter IV)
8. A clustering method for identifying a small set of representative transformer load profiles within a utility service area (Chapter IV)

9. Presentation of a set of archetypical of transformer load profiles based on a utility in Southern Ontario (Chapter IV)
10. Presentation of the differing impacts of new technology penetration and policy implications on various archetypical transformer load profiles (Chapter IV)
11. A dynamic model with real-time visualizations for scenario analysis of utility demand, illustrating the differing impacts at archetypical transformers (Appendix C)

The majority of previous studies addressing the need for long term modeling at finer temporal and technological resolution have been focused on the national level. These require significant data resources which may not be available to local authorities, and often overlook local extremes. The relatively simple, adaptable models developed in this thesis can facilitate wider proliferation of state-of-the-art modeling techniques, for improved local planning. Furthermore, the use of dynamic parameterized techniques allows real-time visualization of scenario impacts. This facilitates navigating the industry uncertainty by allowing the user to: investigate a wide spectrum of scenarios, quickly identify the sensitivity and interactions of each parameter, and assess potential mitigation techniques. Together the models provide a much-improved toolset for utilities looking to plan their future business pathways.

APPENDIX A – PERMISSIONS FOR PREVIOUSLY PUBLISHED WORKS

CHAPTER II: MODELING AND DISAGGREGATING HOURLY EFFECTS OF WEATHER ON SECTORAL ELECTRICITY DEMAND

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CHAPTER III: A SIMPLE PARAMETERIZED MODEL TO ADVANCE VISULAIZATION OF UTILITY LOAD CURVES FOR STRATEGIC SYSTEMS PLANNING

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CHAPTER IV: INVESTIGATING DISTRIBUTION SYSTEMS IMPACTS WITH CLUSTERED TECHNOLOGY PENETARTION AND CUSTOMER LOAD PATTERNS

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APPENDIX B – CHAPTER III SUPPLEMENTAL MATERIAL

Table B-1: IESO Outlook Projected Sector/Parameter Growth Rates

Outlook	Sector		2015 Gross Demand (TWh)	Projected 2035 Demand (TWh)	Annual Growth Rate	Utility Projected 2040 Demand (GWh)
A	Industrial		34.7	28.8	0.9907	262.0
	Com.	Heating	39.0	43.7	1.0057	19.8
		HW	4.0	2.3	0.9730	3.3
		Cooling	4.7	4.4	0.9975	30.5
		Other	41.9	39.3	0.9967	402.3
	Res.	Heating	45.4	41.9	0.9959	51.2
		HW	17.7	16.3	0.9957	39.0
		Cooling	3.5	3.4	0.9976	98.4
		Other	36.1	35.1	0.9985	365.6
B	Industrial		34.7	34.9	1.0003	327.2
	Com.	Heating	39.0	46.6	1.0089	21.3
		HW	4.0	2.5	0.9771	3.6
		Cooling	4.7	4.9	1.0020	33.8
		Other	41.9	43.4	1.0017	451.2
	Res.	Heating	45.4	43.4	0.9977	53.3
		HW	17.7	17.3	0.9989	42.0
		Cooling	3.5	3.5	0.9999	103.8
		Other	36.1	36.6	1.0008	384.6
C	Industrial		34.7	42.8	1.0105	413.8
	Com.	Heating	39.0	42.3	1.0041	19.1
		HW	4.0	3.7	0.9949	5.4
		Cooling	4.7	4.9	1.0020	33.8
		Other	41.9	43.4	1.0017	451.2
	Res.	Heating	45.4	39.0	0.9924	47.3
		HW	17.7	17.6	0.9997	42.8
		Cooling	3.5	3.5	0.9999	103.8
		Other	36.1	36.6	1.0008	384.6
D	Industrial		34.7	50.7	1.0191	502.8
	Com.	Heating	39.0	41.6	1.0032	18.7
		HW	4.0	3.9	0.9984	5.9
		Cooling	4.7	4.9	1.0020	33.8
		Other	41.9	43.4	1.0017	451.2
	Res.	Heating	45.4	37.8	0.9909	45.6
		HW	17.7	17.7	1.0001	43.1
		Cooling	3.5	3.5	0.9999	103.8
		Other	36.1	36.6	1.0008	384.6
*Note these values are estimated total potential demand. See Table S2 for calculation						

Table B-2: Estimated Total Potential Heating & HW Demand

	Residential			**Commercial**		
	% Penetration	Demand (TWh)	Theoretical Total Demand (TWh)	% Penetration	Demand (TWh)	Theoretical Total Demand (TWh)
Current (2015)						
Heating	18%	8.3	45.4	10%	4.0	39.0
HW	23%	4.1	17.7	19%	0.8	4.0
Outlook A						
Heating	17%	7.0	41.9	11%	5.0	43.7
HW	19%	3.1	16.3	17%	0.4	2.3
Outlook B						
Heating	17%	7.3	43.4	11%	5.1	46.6
HW	19%	3.3	17.3	17%	0.4	2.5
Outlook C						
Heating	31%	12.3	39.0	31%	13.3	42.3
HW	32%	5.6	17.6	35%	1.3	3.7
Outlook D						
Heating	42%	15.7	37.8	45%	18.6	41.6
HW	45%	7.9	17.7	48%	1.9	3.9

Table B-3: Projected Equivalent EV Penetration

Outlook	EVs 2015	Ontario Total Vehicles 2015 (<4.5 Tonnes)	Projected EVs 2035	Extrapolated EVs 2040	Projected Total Vehicles 2040 (< 4.5 Tonnes)	Projected Penetration 2040
A	5	7,866	605	755	10,507	7.2%
B	5	7,866	1,003	1,252	10,507	11.9%
C & D	5	7,866	2,401	3,001	10,507	28.6%
Note: all numbers are in thousands of vehicles						

Table B-4: Extrapolated EH & HW Penetration Rates

Outlook	**End-Use**	**Residential Pen.**		**Commercial Pen.**	
		2035	2040	2035	2040
A	Heating	17%	17%	11%	11%
	Hot Water	19%	19%	17%	17%
B	Heating	17%	17%	11%	11%
	Hot Water	19%	19%	17%	17%
C	Heating	31%	39%	31%	40%
	Hot Water	32%	41%	35%	44%
D	Heating	42%	55%	45%	61%
	Hot Water	45%	62%	48%	64%

APPENDIX C – UPDATED CHAPTER III MODEL WITH LOAD CURVE CLUSTERS

1 UPDATED MODEL

The model presented in Chapter III was updated after publication to accommodate additional parameters and incorporate the results obtained in Chapter IV. The current structure and formulae were generally maintained with a few modifications (detailed in Section 2). In this version load curves were developed not only for the total demand, but also the demand curve in each of the transformer clusters identified in Chapter IV. Therefore, when calibrating coefficients using the formulae from Chapter III, one set of coefficients was found for the total data in each cluster and one for the overall total. As in the analyses performed in Chapter IV, the small outlier clusters (2 and 4) were not considered as they represented unique circumstances which are not expected to experience the same changes as the other clusters. Thus, in total seven sets of coefficients (six clusters and one total) were calibrated for the new model and when controls are adjusted to a scenario, the projected load curve can be viewed for each transformer cluster and the total system.

2 UPDATED & ADDITIONAL PARAMETERS & CONTROLS

As well as the additional projected demand curves, the model was updated with some minor modifications and additional controls in order to refine the projections and accommodate changes on the local transformer cluster level. The modifications are detailed in the following sections.

2.1 RELATIVE LOCAL PENETRATION RATES

Firstly, in order to accommodate local differences in each of the clusters, local baseline penetration rates were determined for PV and EH using the techniques discussed in Chapter IV. Since these vary significantly between clusters, it follows that the future scenario penetration rates for a technology at each cluster may vary. Likewise, the growth or decline of sectors may differ. Therefore, each cluster was given a set of relative growth controls to change the impact of different parameters on each cluster. These are available for EV, ES, residential PV, business PV, residential EH, commercial EH, and residential HW penetration rates, as well as for overall residential, commercial and industrial sector growth rates. Note that while the main model includes individual growth parameters for different portions of some sectors (ie. heating, cooling, and other) only one relative control is provided, which impacts all of these portions respectively. The relative controls can range from 0% to 200% and indicate the deviation from the overall increase/decrease in technology penetration or growth/decline in a sector. If the relative control is set to 0%, the cluster curve would show the load curve projected with no additional technology penetration or no sector growth. Whereas at 200%, there would be double the additional technology penetration or double the growth/decline in sector demand compared to the overall scenario setting. This allows the sensitivity of a given cluster to specific parameters and local variations to be assessed. The impact from relative sector growth rates are incorporated into equations (3) and (5) from Chapter III by changing the portion which relates to the growth rate as follows:

$$d^{y}_{s,t,C} = \sum_m \left(\frac{D^{\bar{y}}_{m,C}}{n_s}\right) * (1 + ((1 + i_m)^{(y-\bar{y})} - 1) * Rel_{m,C}) * k_{m,s,t,C} * s_{m,s,C} + \sum_p d^{y}_{p,s,t,C}$$

Eq. (C1) - modified Ch. III Eq. (3)

$$d^{y}_{p,s,t,C} = \left(\frac{D^{\bar{y}}_{p,C}}{n_s}\right)\left(\frac{Pen^{y}_{p,C}}{Pen^{\bar{y}}_{p,C}}\right) * (1 + ((1 + i_p)^{(y-\bar{y})} - 1) * Rel_{m,C}) * k_{p,s,t,C} * s_{p,s,C} * c_{p,s,t,T,C}$$

Eq. (C2) -modified Ch. III Eq. (5)

This is only applied when processing transformer clusters, where $Rel_{m/p,C}$ is the relative growth of sector *m* in cluster *C*, impacting sector *m* or parameter *p* (for example heating parameter *p* for sector *m*). Note all other variables are the same as the original equations with the addition of one more subscript *C*, to indicate the cluster.

The effect on local technology penetration rates is complicated still further by the fact that certain areas already have higher baseline penetration rates than others. For example, the baseline residential EH penetration rate is approximately 10%, however cluster 5 showed an estimated penetration over 63%. If the future scenario being projected estimated a doubling of overall EH penetration to 20%, one would expect the penetration in cluster 5 to increase, not decrease down to 20%. Thus, additional equations are also required to determine the projected penetration in year *y* of a parameter *p* at cluster *C* ($Pen^{y}_{p,C}$) considering both the baseline local penetration and relative penetration growth control. It was assumed that additional penetration of new technologies in a scenario would be evenly distributed among all remaining customers who do not already have the technology and allocated to each cluster accordingly. In this case since cluster 5 already has a disproportionate number of people with EH, a lower proportion of customers are able to get new EH installed and thus the penetration would increase by less than the average 10% increase. Conversely if a decrease in penetration is projected, this would be distributed evenly across all customers with the technology and in the case of EH in cluster 5, would the penetration would disproportionately decrease. Based on this assumption and the relative penetration rate controls, the new penetration rate for each cluster *C* can be calculated based on equations C3 and C4:

$$For\ Pen^{y}_{p} \leq Pen^{\bar{y}}_{p}:\ Pen^{y}_{p,C} = Pen^{\bar{y}}_{p,C} + \left(Pen^{y}_{p} - Pen^{\bar{y}}_{p}\right) * RelPen_{p,C} * \left(\frac{1-Pen^{\bar{y}}_{p,C}}{1-Pen^{\bar{y}}_{p}}\right) \quad \text{Eq. (C3)}$$

$$For\ Pen^{y}_{p} \geq Pen^{\bar{y}}_{p}:\ Pen^{y}_{p,C} = Pen^{\bar{y}}_{p,C} + \left(Pen^{y}_{p} - Pen^{\bar{y}}_{p}\right) * RelPen_{p,C} * \left(\frac{Pen^{\bar{y}}_{p,C}}{Pen^{\bar{y}}_{p}}\right) \quad \text{Eq. (C4)}$$

where Pen^{y}_{p} is the overall penetration rate for parameter *p* in year *y* (or base year $\bar{y}$), $Pen^{y}_{p,C}$ is the local penetration rate at cluster *C*, and $RelPen_{p,C}$ is the relative penetration rate for *p* at cluster *C*.

2.2 HEATING AND COOLING DISAGGREGATION

As mentioned in Chapter IV, the disaggregation model detailed in Chapter II was updated from its original description to include more data for modeling the effects of changing day lengths and sunlight. In addition to the dummy variable based on sunrise and sunset times, two similar dummy variables were added for ‘Nautical’ and ‘Civil’ sunrise/sunset [1], as well as a variable for sun angle at each hour of the day (set to 0 if below the horizon) [2]. These better accounted for times with partial daylight. They were found to improve the fit with both the total residential and commercial data, decreasing MAPE from 4.57% and 1.85% to 4.36% and 1.80% respectively, while also smoothing the disaggregated profiles around sunrise and sunset hours.

In addition, since the load curve of each transformer cluster is modeled, this disaggregation was applied to the data from each cluster. A poor fit was found with data showing very high heating demands and minimal cooling (as in cluster 5), with base demand being significantly underpredicted by the model. This was discovered through comparison with the locus of minimum load which assumes that the days with minimal load in the transitional seasons will have little to no space conditioning and thus be representative of the base load [3]. It was found that the poor fit could be alleviated by adding a buffer temperature range in which no CD or HD were assigned. This suggests for households with high heating and low cooling there is comfort zone (perhaps due to thermal inertia), which is a range of temperature over which minimal or no space conditioning is used. Thus, equations 2 and 3 from chapter II were modified to include a buffer temperature *Tb:*

$$DH_{t,R,d} = Max((Tc_{t,d,R,w} - Tb) - T_{t,d,R,w}, 0) \qquad \text{Eq. C5}$$

$$DC_{t,R,d} = Max(T_{t,d,R,w} - (Tc_{t,d,R,w} + Tb), 0) \qquad \text{Eq. C6}$$

For cluster 5 it was found that the optimal buffer was 3 and 2.5 degrees respectively for residential and commercial data. The resulting modeled base demands and locus of minimum load for each sector in the transition months can be seen in Figure C-1 and C-2. A constant buffer was used, however just like changepoint temperatures, it is likely that the optimal value may change with different behaviours and occupancies at different times and types of days. Furthermore, preliminary experimentation showed that using a smaller buffer temperature could slightly improve the fit of the model with datasets that did not include significant heating. This suggests that future work should be done in implementing a variable buffer temperature to accompany the variable changepoint. However, since for most clusters the improvements were only marginal and the locus of minimum load showed a good fit, a buffer temperature (manually optimized) was only implemented for cluster 5.

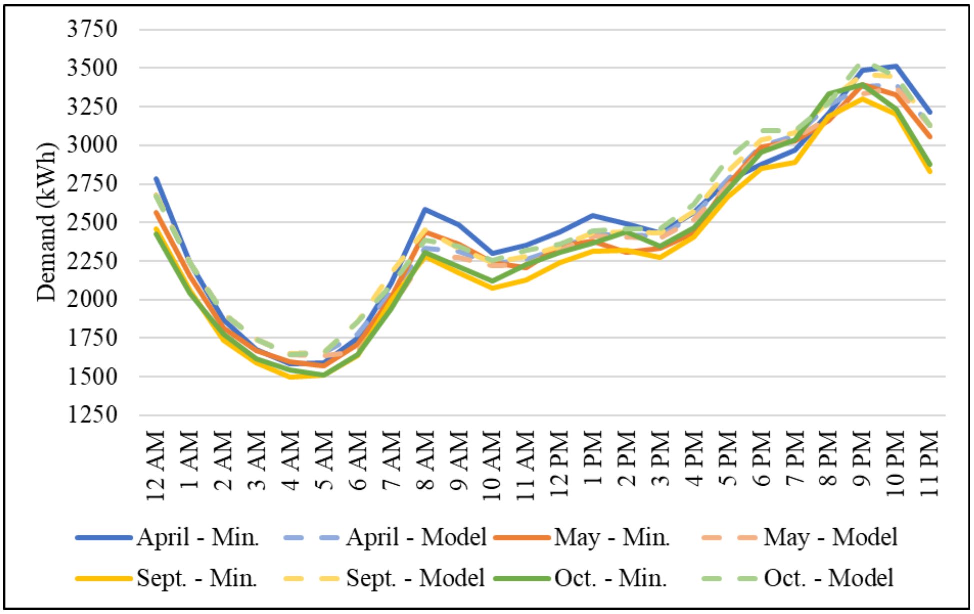

Figure C-1: Cluster 5 Residential Locus of Minimum Load and Modeled Base Demand

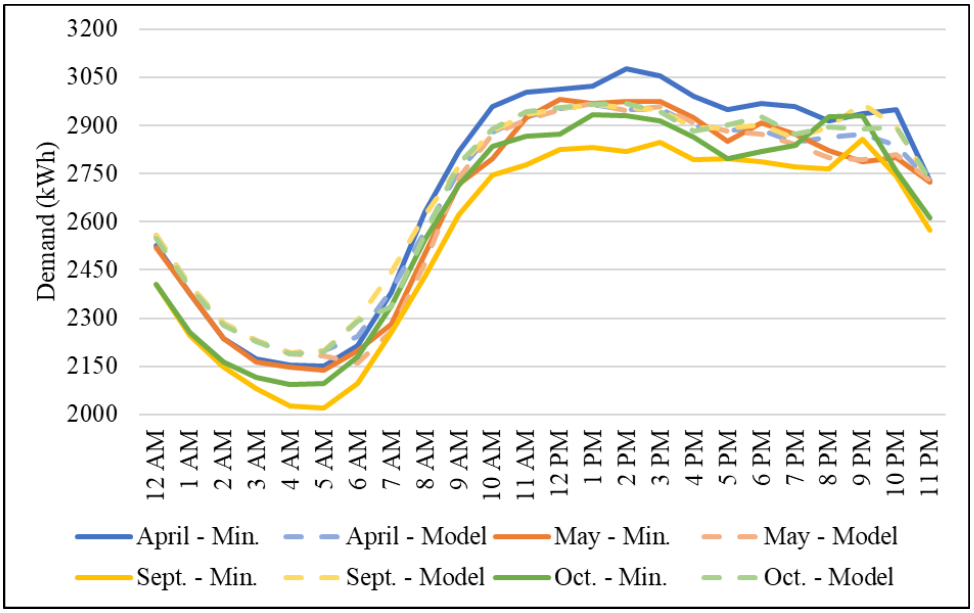

Figure C-2: Cluster 5 Commercial Locus of Minimum Load and Modeled Base Demand

2.3 ELECTRIC HEATING, COOLING AND HOT WATER

The electric heating, cooling and HW were disaggregated from each the transformer cluster curve using the same method as in Chapter III, using the updated regression model discussed in the previous section. However, the commercial HW demand was not disaggregated in the new model because each transformer cluster would include a different cross section of commercial customers with potentially significantly different quantities and distributions of HW demand. Thus, the assumptions made around this parameter in the aggregate model would not be true locally. Less variability would be expected between residential household types, therefore the residential HW demand was still disaggregated using the average expected curve. One other difference in the updated model was that the baseline penetration rates for EH in each cluster and the total were determined using the clustering method detailed in Chapter IV rather than from historical literature.

The application of the regression model to each of the clusters revealed different residential heating and cooling profiles in each cluster, as demonstrated in Figure C-3. While the cooling profiles showed generally the same distribution with varying degrees of afternoon peaking (some profiles more evenly distributed through the day), the heating profiles showed more significant differences. This was particularly notable when comparing the results for cluster 3 which has very minimal heating demands (4.0% EH penetration) to cluster 5 where EH was the group's defining characteristic (63.4% penetration). Meanwhile, cluster 1, which had a mix of cooling and heating demands, shows a similar curve to the total demand and appears to be close to the average of clusters 3 and 5. One potential explanation for these differences is that in the regions with low primary EH, there may still be use of supplemental electric heating such or portable heaters. These would tend to depend more on consumer occupancy patterns, thus explaining the evening peak seen in cluster 3. Furthermore, since the proportion of heating demand is low, any errors in disaggregation due to seasonal differences in non-heating demand will be much more significant. Meanwhile, in cluster 5 while these same demands might still be present in certain households, the high quantity of demand from households with EH as their primary source is much larger and thus is the determining factor for the shape of the disaggregated demand curve. By this reasoning it was assumed that the heating profile disaggregated from cluster 5 would provide the best representation of the heating profile which could be expected in scenarios of increasing EH penetration. Thus, any additional EH added in a scenario was assumed to follow the characteristics that were derived from the cluster 5 disaggregation.

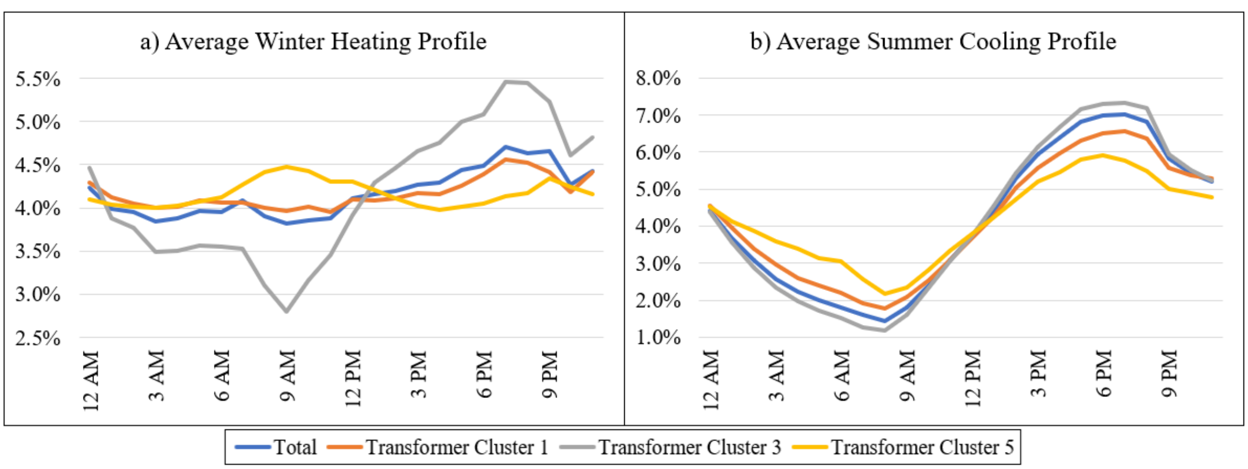

Figure C-3: Average Cluster Residential Heating and Cooling Profiles

Two additional controls were also added to the model to account for the potential for new EH to be in the form of HPs. The new first control allows the user to determine the percentage of future households with EH which will use HPs and the second determines what type of HP is to be used. The three types of HPs which can be selected (Single Stage, Variable Speed Centrally Ducted, and Variable Speed Ductless) were based on the parameters presented by Szekeres and Jeswiet [4]. The baseline HP penetration was estimated at 25% for residential customers based on various sources [5], [6]. These were assumed to have average characteristics similar to a single stage heat pump. No data could be found for commercial heat pump installation rates, so this is currently set to 0%. These values are currently rough estimates, however, could be easily modified with additional data.

In all cases it was assumed the HPs were sized to meet all household demand. The coefficient of performance (COP) was estimated for each hour of the year using the local temperature data, and assuming the use of back-up resistance heating (COP=1) at temperatures below the minimum HP operating temperature. Using this data and the disaggregated heating demand, seasonal average COPs were found for each hour of the day (and for each HP type), along with values for the peak day. In order to account for the effect of currently installed HPs, the electric heating demand disaggregated using the regression model must first be adjusted to the actual heat demand based on baseline HP penetration and COPs. This heating profile can then be scaled based on the scenario growth rate and change in penetration (as in Chapter III) to get the future heat demand. The future heating demand must then be converted to actual electricity demand using the new projected HP penetration and COP. In both steps the conversion between electricity demand for heating and actual heat demand (or visa versa) can be accomplished using Eq. (C7):

$$Electricity\ Demand\ for\ Heating = Heat\ Demand\left((1 - HP_{Pen}) + \frac{HP_{Pen}}{HP\ COP}\right) \quad \text{Eq. (C7)}$$

2.4 ELECTRIC VEHICLE PROFILES AND ALLOCATION

This updated version of the model maintains the same structure for controlling EV penetration and charging, however the data sources and control options have been updated in order to allow differentiation between expecting charging profiles and demands at different clusters. Fischer, Harbrecht, Surmann and McKenna, used stochastic Markov chains to model EV demands producing different daily charging distributions depending on charger location, driver occupation and a variety of other factors [7]. These results were adapted and combined with local statistical data on labour forces [8], and the number of people using their vehicles to drive to work each day [9] to produce overall weighted load curves in different charging scenarios (see Figure C-4). The control for EV penetration remained unchanged, however the other two were modified to match this new data source. Instead of allowing the user to choose between IESO or NREL data, this was adapted to the choice of whether consumers would be assumed to charge only at a single location, or whenever charging is available (two locations: residential and workplace). When single location charging is selected, the second slider control determining the shape of the distribution allows the used to adjust what percentage of consumers charge exclusively at their workplace (with the remaining portion charged only at home). If it is selected that EVs will be charged whenever a station is available, the second control instead allows the user to set what portion of workplaces are assumed to have charging stations available. The adapted profiles for each of these charging situations can be seen in Figure C-4, and a weighted average is produced based on the settings of each control. It should be noted that in Figure C-4 the 'Only Home' and 'Only Workplace' curves each add to a total of 100% since charging exclusively occurs at either of these locations, whereas the 'Both – Home' and 'Both- Workplace' curves cumulatively add to 100% as the demand is distributed between the two locations as adapted from Fischer et al.'s study.

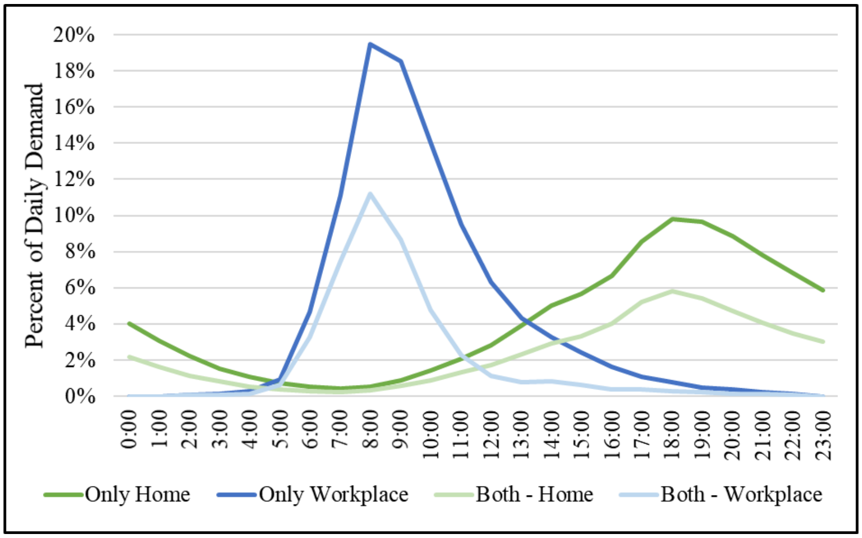

Figure C-4: Electric Vehicle Residential and Commercial Load Curves

In this method since there is a differentiation between home and workplace charging demands, these are allocated separately to each of the clusters based on the cluster characterises (similarly to Chapter IV). The total expected residential charging demand is allocated to clusters based on the percentage of residential customers in each cluster. Similarly, the workplace EV charging demand is allocated based on the businesses at each cluster. However, this demand is assumed to be proportional to the total electricity demand as opposed to the number of businesses. This is an approximation based on the assumption that larger businesses with higher electricity demand will have more employees (and therefore more workers' vehicles). This allocation was done separately for the commercial and industrial sectors, using statistical data on the number of jobs in each sector to determine the relative proportion for each [10]. The result of this method is that, each cluster will have a different proportion and temporal distribution of EV charging, depending on the local customer mix. As an illustrative example, Figure C-5 shows the total EV charging demand split by each cluster (a) and the distribution of demand at each cluster (b) in a scenario of 25% EV penetration with both home and work charging and 50% of workplaces having chargers available.

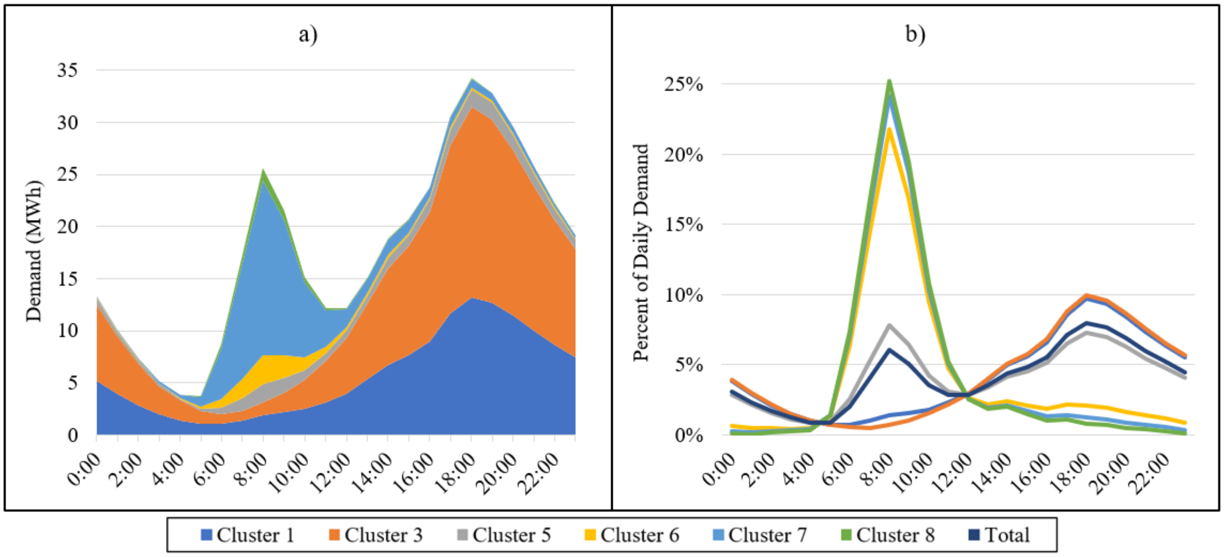

Figure C-5: Example EV Demand a) Total by Cluster b) Distribution by Cluster

2.5 LOCAL PHOTOVOLTAIC CAPACITIES AND ALLOCATION

The controls for PVs remain the same as in Chapter III apart from the 'commercial penetration' being changed to 'business penetration' in order to account for the fact that both commercial and industrial facilities may install solar panels. However, similarly to the EVs, in this updated model PV capacity from the total demand curve must be allocated to each cluster based on the local customer characteristics and the estimated potential. As such, the baseline and estimated potential capacities were split into a residential and business portion. The total and local baseline capacities were divided based on the contract structure, assuming smaller installations under the IESO's microFIT (MF) contracts (<10kW capacity [11]) would be residential, while larger Feed In Tariff (FIT) contracts would be businesses. While this is not completely accurate, it is a sufficient approximation as the vast majority of MF contracts are residential, and the small proportion of business ones are insignificant compared to the much larger FIT capacity. As in Chapter III, capacities were estimated from annual production using a regional capacity factor [12].

The total estimated potential capacity was assumed to be 60% residential and 40% business based on the formulas from Wiginton, Nguyen and Pearce [13]. These total potentials were then allocated to each cluster similarly to the EV demand: residential capacity based on the proportion of residential customers in each cluster, and business capacity based on the proportion of total business electricity demand (commercial and industrial) in each cluster. Once again, it is assumed that the number of households is the best metric for allocating residential technology, whereas with businesses it was assumed that on average those with larger demands would likely have larger workplaces and therefore more roof space and solar potential.

A unique set of hourly and seasonal coefficients was determined for the total demand curve and each cluster. Figure C-5 shows the summer (a) and winter (b) seasonal production curves (hourly coefficients times seasonal coefficients) for each cluster. While solar production would be expected to have generally the same distribution throughout the city, slight differences can be seen observed. These could be caused by factors such as slightly different geographical positioning, panel efficiencies, or building differences including proximity, roof angles and shading. Cluster 6 had very low baseline PV penetration (0.3% residential and 0.0% business), with the majority of these being installed mid way through the year. Therefore, the hourly and seasonal coefficients for the total demand curve were also used as the best approximation for cluster 6. Since no actual generation data is available for west facing panels in each cluster, the same control and approximate curves detailed in Chapter III were used for all clusters.

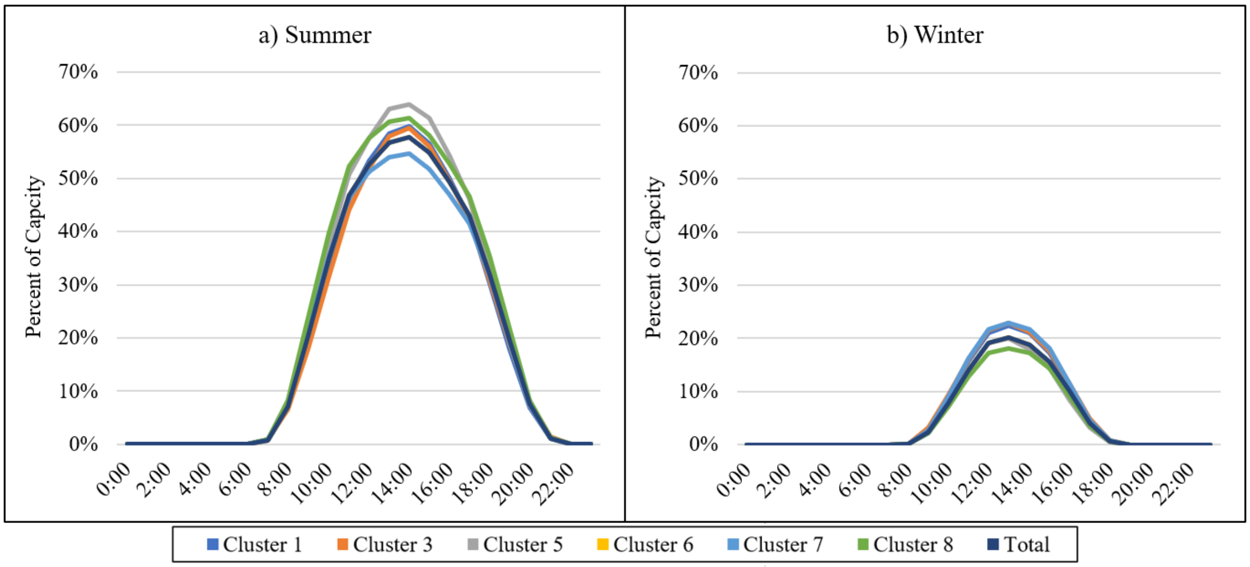

Figure C-6: Cluster Solar Production

2.6 ENERGY STORAGE CHARGING STRATEGY

The energy storage algorithm functions with generally the same iterative method outlined in Chapter III, however with one additional choice was added to the control which determines how the energy storage operates. In addition to the 'Grid' and 'Solar Only' methods there is also a "Local" option. The original two choices function as previously, allocating demand to the total curve based on its distribution. The demand and supply are then allocated to each cluster based on the percentage of total demand seen in that cluster (ie. clusters with higher demand have a larger proportion of ES), retaining the same temporal distribution. These methods reflect the operation of ES for balancing the total supply and demand, as would be expected if the ES was optimized from a system operator perspective. As a result, the ES operation may not be optimal for local clusters and could potentially even increase transformer overloading. Meanwhile, the "Local" method takes the opposite approach. Once again total ES capacity is allocated to each cluster based on demand proportions, but the charging and discharging are then scheduling in each cluster based on the local demand distribution. These demands and supplies are then summed up to the overall total demand curve. This simulates how ES would operate if optimized for the needs of the distribution grid and on an aggregate level can lead to simultaneous charging and discharging of

ES in different parts of the grid (different clusters). These alternative options are available to visualize the contrast between different ES operation strategies in future scenarios, and support identification of locations where ES can most effectively be deployed to balance both needs.

3 UPDATED MODEL INTERFACE AND OUTPUTS

The updated model interface includes the same views and controls (with changes detailed in Section 2), along with additional views for each cluster. Figure C-7 shows an example of the updated main interface for the total demand curve where a variety of parameter controls are available. Comparing this to the interface shown in Figure III-1, an additional toggle box can be seen at the bottom where the user can switch to view load curves for other transformer clusters. A sample of this view for Cluster 6 is shown in Figure C-8. In this interface the relative penetration and growth controls for the cluster being viewed are located on the left-hand side. The same set of load curve metrics can be seen below the demand curve graph. From this interface the user can return to the main scenario controls by either selecting ‘Total’ in the ‘Transformer’ toggle box, or by clicking the button on the bottom left. A similar interface is available for each transformer cluster.

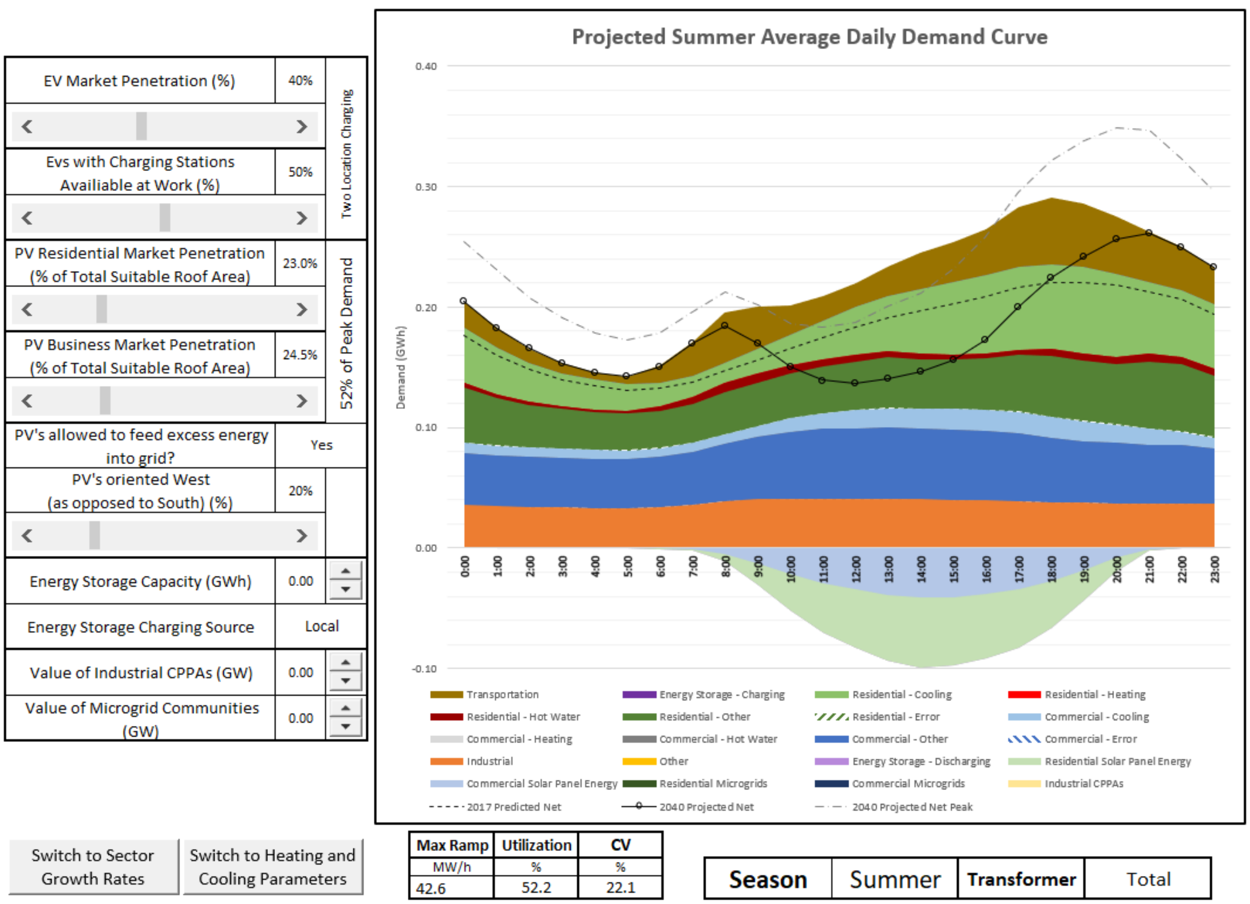

Figure C-7: Sample Modified Model Interface – Total System Demand

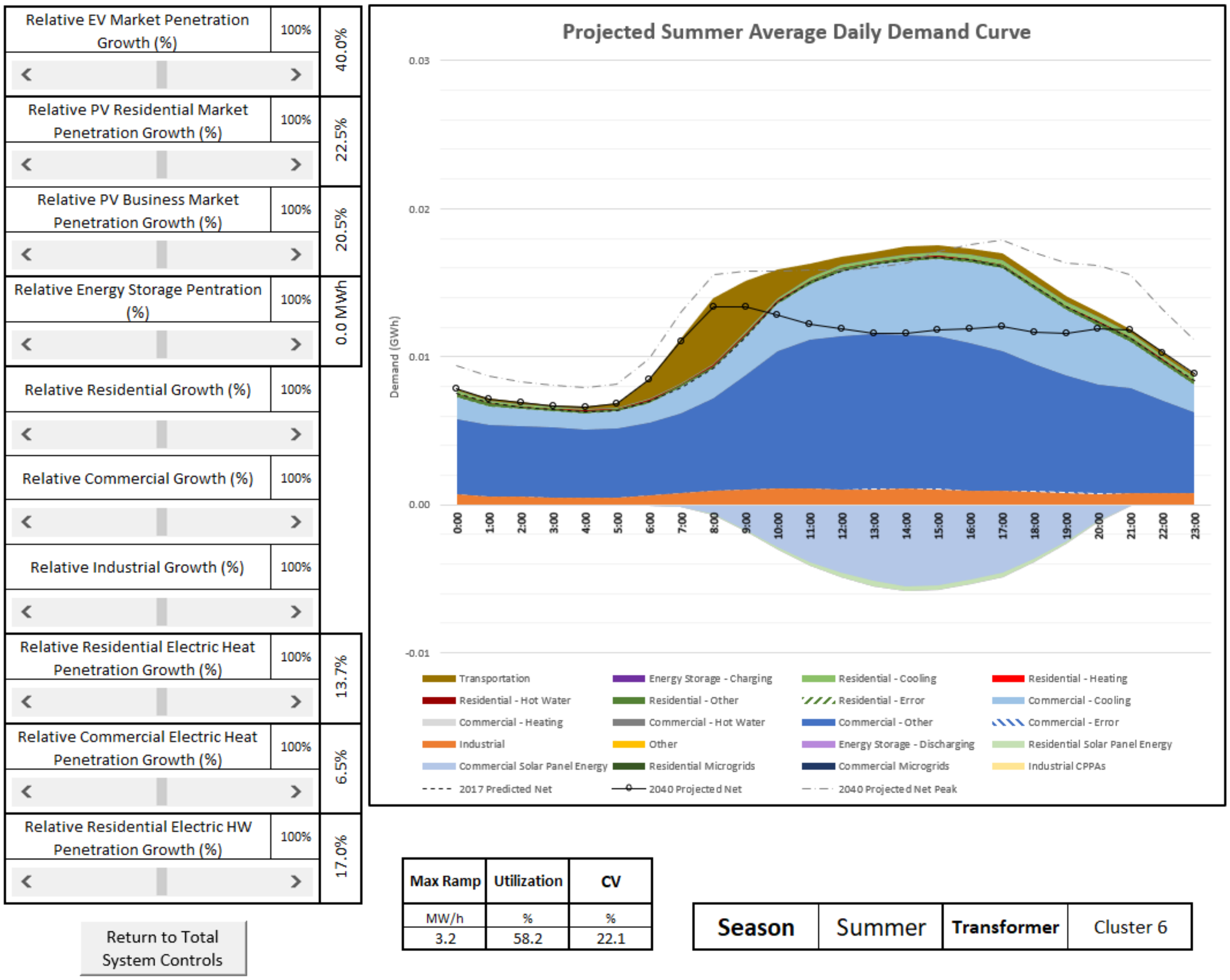

Figure C-8: Sample Modified Model Interface - Cluster 6

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