Urban Building Energy Modelling (UBEM) in Data Limited Environments

by

Garrett E. S. Therrien
B.Eng., University of Victoria, 2018

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Supervisory Committee

Dr. R. Evins
Department of Civil Engineering,
Supervisor

Dr. T. Froese,
Department of Civil Engineering
Departmental Member

ABSTRACT

To help solve the climate crisis, municipalities are increasingly modifying their building codes and offering incentives to create greener buildings in their cities. But, city planners find it difficult to set and assess these policies, as most municipalities do not have the types of data used in urban building energy modelling (UBEM) that would allow their planners to forecast the impacts of various building policies. This thesis offers techniques for operating in this data-poor environment, presenting best practices for developing data-driven archetypes with machine learning, demonstrating inference of parameter values to improve archetypes by using surrogate modelling and genetic algorithms, and a demonstration of techniques for assessing residential retrofit impact in a data-limited environment, where data is neither detailed enough to create an in-depth single archetype study, nor broad enough to create an UBEM model.

It will be shown that inference techniques have potential, but need a certain amount of detailed data to work, though far less than traditional UBEM techniques. For performing residential retrofit, it will be shown the lack of ideal detailed data does not present an overwhelming obstacle to drawing useful conclusions and that meaningful insight can be extracted despite the lack of precision. Overall, this thesis shows a data-poor environment, while challenging, is a viable environment for both research and policy modelling.

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Chapter 1

Introduction

The broad field of Urban Energy Modelling (UBEM) is just beginning: in 2016 Reinhart and Cerezo Davila [2016] called the field 'nascent' and point to increasing energy efficiency targets for buildings by cities as driving UBEM growth. Because the field is relatively new, research has focused on areas where rich data sets exist, as these are the easiest to work with when developing new techniques and exploring new ideas.

But, as climate change becomes an increasingly important focus for governments, so too does the focus on retrofitting the built environment for a better carbon footprint. Unfortunately, the tools traditionally used to project the impact of retrofit policy rely on rich and specialised data sources with detailed building-by-building information that take months or years to collect. In North America, very few of these data sets exist. This has left policy makers struggling to find localised data driven decision making tools: they have the generic recommendations, but wonder if and how they apply to their area, as they lack the detailed data sets to build a UBEM. This is described as a data poor environment: any environment which lacks the data to build a traditional UBEM.

This thesis explores ways to work with and augment poor data to obtain practical results. Generally, there are three options: move data/models from somewhere else, use a baseline model as a 'guess' and iteratively improve it, and use existing knowledge to fill in the gaps.

1.1 Terms and Definitions

Based on the terms and definitions given in chapter 2, the following expanded list is provided for the convenience of the reader:

- data-poor environment: any environment lacking the data necessary to build a UBEM using traditional techniques.
- (Building) Archetype: a generalised building that represents a class or type of buildings in a larger building group. A building archetype will have all necessary components for modelling; while this depends on the program used, generally this means all major materials used (especially their insulation values), equipment descriptions (HVAC, heating, lighting, plug loads etc.), occupant schedules, and any other detail relevant to the building's energy use.
- Constructed Archetype: an archetype that is made by reference to engineering judgment, codes and standards — it is 'constructed' from idealised knowledge. For example, the DOE reference buildings detailed in Deru et al. [2011]
- Data Driven Archetype: an archetype built from data sources, often using machine learning.
- Hybrid Archetype: An archetype built using both constructed and data driven methods; the most common hybrid archetypes use data-driven methods to refine constructed archetypes.
- (Building) Stock Modelling: Creating a model of a large number of buildings ('building stock').
- Urban Energy Modelling (UBEM): A form of stock modelling that attempts to model entire urban regions.
- Bottom Up (model): a model which builds sub-systems into an overall system model. In building stock modelling, most data-driven archetypes are part of bottom up models.
- Top Down (model): a model which starts with a high-level system then breaks that system down into sub-components for analysis. In building stock modelling, this means considering the stock as a whole first.

- cluster verification: any machine learning or statistical technique which quantifies the quality of produced clusters on the basis of the input data set and produced clusters alone.
- (model) verification: the process of validating a UBEM, usually by prediction of a known energy series. Sometimes referred to as verification.

1.2 Methods of Dealing with Data Poor Environments

There are specifically three general ways to to deal with data poor environments:

1. Moving models: Either moving the models themselves without adjustment, or using machine learning techniques to improve them after moving (transfer learning).
2. Approximations: using literature, engineering judgement, and relative comparison to produce usable insight into the problem. The most detailed approximations are whole building models made out of assumptions and building codes which are referred to as constructed archetypes. and
3. Inference: taking a base model assumption and improving it by successive checked 'guesses'. This base model may either be moved or an approximation.

At times, these methods may be partially combined to fill in several different types of data gaps.

Another way of looking at the problem is found in fig. 1.1, which detail the methods that may be used to create building archetypes (whole building models) as the base for UBEM. The 'yes' path in fig. 1.1 is the data-rich path and well documented and common — there is plenty of data, which easily clusters, allowing UBEM based on the actual city. The other two paths are what this thesis focuses on: what do you do when you lack data to create a UBEM that is entirely based on the city in question? As the figure shows, you have two options: if you have some data, you can make approximations and create deterministic clusters — basically lump buildings together into average buildings based on engineering judgement informed by what data you have (as demonstrated in chapter 4) or you can use some form of approximation and try to improve that approximation by inference (as demonstrated in chapter 3).

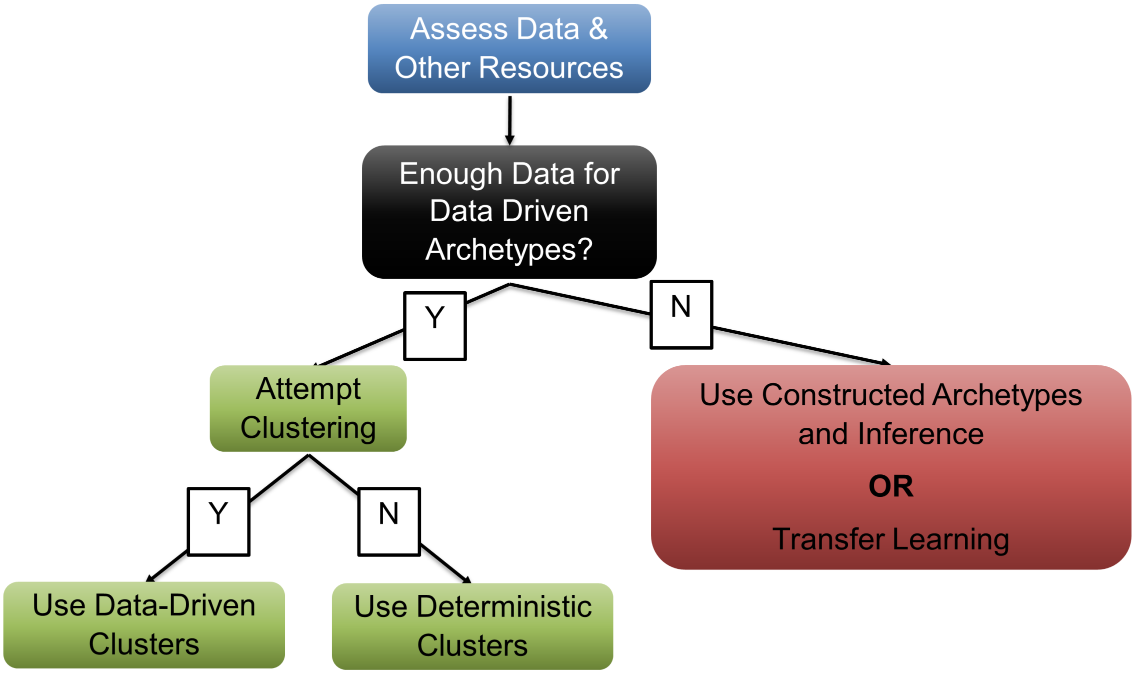


Figure 1.1: Initial overview of UBEM Methods for Archetype Creation

Transfer learning — training models on a smaller subset of the city (or in another city) — and then retraining them for the city in question, may work, but it is the highest complexity of the three methods, currently still under research in its own field (computer science), and requires a rich data source for the base models, and as such was not investigated in this thesis. Currently, there has been little research presented on any of these options, as they are complex and do not, generally, create clear, obvious, answers.

1.2.1 Moving models

This method is the least likely to work. It relies on the assumption that buildings in one place will be the same as in another place. Unfortunately, factors such as weather, jurisdiction (different governments have different building codes), and occupant habits (studies such as Ben and Steemers [2019] have shown impacts of occupants), makes this assumption false.

Transfer learning , using machine learning to train building models in one place then moving those models and adjusting them in another place, has promise, but still suffers from the issues discussed. Attempts have been made to solve portions of this problem, such as Li et al. [2021] and Ribeiro et al. [2018], but the complexities and difficulties of the method encountered further reinforced the belief that, overall, transfer learning was not as promising as other, simpler techniques such as inference.

1.2.2 Approximations

Approximations fall into two categories: deterministic assumptions and building archetypes (generic buildings). Deterministic assumptions are applications of knowledge from literature or engineering judgement to fill in a missing piece of an analysis: for instance, sometimes knowledge of city's building stock is used to assume the number of archetypes needed. This assumption is then used as the 'k' value (the number of clusters) in k-means clustering. It may also be assuming an R-value of wall or another building property based on literature or the author's experience.

Building archetypes, by contrast, are the construction of entire generic buildings (including all building properties such as insulation values, heating systems, occupancy schedules etc.) either on the basis of codes and deterministic assumptions ('constructed archetypes'), as in Deru et al. [2011], or more recently on the basis of rich data sources and machine learning, as in Roth et al. [2020b], Li et al. [2018], and Ali et al. [2019].

Mata et al. [2014] lays out one process for creating constructed archetypes, on the basis of past work, and chapter 2 gives a best practices process for data-driven archetypes.

1.2.2.1 Existing Tools for Archetype Creation

One tool currently exists to provide building data by archetype for Canada, the Building Assessment Technology Platform (BTAP), developed by NRCan CanmetENERGY. The BTAP project adapts a series of archetype building energy models developed by the US Department of Energy (DOE) as baseline buildings for US UBEM to Canadian use, with Canadian weather files and codes. Supported by the OpenStudio Parametric Modelling Tool, a building simulation tool, the BTAP platform allows multiple runs of these buildings over a large variety of conditions, and can allow exploration of the design space. These archetypes can also be generated as base archetypes for work out side of the BTAP paradigm. [noa, b, CanmetENERGY]

1.2.3 Inference

This method seems to hold the most promise. Simply, it consists of starting with an approximation of the building stock (base building archetypes) and successively improving the approximation by comparison to real world energy use data — model the city, see if it is accurate, change parameters, see if the accuracy has improved, and repeat. The most obvious tool for this is a genetic algorithm (GA) to perform the improvement steps and do the comparison; this is, essentially, an optimisation problem. Several difficulties, including speed of modelling inside a genetic algorithm and the construction (or finding) of base archetypes, present themselves. Speed of modelling is especially concerning; most building modelling software is physics based and takes quite a bit of time to run, but it is believed that surrogate modelling can be of assistance here. The data issue is covered in both section 1.3 and chapter 2.

1.3 Data Review

There are two kinds of data that must be considered: open data and restricted. Open data is freely accessible, public, data sets that anyone may use or access. These are frequently the only data sets available in a data poor environment. The other type of data, restricted, is generally held by government agencies and access is restricted due to privacy concerns. Some data may fall into a gray area, such as the BC Hydro data used in chapter 3: while it is technically restricted (it has to be requested from BC Hydro), it contains no information that jeopardizes personal privacy or BC Hydro's commercial interests, and as such is readily accessible.

1.3.1 Open Data

The usual sources for open data in Canada are twofold: NRCan and StatsCan. Additionally, as BC is of interest, the BC government maintains its own open data platform, DataBC. These sources were searched for terms such as ”housing”, ”energy use”, ”building”, ”building stock data”, and ”structure”.

Unfortunately, no database containing exactly the desired information — number of buildings by structure, type, and year — was found. However, NRCan maintains datasets of residential and commercial building energy uses, including information on ages and types of buildings, by Province and Territory. These energy use datasets also include a breakdown of the kinds of energy use, unfortunately not correlated to building type. (Government of Canada [2004a], Government of Canada [2004b], noa [c])

Other data sources investigated included the DataBC Cadastral data, which is the survey parcels for BC, building permit data for BC (also from DataBC), which is largely just one number — permits applied for by year — the StatsCan Open Database of Buildings, which merely contains building locations and footprints, and the StatsCan 2016 Census results for type of dwelling. (Government of Canada [2018], Government of Canada [2017],noa [c])

For work inside the City of Victoria (CoV), the city maintains its own open data portal at `http://opendata.victoria.ca/`.

1.3.2 Restricted Data

By its nature, it is difficult to review restricted data, as there is no list of data sources available. A researcher must discuss the availability of this data with their research partners. Two such data sources are made use of in this paper, the previously mentioned BC Hydro energy data for Victoria in chapter 3, and a database of building audits in chapter 4 which was provided by the City of Victoria as a result of ongoing research partnerships.

1.4 Summary of Contributions

This thesis will show ways of working in and around data poor environments.

Chapter 2 is a journal paper ready for submission, *Best Practices for the Application of Machine Learning to Building Energy Archetype Development*, which contains best practices for constructing data driven archetypes based on a review of the literature in the field;

Chapter 3 is a paper presented at the eSim 2021 conference, *Inference of Building*

Archetypes and Schedules from City of Victoria Open Data, which describes in detail an attempt to use inference techniques to solve the data problem;

Chapter 4 is a journal paper ready for submission, *A Practical Process for Determining the Impacts of Residential Retrofits From Limited Data* which gives a practical demonstration of techniques that can be used on poor data to acquire worthwhile results;

Chapter 5 Provides conclusions from the above work and suggestions for future work.

1.5 Author Contributions

This thesis will show ways of working in and around data poor environments.

Chapter 2: for *Best Practices for the Application of Machine Learning to Building Energy Archetype Development* Garrett developed the methodology, performed the review and analysis, and wrote the manuscript. Dr. Christiaanse contributed to the methodology and analysis. Dr. Evins supervised the project and revised the manuscript.

Chapter 3: for *Inference of Building Archetypes and Schedules from City of Victoria Open Data*, Garrett developed the methodology, performed the modelling and analysis, and wrote the manuscript. Dr. Christiaanse contributed to the methodology and analysis. Dr. Evins supervised the project and revised the manuscript.

Chapter 4: for *A Practical Process for Determining the Impacts of Residential Retrofits From Limited Data*, Garrett developed the methodology, performed modelling, did the analysis and wrote the manuscript. Rachel Barton assisted with the modelling, and Dr. Evins supervised the project and revised the manuscript.

Chapter 2

Best Practices for the Application of Machine Learning to Building Energy Archetype Development

During the process of preparing *Inference of Building Archetypes and Schedules from City of Victoria Open Data* it became obvious that the field was rapidly advancing: the same search of literature after a period of months pulled up new results. During review of how the field had progressed during 2020/2021 since an original survey of the literature in the field in 2019, it became apparent that the field was fragmented, and there was no synthesis of how archetypes were being generated across building modelling disciplines. This paper was the result.

2.1 Best Practices for the Application of Machine Learning to Building Energy Archetype Development

Garrett E. S. Therrien[1], *Dr. Theo Christiaanse* [1], *Dr. Ralph Evins*[1]
[1] *University of Victoria, Victoria, Canada*

Abstract

While building archetypes have been in use for decades in urban planning applications, in the last few years advances in computer science have made various powerful machine learning tools readily available. Fathi et al. [2020] cover many of these advances, showing how surrogate modelling techniques have spread and thrived throughout the field, reducing modelling time and computational load and allowing more complex modelling techniques to be deployed. However, often these models require archetypes, whether data driven or constructed, and no good overview exists of the archetypes being produced, how these production methods have been updated, and how these archetypes are being fitted to their uses. This paper seeks to remedy that gap and provide a typical workflow for making data-driven archetypes, while providing advice on best practices, overcoming identified weaknesses in existing techniques, and identifying opportunities for future study.

2.2 Introduction

Over the last decade, data driven and hybrid archetypes have become the base for much research; over the last 5 years, driven by machine learning tools, this trend has accelerated. [Reinhart and Cerezo Davila, 2016, Abbasabadi and Ashayeri, 2019, Johari et al., 2020, Fathi et al., 2020] Yet, they are seldom considered on their own — archetype research is buried in studies of residential retrofits (residential retrofit modelling (RRM)), urban building energy modelling (UBEM), and in computer and data science focused papers. This has led to fragmentation of knowledge about archetypes — a study of UBEM will not, generally, cite residential retrofit papers and vice versa. This is most evident in Abbasabadi and Ashayeri [2019], a review of UBEM which, while covering archetypes in some detail, fails to note advances in archetype modelling (the basis for many of the UBEM models discussed) which have occurred in residential retrofit modelling, even going so far as to recommend studies in areas which already have studies (notably stochastic methods for occupancy). [Abbasabadi and Ashayeri, 2019, Buttitta et al., 2019, Li et al., 2018, Ben and Steemers, 2019] Another similar, recent, review, [Johari et al., 2020], while having a broader selection of papers, makes a similar recommendation, noting how important archetypes are to UBEM and how much more research on machine-learning techniques for archetypes needs to be done, at least partially because of a lack of standard method for data-driven archetypes.

However, as Johari et al. [2020] were focused on UBEM they do not to propose a standard method for data driven archetypes, despite noting agreement between papers on several techniques. [Johari et al., 2020, Li et al., 2018, Ali et al., 2019, Ben and Steemers, 2019, Pasichnyi et al., 2019]

Another recent review, this time from machine learning, Fathi et al. [2020] has a similarly tight focus: this paper discusses some of the methods used to develop archetypes, but does not mention archetypes even once. Roth et al. [2020a] focuses on the data science involved in collecting and processing data for data-driven archetypes; the actual archetype construction is barely addressed. Earlier studies, such as Reinhart and Cerezo Davila [2016], barely touch data driven archetypes: the tools were just being becoming readily available, and discussions of data-driven archetypes are more theoretical. Though papers such as Famuyibo et al. [2012] can be found in the early 2010s the machine learning techniques were not broadly available (the programming packages for them were still being developed), and as such these papers did not consider the technique to be broadly usable. It is only after the release of major machine learning libraries (such as TensorFlow in 2015) that these techniques were broadly used and data driven archetype papers began to proliferate.[Aggarwal and Reddy, 2016]

So, the field is both relatively new and fragmented: papers addressing data-driven archetypes all come after Reinhart and Cerezo Davila [2016] and recent papers tend to be in one of three fields (RRM, UBEM, and machine learning/data science), with minimal crossover. Further showing how recent a development broad archetype use is, the commonly used U.S. Department of Energy Standard reference buildings date from 2011. [De Jaeger et al., 2020, Deru et al., 2011]. While these are constructed archetypes (ones built using building codes and engineering judgement, as opposed to data), they are frequently used as a base for data-driven techniques and can be considered a major step in archetype development. Another paper from about that time, Mata et al. [2014], gives a purely deterministic method for constructing archetypes from data; machine learning is not yet considered a tool for building archetypes despite the presence of papers such as Famuyibo et al. [2012].

Additionally, none of these studies directly address parameterizing archetypes: this oversight is easy to explain, as it is only important when using machine learning methods to refine an archetype or clustering methods to create archetypes — earlier parameterization was deterministic and engineering-driven designed to study a specific building sub-system and as such not an area of study.

Given how the use of data-driven archetypes is rapidly expanding in two different fields, it has become necessary to compile a review of the advances in the last three years across these fields and distill a recommended procedure for data-driven archetypes, as well as identify areas were there is poor consensus and further detailed studies are warranted. Of particular interest is the use of clustering algorithms (which are the core of data-driven archetypes, enabled by the use of relatively new machine learning tools), the use (if any) of new machine learning tools to handle stochastic variables, such as occupancy, and methods of parameterization of archetypes.

2.2.1 Terms and Definitions

Due to the fragmented nature of research, many different terms are used across papers. The same concept may be referred to by one name in one paper, and by another in another — there is no standard terminology. To aid the reader, the following terms are proposed:

- (Building) Archetype: a generalised building that represents a class or type of buildings in a larger building group.
- Constructed Archetype: an archetype that is made by reference to engineering judgment, codes and standards — it is 'constructed' from idealised knowledge. For example, the DOE reference buildings detailed in Deru et al. [2011]
- Data Driven Archetype: an archetype built from data sources, often using machine learning.
- Hybrid Archetype: An archetype built using both constructed and data driven methods; the most common hybrid archetypes use data-driven methods to refine constructed archetypes.
- (Building) Stock Modelling: Creating a model of a large number of buildings ('building stock').
- Urban Energy Modelling (UBEM): A form of stock modelling that attempts to model entire urban regions.

- Bottom Up (model): a model which builds sub-systems into an overall system model. In building stock modelling, most data-driven archetypes are part of bottom up models.
- Top Down (model): a model which starts with a high-level system then breaks that system down into sub-components for analysis. In building stock modelling, this means considering the stock as a whole first.

2.3 Methods

Two fields were reviewed: UBEM and RRM. For UBEM, we searched for 'ubem archetypes' and studies were selected where archetypes were actually developed as opposed to just used. (For example, Alajmi and Phelan 2020, while a useful example of tuning, would not be included in the papers reviewed, as they do not create archetypes.) For residential and machine learning archetype studies, we searched for 'building archetypes' and studies were selected where archetypes were actually developed from data (data-driven archetypes), as opposed to just used (generally this meant eliminating studies using constructed archetypes, however certain of these were retained as examples of tuning or refining.) Additional papers were added based on references in these papers, where such papers seemed especially relevant, or where a useful technique for refining archetypes was demonstrated, even if the base archetypes for the demonstration were constructed.

Lastly, a few critical papers will be added that provide additional insight. For instance, Deru et al. [2011], while outside of the data range and not data driven, is the paper outlining the process for the development of the U.S. DOE archetypes, which are the most commonly used constructed archetypes and often either refined through data-driven processes or used as a comparison, the previously mentioned Alajmi and Phelan [2020], which is an example of archetype tuning, and Mata et al. [2014] which provides one of the earliest archetype development procedures.

Algorithm data collected will be:

- Algorithm
- Performance indicator: how is the success of the archetype being judged?
- Verification: qualitative/numeric performance indicator.

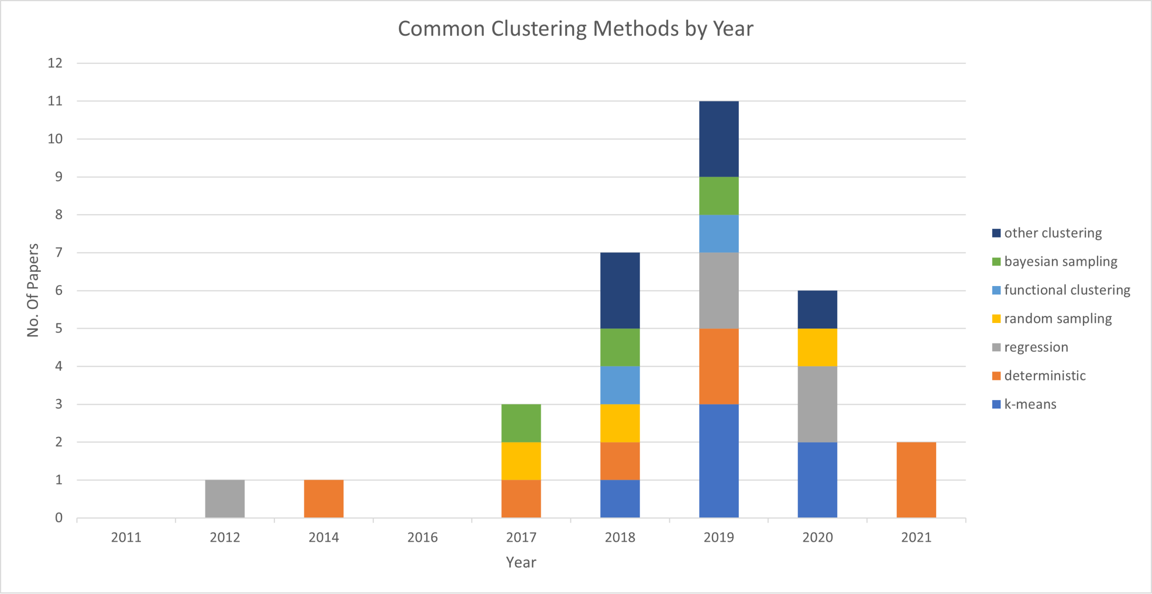


Figure 2.1: Clustering Methods with more than one use, by year

Performance indicators are:

- Validation: quantitative data and numeric methods, detailed in the next column of the table
- Comparison: qualitative comparison to actual data. For instance, comparing wall composition of an archetype to wall compositions of known buildings.

Verification methods are:

- comparison: comparison of predicted energy use to actual energy
- performance testing: comparison of developed archetypes to another set of archetypes
- ASHRAE: ASHRAE Research Procedure 1051/ASHRAE Guideline 14 which gives a standard for calibrating models based on a comparison of predicted energy use to actual energy

2.4 Overview of Review Papers

Table 2.2 contains the results of the literature review. Figure 2.1 to fig. 2.3 contain more detailed analysis. Overall, it was found that a wide variety of methods were

Category	Item	Definition	Abbreviation
Building Type	Commercial		C
Building Type	Residential		R
Building Type	Residential and Commercial	both residential and commercial buildings, as found in a typical city-scale model	R/C
Scale	Campus	a group of buildings such as a university	C
Scale	District	a neighbourhood or similar area. Often will be mostly one type, i.e. all residential	D
Scale	Regional	a city or other large aggregation of mixed buildings	R
Scale	National	a country	N
Parameter Selection	Algorithmic	Use of a machine learning algorithm or statistical tools	A
Parameter Selection	Deterministic	engineering judgement or other methods relying on the judgement of the researchers	D
Parameter Selection	Available Literature	similar to deterministic, but based on existing literature	AL
Parameters	Size	building size properties, such as area or number of storeys	
Parameters	Set points	heating and/or cooling set points	
Parameters	Fabric	Building fabric properties, such as material or insulation value	
Parameters	Orientation	building orientation to sun	
Parameters	Year	year constructed or renovated	
Parameters	Type	building use	
Parameters	HVAC system	details of a building HVAC system such as fan efficiency or type of plant	
Parameters	Hot water system	details of building hot water system, such as boiler type	
Parameters	Plug/Internal Loads	all loads internal to the building, including lighting	
Parameters	Glazing	all details about windows, including wwr, window type, ssize shape, etc.	
Parameters	Natural Ventilation	all details of ventilation not in HVAC, including infiltration	
Performance Indicator	Validation	Numeric-based methods	V
Performance Indicator	Comparison	Comparison to a non-numeric data source (such as comparing wall composition)	C
Validation	Actual Data Comparison	Numeric Comparison to actual data	ADC
Validation	Performance Testing	Numeric comparison to other simulations	PT
Validation	ASHRAE Research Procedure 1051/ASHRAE Guideline 14	a standard for calibrating models based on a comparison of predicted energy use to actual energy	ASHRAE

Table 2.1: Definitions

Paper	Year	Archetype Type	Result	Purpose	Building Type	Scale	Region	Dataset														Parameter Selection	Clustering Parameters													No Parameterization	Algorithm												Performance Indicator	Validation
								TABULA	EPISCOPE	CRECS	UK TUS	EPSH/INSHQ	CECB PLUS	LL84	PLUTO	Author Collected	National Statistics	Building Audits	Google Streetview	Metered	City Open GIS		Size	Setpoints	Fabric	Orientation	Location	Year	Occupancy	Type	HVAC Systems	Hot Water	Plug/Internal Load	Glazing	Natural Ventilation		k-means	deterministic	regression	random sampling	bayesian sampling	random forest	functional clustering	hierarchical clustering	GMM	ANOVA	AIC	No Clustering		
Aguilera et al. 2017	2017	Constructed	19 common factors in archetypes	Review Residential Archetypes	R	A	SA									✓	✓					AL	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓															✓	N/A	N/A
Ali et al. 2019	2019	Data Driven	N/A	Investigate Impact of Scale on Data-Driven Archetypes	R	A	EU	✓														D	✓		✓						✓						✓												V	ADC
Ben and Steemers 201	2019	Data Driven	Behaviour of occupants affects retrofit benefits inside the same archetype	Assessing the impact of a differentiated retrofit approach in UK domestic buildings	R	B	EU	✓														N/A														✓												✓	N/A	N/A
Bhatangar et al. 2019	2019	Data Driven	Low and High Rise Office Reference Buildings	Develop reference buildings for India similar to the US DOE Reference Buildings	C	N	AS									✓						AL		✓		✓	✓		✓		✓		✓	✓	✓		✓									✓			V	ST
Buttitta et al. 2019	2019	Data Driven	An overall better building stock model	Augment building archetypes with occupancy information	R	N	EU				✓						✓					AL			✓				✓	✓				✓	✓													✓	V	ADC
Cerezo et al. 2016	2016	Hybrid	UBEM model for Boston	Build a GIS based UBEM model for Boston	R/C	R	NA										✓				✓	N/A						✓		✓																		✓	V	ADC
Cerezo et al. 2017	2017	Data Driven	Bayesian Clustering	Investigate Bayesian Clustering	R	D	ME									✓						AL		✓					✓		✓	✓	✓					✓		✓	✓								V	ADC
De Jaeger 2020	2020	Hybrid		Develop a simpler heating and cooling setpoint based stochastic occupant profile technique	R	D	EU	✓											✓			N/A														✓	✓		✓										V	PT
De Jaeger et al. 2019	2019	Hybrid	The clustering approach performed better than straight up archetypes	Improve a district energy model with tailored clustering of archetypes	R	R/D	EU	✓														N/A	✓	✓				✓			✓			✓			✓		✓								✓		V	PT
Deru et al. 2011	2011	Constructed	US DOE Reference Buildings	Representative archetypes for US Building Stock	R/C	N	NA									✓	✓					N/A														✓												✓	N/A	N/A
Ding and Zhou 2020	2020	Constructed	Data-driven residential and office archetypes and a web platform	Build archetypes and customise occupancy	R/C	R	AS			✓												AL		✓	✓				✓				✓						✓	✓									V	PT
Djebbar et al 2019	2019	Data Driven	Residential Building Archetypes for North Africa	Develop a building stock model that takes into account different years of construction	R	D	AF									✓						N/A														✓		✓											N/A	N/A
Dochev et al. 2020	2020	Hybrid	The many difficulties in matching GIS data to non-GIS data	Test assigning and fitting building archetypes to cadastral data	R/C	R	EU										✓			✓	✓	N/A														✓												✓	V	ADC
El Kontar and Rakha 2	2018	Data Driven	More accurate archetype schedules	Test creation of schedules using bayesian/probablistic means	R	R	NA													✓		N/A		✓							✓		✓				✓				✓		✓						V	PT
Famuyibo et al. 2012	2012	Data Driven	Datasets are deficient in usable variables for archetypes	Early investigation of important archetype parameters	R	N	EU					✓										AL	✓		✓						✓								✓										N/A	N/A
Fernandez et al. 2020	2020	Data Driven		Develop a bottom up methodology for using residential stock archetypes	R	R	EU										✓					N/A														✓	✓												C	ADC
Gholami et al. 2021	2021	Data Driven		Test creation of archetypes with bayesian calibration	R	D	EU	✓													✓	N/A		✓		✓				✓		✓		✓				✓											V	ADC
Kim et al. 2019	2019	Hybrid	Over simplifying HVAC can lead to significant performance errors	Test the importance of HVAC in an archetype	C	B	AS													✓		AL						✓		✓								✓	✓										V	PT
Kirstensen et al. 2020	2020	Data Driven	Highly accurate archetypes for one type of single family residence	Develop a method for taking into account in archetypes the variability in building stock	R	R	EU	✓									✓			✓		N/A														✓												✓	V	ASHRAE
Krayem et al. 2019	2019	Data Driven	Decent UBEM model for Beirut	Calibration of a bottom up archetype model	R	D	ME									✓	✓	✓				N/A														✓												✓	V	ADC
Lavagna et al. 2018	2018	Data Driven	Residential stock model for europe, and an LCA assessment of it	Archetype based building stock LCA	R	O	EU	✓	✓								✓					AL					✓	✓		✓								✓											N/A	N/A
Li et al. 2018	2018	Data Driven	k-means may not be the best choice	Investigate typical clustering methods at a campus scale	C	C	OC											✓				N/A														✓								✓	✓				V	ADC
Mata et al. 2014	2014	Data Driven		Investigate the use of archetypes to aggregate national building stocks	R/C	N	EU										✓	✓				D		✓	✓						✓			✓	✓			✓											V	ADC
Mohammadiziazi et al.	2021	Hybrid	Reasonable archetypes for Pittisburgh	Construct an UBEM from sparse data and image recognition on Google Maps data	R/C	R	NA														✓	D																✓											V	ADC
Nageli et al. 2018	2018	Hybrid	Reasonable archetypes for Switzerland	Develop synthetic models of national building stock	R/C	N	EU										✓					N/A														✓				✓									C	ADC
Nagpa et al. 2018	2018	Data Driven	Surrogate-based tuning can improve individual surrogate models of buildings	Investigate the use surrogates and archetypes to approximate buildings	R/C	C	NA											✓				N/A			✓				✓		✓		✓	✓														✓	V	ASHRAE
Pasichnyi et al. 2019	2019	Data Driven	N/A	Investigate the use of rich datasets for building stock performance prediction	R	R	EU											✓		✓		N/A									✓																	✓	V	ASHRAE
Rakha and El Kontar 2	2019	Data Driven	Improved district results	Test imputation formula/calibration of residential UBEM	R	D	NA									✓				✓		N/A		✓							✓		✓								✓		✓						V	PT
Roth et al. 2020	2020	Hybrid	tuned UBEM from data-driven archetypes. Random forest worked best	Calibration of a bottom up archetype model	R/C	R/D	NA							✓	✓							N/A	✓				✓		✓													✓							V	ADC
Soko et al. 2017	2017	Data Driven	More accurate archetypes	Test bayesian calibration of uncertain parameters	R/C	D	NA									✓				✓		N/A		✓	✓			✓		✓				✓	✓													✓	V	ADC
Streicher et al. 2019	2019	Data Driven	manual archetype tuning	Investigate archetypes for energy prediction based on heating demand	R	N	NA	✓					✓									N/A		✓	✓																							✓	C	N/A

Table 2.2: Overview of reviewed papers

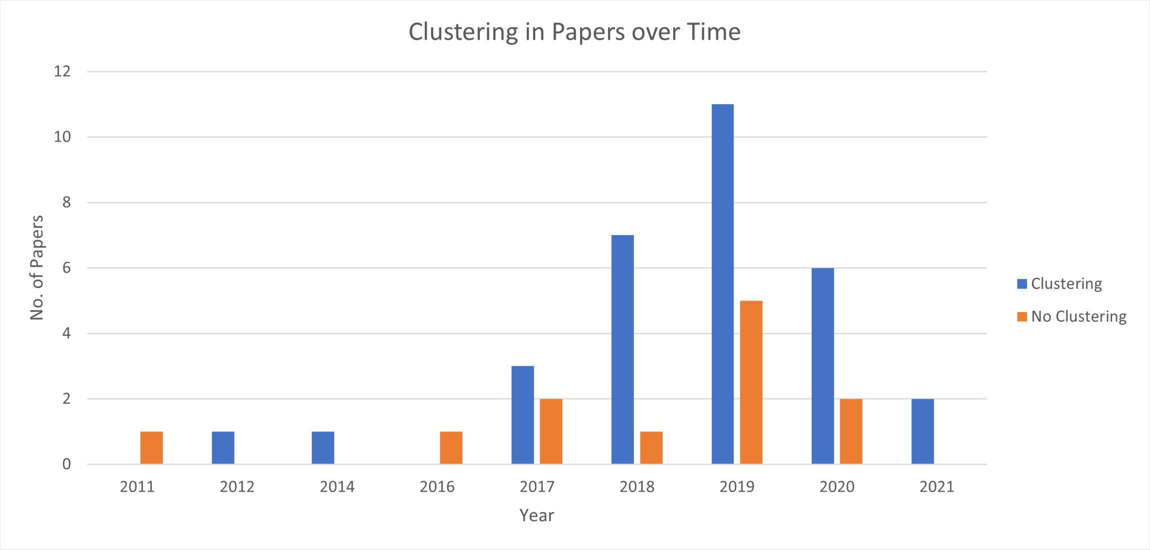


Figure 2.2: Clustering vs No Clustering over Time

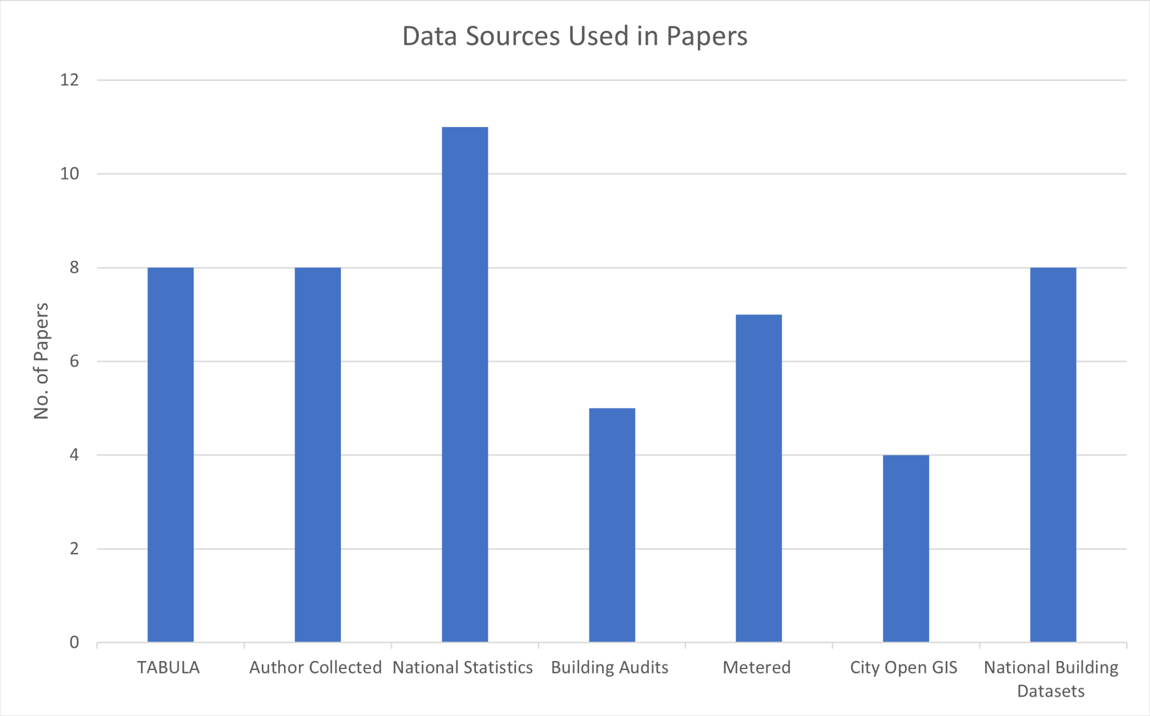


Figure 2.3: Total Uses of Various Data Sources

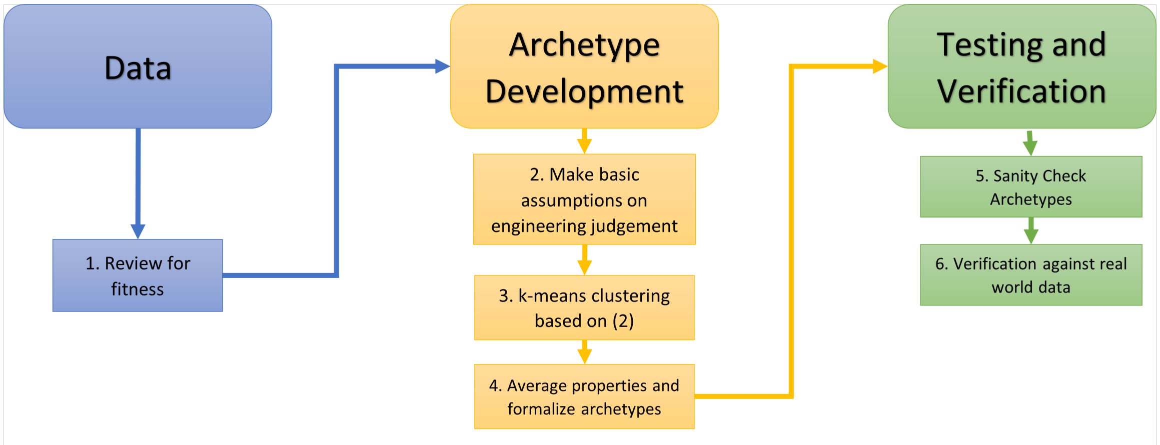


Figure 2.4: The Typical Archetype Creation Process

employed, and no single paper had all the features that an idealised process would incorporate. Algorithmically, it was found that deterministic methods of clustering are still in use, though machine learning (especially k-means) is more prevalent. Data was mostly limited to pre-collected data sets.

2.4.1 Typical Workflow

As the use of machine learning processes for archetypes is still in its infancy there is a lot of literature review and engineering judgement still used in the process. Therefore, most workflows resemble a hybrid of the more modern workflow, given above, and the one detailed in Mata et al. [2014]. Based on the papers given in table 2.2, a typical workflow looks like fig. 2.4. The steps in more detail are:

1. Review Data for Fitness: Check the data source will work for the study. Generally, the data sets are relatively 'clean', so only basic formatting preparation is necessary. Informal exploration of the data set is done at this stage, giving a researcher a 'feel' for the data — what parameters are available? are there large holes in the data set? Roth et al. [2020a] gives a good overview of the decisions at this stage. This phase is seldom found explicitly in the literature — the typical clean data sets require little preparation.

2. Broad archetype decisions based on the data: number, type, characteristics. While not explicit in most papers, researchers approach archetypes with an expectation based on their understanding of the building stock. These will

drive later data injections. For studies that develop and compare archetypes by multiple means, this is the stage at which the decision criteria for deciding which set of archetypes will be used is set. For clustering, decisions around number of clusters and what to cluster on may need to be made, and these are also made at this step.

3. Apply k-means clustering on building properties. K-means is used because it is easy to implement and the most general clustering algorithm in machine learning. fig. 2.1 shows that k-means is the most commonly used machine learning algorithm. [Ali et al., 2019, Bhatnagar et al., 2019, De Jaeger et al., 2020, Jaeger et al., 2020, Fernandez et al., 2020, Fathi et al., 2020]

4. Average cluster properties to create archetypes. The k-means algorithm clusters buildings together; the properties in these buildings have to be averaged to create a typical building. Often, at least some engineering judgement is applied here to create a more 'typical' building.

5. Check the building clusters for adherence to engineering judgement and literature ('sanity check') — did the clusters come out roughly how was expected based on what is known? This may also be a sanity check — did the k-means cluster together odd bunches, such as single family homes and shopping malls? This step is un-acknowledged in the literature; however most papers use a combination of a deterministic method (i.e. engineering judgement) and a clustering approach by deciding in advance which properties to cluster on.

6. Verification: compare generated energy time series to known to check if the archetypes are 'right'.

More recent papers are beginning to deviate from this typical flow, exploring alternative clustering strategies and choosing to use more sophisticated tools in place of engineering judgement. For instance, we are beginning to see clustering by energy time series, instead of building properties, and the use of clustering methods such as the random forest. Generally, these approaches are more accurate than the earlier ones, but they require greater programming and data science skills. [Famuyibo et al., 2012, Ali et al., 2019, Ben and Steemers, 2019, Streicher et al., 2019, De Jaeger et al., 2020, Roth et al., 2020b, Li et al., 2018, Cerezo et al., 2017]

Another technique appearing for increasing model accuracy is the use of multiple clustering methods and comparing their machine learning accuracy metrics (such as cluster spread) to select the best clustering technique. [Aggarwal and Reddy, 2016, Li et al., 2018, Roth et al., 2020b] Additionally when building a UBEM the following may be applied to archetypes constructed from the above processes:

- Refinement: adding additional specific data or using codes and engineering judgement to improve large-scale archetypes for smaller scales (e.g. adding city-specific details to national archetypes) Bhatnagar et al. [2019], Famuyibo et al. [2012]
- tuning: modifying archetype properties to match existing energy data [Roth et al., 2020b, Krayem et al., 2019, Buttitta et al., 2019, Streicher et al., 2019]

The goal of these processes is to improve otherwise too general to be accurate archetypes; generally these processes are applied to constructed archetypes to bring them into conformance with observed data. The tuning phase is quite rare; only a handful of papers perform it, most of them quite recent.
Refinements in the literature include:

- Occupancy changes Ben and Steemers [2019], Sokol et al. [2017], Cerezo et al. [2017], El Kontar and Rakha [2018], Kristensen et al. [2020]
- GIS-based shading Krayem et al. [2019]

When clustering is being done, these refinements sometimes take place at the archetype development stage instead; for instance when clustering a region Cerezo et al. [2017] included occupant behaviour in their clustering. The more specific the archetypes used, the less refinement needed — fundamentally these steps are ways of fixing archetypes.

2.4.2 Data Sources

As expected, it was rare (just eight studies) that researchers collected their own data, as it is a time consuming process. Generally major data collection efforts are government driven, and researchers take advantage of these pre-existing datasets. This is one reason studies in the EU are common; excellent data sets exist. TABULA was especially frequent and is mentioned in 26% of studies. [Ali et al., 2019, Ben and Steemers, 2019, Streicher et al., 2019, Roth et al., 2020a]

Most common (35% of studies), however, was the use of national statistics — census records and surveys of housing stock carried out by governments — most likely because of their widespread abundance. However, this information is often fairly superficial, and was often used in conjunction with other data sources, such as building surveys.

2.4.3 Clustering Methods

Clustering was used in 61% of the papers surveyed; of those the most frequently used was k-means, used 32% of the time. Deterministic methods came in tied for second most frequently used, at 23% of the papers each.

Most clustering was done on properties of the buildings; however Li et al. [2018] clustered on electricity use profile and Kristensen et al. [2020] was unique in clustering by year.

Very little research was found on effective clustering of buildings; only three papers, De Jaeger et al. [2020], Li et al. [2018], Roth et al. [2020b], explicitly address what makes their clustering effective.

This is the weakness of machine learning algorithms, and especially unsupervised algorithms such as k-means: generally they will always work. The quality of the result, however, will vary widely, so an additional, post-processing, step must happen to address the quality of the end result and justify its use. For k-means, one the most popular methods is the elbow plot, which shows that the correct number of clusters have been used. Studies which fail to show such indicators are flawed because readers have no way of knowing if the machine learning result is high or low quality. [Aggarwal and Reddy, 2016]

2.5 Discussion

Overall, the general quality of the papers was mixed — the building science was well done, but there was inadequate thoroughness on the clustering side. When deploying clustering algorithms, it must be shown the number of clusters is appropriate. This cannot be done using building science — it must be done using machine learning techniques referred to as ”cluster validation”. If cluster validation is not done, the validity

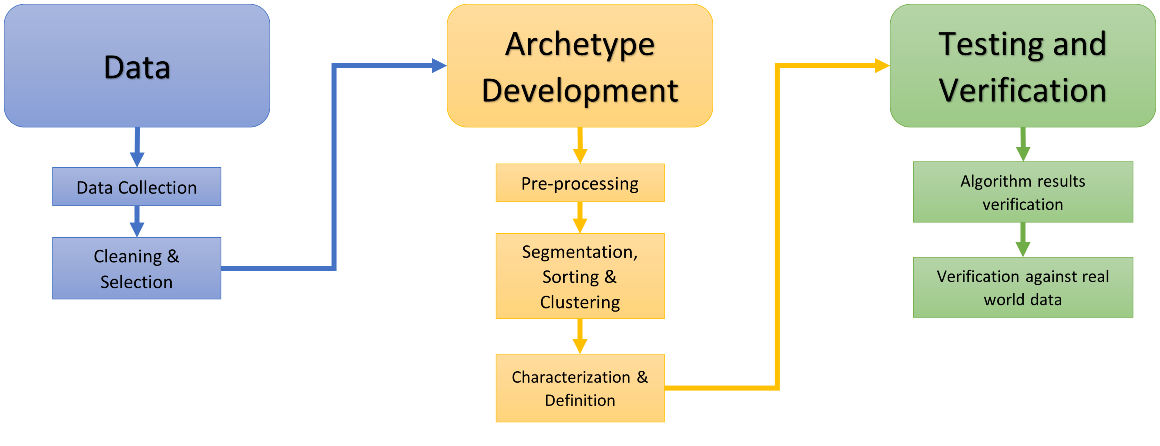


Figure 2.5: The Ideal Archetype Creation Process

of the clustering is in question. Most commonly employed are the elbow method, the silhouette method, and the gap statistic. Broadly speaking, these measure the spread of the individual clusters created against the number of clusters; fewer clusters with less spread is the ideal. (Generally, more clusters gives less spread, making this a trade-off analysis.) [Aggarwal and Reddy, 2016] While a deterministic method may seem to avoid the need for this kind of complicated, machine learning based approach, it creates a different problem: why wasn't a machine learning approach used? Properly deployed, machine learning approaches are more empirical than deterministic, engineering-judgement dependent approaches. A paper which uses a deterministic approach must justify it; citing prior literature is common, but often flawed: no two data sets are identical, so what worked on one may not work on another. Furthermore, past studies may themselves be deterministic, creating a chain of deterministic studies. With ready access to clustering algorithms, it must be shown that these cannot be used. Even if clustering algorithms cannot be used, common data science techniques for testing the presence of clusters may be used to inform a deterministic analysis.

While technically part of machine learning, a decision tree is a way of formalising a deterministic analysis. For situations where deterministic approaches must be used, creating a decision-tree based approach would offer a rigorous methodology. As most deterministic studies already use a decision tree-like chain of rules, this may simply be a matter of changing terminology and the structure of the study's methodology.

2.5.1 Idealised Data-Driven Process

The following idealised process for building data-driven archetypes collates the best practices found in many of the papers in the previous section:

1. Data phase:

    - Data Collection. This is one of the hardest steps, and the one researchers are least likely to do, due to its time consuming nature. The pre-existence of excellent data sets is one reason why so much research has been done in the EU. (See the prevalence of the TABULA data set in fig. 2.3) [Deru et al., 2011, Famuyibo et al., 2012, Roth et al., 2020a]
    - Data Selection/Cleaning: if the data from the previous step is 'messy'

  (missing values, incorrectly formatted, or other standard data issues), it must be cleaned before it can be worked with. [Roth et al., 2020a]
    - Inference of missing values. [Roth et al., 2020a, Rakha and El Kontar, 2019]. This is a common place for 'engineering judgement' to come in.

2. Archetype development phase:
    - Pre-processing. Data exploration and characterization into forms suitable for the algorithms employed. For instance, checking that a group of parameters is independent. [Li et al., 2018]
    - Segmentation, sorting, and/or clustering: divide the data into 'bins' that will become archetypes. Researchers will often 'help' the algorithm in use here by injecting their judgement (or pre-existing categories) into the binning. [Li et al., 2018, Roth et al., 2020a,b]
        - cluster verification: if a machine learning algorithm has been used, perform cluster verification to show that the appropriate clusters have been created.
    - Characterization/definition: create the appropriate properties for each archetype. This is often the step at which additional data will be injected by researchers from literature or codes.

3. Testing/verification phase. This comprises two steps: a machine learning algorithm results verification and an archetype verification:
    - Algorithm results verification: use machine learning metrics to verify the results of the clustering step are high quality, as most algorithms will not fail 'noisily' when the end product is poor quality, but rather will work no matter what.
    - Archetype verification: verify the archetypes against real world data. This can be done by comparison to a known data set of buildings, energy time series, or both.

This process was developed based on data science best practices for segmentation of data set by clustering and literature review. While not all steps are necessary (especially data collection and cleaning, if the researchers are working with a pre-existing clean data set), there needs to be reasons for skipping steps — a missing step with no explanation is a flaw. [Mata et al., 2014, Deru et al., 2011, Aguilera and Ossio, 2017]

While it is not always possible (especially in data-poor environments) to adhere to this process, it should be shown that this process will fail as part of the justification for using engineering judgement or literature review as an archetype basis. This is where verifying the machine learning algorithm results with metrics such as Dunn index, indicating how spread internally the clusters are, is useful. If the clusters are huge, these clusters are probably poor and an alternative method is necessary. This is discussed more in section 2.5.3.5. [Aggarwal and Reddy, 2016]

2.5.2 Data Phase

In the literature, as expected, most researchers skipped the the data phase. This is not a flaw: data collection is hard and studies are done where data sets exist. For the most part, these data sets are of high quality, and require no cleaning before use, which is why they were selected for use by researchers.

2.5.2.1 Data Collection

Very little in the literature review covered data collection specifically, as most researchers were using pre-collected data sets. Roth et al. [2020a] is the only paper to take a detailed look at what kind of data to collect.

2.5.2.2 Data Selection and Cleaning

For the most part, the data sets used were 'clean' data sets — ones that did not require work to use. This is because of the difficulty of working with messier data sets, both in time to clean them and in the complications of the techniques needed to infer missing or eliminate bad data. Techniques for operating in data-sparse areas are equally rare, despite the rarity of good data sets such as TABULA. Such techniques, however, would be very useful — very little of the world's building stock is covered in the available rich data sets. These techniques are covered in section 2.5.5.1, as they are ways of modifying/tuning/refining archetypes, not creating them.

Generically, rich data sets have two issues: bad entries and data gaps in specific entries. The techniques for handling these are well known in the data science community: inference of missing data and dropping bad entries. However, the validity of the techniques on building data is worth examining. There were several studies addressing these data issues in rich building data sets. Roth et al. [2020a] gives a data-science overview of handling building data, including analysis of which variables may be safely ignored. Rakha and El Kontar [2019] offers an inference technique on building data. The sophisticated techniques using machine learning image recognition and Google Streetview images to impute building properties used by Mohammadiziazi et al. [2021] are another option for filling in data gaps. Constructed archetypes may also offer a method of filling in data gaps; however if such measures are required it is likely the work is being done in a data sparse environment, which is covered in section 2.5.5.1.

2.5.3 Archetype Development Phase

2.5.3.1 Pre-processing

Pre-processing was relatively common; the simplest form of pre-processing is deciding what to cluster on. However, De Jaeger et al. [2020], Roth et al. [2020a], and Li et al. [2018] show that sophisticated pre-processing techniques, such as analysis of independent variables in the data set and considerations of which variables have the greatest impact, are best.

2.5.3.2 Segmentation Sorting and/or Clustering

Machine learning tools are just being widely deployed, as shown in fig. 2.2. fig. 2.1 further breaks this down, showing the adoption of various algorithms. Many studies are still using only deterministic methods — of the studies with clustering, 37% used deterministic methods. This may be a partial response to data issues; when data is limited the ability to use data-driven techniques is also limited. Many papers will blend these techniques, using both deterministic and machine learning methods.

Another sign that these tools are just being widely deployed in archetype modelling is the prevalence (32% of papers with clustering) of k-means. This is the most broadly used categorization clustering algorithm as it is easy to deploy; however it is sensitive to outliers and requires the clustering parameters used to be correctly chosen in a machine learning (as opposed to UBEM) sense. [Aggarwal and Reddy, 2016]

Li et al. [2018] and De Jaeger et al. [2020] show how mixed the results of k-means can be for buildings — Li et al. [2018] showing k-means to be worse than other methods, while De Jaeger et al. [2020] shows k-means can work very well, provided a proper parameterization (using machine learning techniques) is done.

Alternatives to k-means are varied; the most direct substitute would be k-mediod, which is essentially the same technique but with one of the points (instead of mean) serving as the cluster archetype. This variation is less sensitive to outliers. [Aggarwal and Reddy, 2016]

fig. 2.1 also shows that other methods have been tried: Roth et al. [2020b] used random forest clustering, after trying several other methods, used . This is effectively a problem in categorical data clustering and very few of the many techniques available have been studied. [Aggarwal and Reddy, 2016, Li et al., 2018, Roth et al., 2020b]

Additionally, initial studies have been done on time series based clustering, with mixed results. This technique shows promise, but is difficult and requires refinement.

2.5.3.3 Cluster Verification

Cluster verification is a standard part of clustering techniques, though most basic programming tutorials don't include it — they are focused on implementing the algorithm, not the actual data science. This, perhaps, explains why just three studies (Li et al. [2018], Roth et al. [2020b], Buttitta et al. [2019]) explicitly performed some form of cluster verification. De Jaeger et al. [2020] performed testing of their various numbers of clusters as part of their investigation of k-means clustering vs. 'regular' archetypes; their results showed their can be large accuracy differences between different numbers of clusters. [Aggarwal and Reddy, 2016]

2.5.3.4 Characterization/definition

This is the stage where the work of the previous stages is consolidated into a set of parameters that can be modelled. For k-means, this is the time when the mean of the variables in a cluster is taken to generate typical values.

2.5.3.5 Model Testing and Verification

At this stage, the UBEM created by the archetypes is verified.The hardest part of this stage is acquiring real-world comparison data. Without this data, it is difficult to conclude anything about the accuracy of the model. Most commonly used in this study was RMSE, which gives the difference between a predicted and actual value. This is a generally accepted measure, but does not include considerations of the shape of the two time series compared. Adding bias to RMSE can help with this. Aggarwal and Reddy [2016]

Another option is the ASHRAE research procedure 1051 and the related ASHRAE Guideline 14, which give a method for combining error measures from all energy sources in a building. This was used a handful of times in the literature, especially where multiple energy types in a building were present. It is a building-specific method, however, so its use on a city scale is untested. [Nagpal et al., 2019, Pasichnyi et al., 2019, Kristensen et al., 2020]

While sanity checks — comparison of results to engineering judgement — are useful, they are over relied upon to check the results of clustering. Instead, machine learning techniques should be used, such as the previously mentioned elbow plot for k-means. For clustering in general, both Dunn index and Silhouette co-efficient should be computed, giving the size of clusters and the distance between them, respectively. This shows that the clusters are well distributed and of an appropriate size for use.

2.5.4 Three Scales of Archetype

There are effectively three scales of archetype development: very large scale UBEM, very small scale RRM, and an intermediate scale that might be either. Each scale has its own challenges and opportunities, especially the intermediate scale where both scaled down UBEM and scaled up RRM is being used.

2.5.4.1 UBEM

For UBEM, there are two issues worth additional consideration: scale of model and HVAC. In Ali et al. [2019] it is shown the difference between archetypes developed on a neighbourhood basis and those developed on a city wide (or national) basis is significant. If archetypes are not developed as part of the paper, the scale of the previously developed archetypes needs to be factored into any decision on use or tuning for UBEM, as accuracy will depend on the scale the archetypes were meant to be used.

Another significant factor to consider in larger models is HVAC. While HVAC is often genericized for these larger models, Kim et al. [2020] show that failure to consider HVAC systems in archetypes can lead to up to 15% error.

2.5.4.2 Residential Retrofit

For classical residential retrofit an extremely focused set of models are developed — one or two archetypes determined by engineering judgement such as in Jermyn and Richman [2016]. For these models, both Buttitta et al. [2019], Ben and Steemers [2019] show that occupancy should be considered and offer stochastic techniques to help. Another approach to occupancy is given by Pasichnyi et al. [2019], which models the heating demand stochastically rather than the occupants themselves.

Archetypes for residential retrofit can make forecasting of energy demand possible; Alajmi and Phelan [2020] takes Cerezo et al. [2017] and performs detailed analysis of systems such as air conditioning, laundry, and dish washers to forecast future electrical loads.

2.5.4.3 Intermediate Scales

Intermediate scales, given in table 2.2 as campus (closer to RRM) or district (closer to UBEM), can have either UBEM or RRM techniques used, but UBEM techniques should be prefered as De Jaeger et al. [2020] shows that clustering works better than an RRM approach of constructed bottom up archetypes. However, techniques such as Roth et al. [2020b] allow more focussed archetypes to be broadened, which would allow the use of RRM archetypes.

These scales also offer the opportunity to experiment with UBEM techniques, as the size is small enough to be manageable with a new technique, but large enough to provide results that could be scaled to a full UBEM. Notable is Nagpal et al. [2019], which provides a surrogate model based inference technique for building properties, tested on a campus scale. Roth et al. [2020b] uses a similar but simpler surrogate modelling process to infer properties on a city-wide scale.

2.5.5 Additional Techniques and Considerations

This section covers methods that can be added to the above process to create better archetypes, but are not, strictly speaking, part of the process, specifically methods to handle areas which have little data, the use of GIS data in archetypes, and the methods being developed to handle random behaviour as part of archetypes. For certain researchers, such as those attempting to create high-fidelity models with hourly resolution or those dealing with building controls who must deal with occupant behaviour, these techniques may be invaluable; for others, who are simply seeking a broad overview model as a base for forecasting the impacts of building stock changes, they may not be necessary.

2.5.5.1 Data-sparse techniques

These techniques are generally deployed after the creation of archetypes, whether from data or constructed archetypes. The idea is simple: take a small amount of detailed data, a set of general archetypes which are not precise enough to use as-is, and a general overview of the building stock, and use the detailed data to refine the general archetypes into something more precise. The kinds of data used range from open general building stock data (often with GIS), the kind of data which is often available online from cities with no access controls, to smaller data sets of building audits, insufficient to create representative data-driven archetypes over the whole building stock, to large-scale aggregated electricity use.
One option, is the use constructed archetypes did occur to fill in the data gaps where there is little or no detailed data. As of yet, refining and tuning data driven archetypes is quite rare, though has promise — take a small scale, detailed, data set and generalise to a larger area.[Nagpal et al., 2019, Roth et al., 2020b]. This is one use for partial data sets, where there is insufficient data to cluster, but sufficient data verify archetypes and/or refine/tune existing archetypes. As of yet, there has been little work done on refinement or tuning of constructed archetypes with what data is available, to create better archetypes for an overall UBEM of the area: the two key papers are Nagpal et al. [2019] who infers campus scale building information from an energy

time series, and Roth et al. [2020b] who uses a small, detailed, data set to create a general model of a city. Both these studies, and those similar to them, require a fairly rich data set and use sophisticated techniques which may be difficult to deploy widely. It has been shown, by Therrien et al. that at least some detailed building data is required: in their paper they attempted to tune the archetypes created by Deru et al. [2011] with nothing but general electrical consumption data for the city. While the genetic-algorithm based tuning method showed promise, the attempt was ultimately unsuccessful. [Nagpal et al., 2019, Roth et al., 2020b, Alajmi and Phelan, 2020]

A final option, currently almost unexplored, is using the energy time series of a building to infer its properties, then creating archetypes from these inferred properties, as shown in Westermann et al. [2020a] This is due to difficulties in obtaining such data as well as the complexities of constructing such a machine learning model.

2.5.5.2 GIS

The use of open city GIS data sets is a relatively unexplored field — just 13% of papers used them. For the most part, these data sets are being used for their non-GIS information (these data sets are an easily available source of general data on a city's buildings) and to create interesting post-model graphics. Even in simple applications, using the geographical information itself may prove challenging, as Dochev et al. [2020] show. However, these data sets have great potential to increase the accuracy of models by allowing shading to be considered for each building in a city, as demonstrated by Krayem et al. [2019].

Beyond shading, smart grid analysis is another use for GIS-based UBEM. Krayem et al. [2019] gives an example of this type of modelling. While not using GIS, Pasichnyi et al. [2019] also analyses grid demand based on a UBEM. Any archetype incorporating smart grid (or district energy) will have to include some model of the connections; GIS position of the buildings implicitly contains distance data.

2.5.5.3 Stochastic and Bayesian Modelling

In areas with uncertainty or variation (such as occupant schedules), data-driven probabilistic techniques have been used and show great promise for increasing UBEM accuracy, solving such as issues around schedule stacking with archetypes where all the systems in a given building type turn on at the same time everyday. For monthly or yearly UBEM models, this is not an issue, but on a daily basis it is. [Ben and Steemers, 2019] Attempts have been made to create a 'random' occupant to fix it using bayesian/probabilistic techniques. [Cerezo et al., 2017, Ben and Steemers, 2019] Another approach is Pasichnyi et al. [2019], using probabilistic heating models, by using statistical methods to represent the range of possible parameter values inside a cluster, instead of assigning a single value, where there's occupant-driven uncertainty.

2.6 Conclusions

Overall, the use of machine learning algorithms is increasing. The most common algorithm used is k-means, though other algorithms are being experimented with. Most uses of k-means do not perform cluster validation, making their results less useful as there is no way of judging the quality of the clusters. Future studies should include machine learning metrics for quality of results. Li et al. [2018] uses various clustering methods and provides metrics, and De Jaeger et al. [2020] shows how k-means can be used well.

If deterministic techniques are used, they should be justified by first showing that clustering or other data-driven techniques will not work for the given data set. If data is missing, inference techniques such as those developed by Nagpal et al. [2019] and Roth et al. [2020b] should be considered. Deterministic techniques should be distilled to a procedure, such as a decision tree, in papers for clarity.

For UBEM models, the scale at which the archetypes are developed may affect the accuracy of the results, as shown by Ali et al. [2019]. For best accuracy in UBEM, Kim et al. [2020] show HVAC system specifics must be considered as part of the archetype, rather than using broad HVAC generalities.

At a more limited scale, De Jaeger et al. [2020] show that campus or district scales are best considered limited UBEM, as bottom-up, constructed, archetypes start to break down as the scale increases and more variations are seen. Techniques of inference, such as Nagpal et al. [2019] and Roth et al. [2020b] can help to genericize these archetypes, however.

At the RRM scale, occupancy becomes an issue. Stochastic and Bayesian methods are being developed to help with this, such as in Ben and Steemers [2019] and Pasichnyi et al. [2019]. It would be interesting to expand these techniques further on a larger, UBEM, scale.

Areas of ongoing work include inference of missing data, the use of GIS for shading (such as in Krayem et al. [2019]), stochastic and bayesian methods of dealing with uncertainty, and best clustering algorithms. Lastly, a best practices technique for developing data driven archetypes, shown in fig. 2.5, was created from the literature.

Chapter 3

Inference of Building Archetypes and Schedules from City of Victoria Open Data

Originally intended as a short test of an inference technique for eSim 2020, when the conference was delayed to 2021 due to COVID, the base technique, due its strong promise, was expanded into a large software tool for inferring building properties.

3.1 Inference of Building Archetypes and Schedules from City of Victoria Open Data

Garrett E. S. Therrien[1]*, Theo Christiaanse* [1]*, Ralph Evins* [1]
[1]*University of Victoria, Victoria, Canada*

Abstract

Building-by-building modelling of districts using existing archetypes has become common practice for creating detailed district models. But, this technique scales poorly:

detailed data on each building in a large area is usually non-existent or not publicly available. However, there are open data sources, such as zoning and building footprint area, commonly available from cities and municipalities that allow the assignment of archetypes. This paper presents a method using municipality open data sets and the Building Technology Assessment Program (BTAP) archetypes to create an urban district building stock model, enabling detailed analysis of a city's building stock. The method developed will be demonstrated on City of Victoria open data, and the model will be verified by comparing daily electricity use.

Introduction

Urban building energy modelling (UBEM), or modelling of the building stock of city or other urbanized region, is a generally underdeveloped field of study inside building modelling. Yet, with the growing challenges of climate change and the matching growth cities' climate change policies, it is a critical field, able to provide guidance on the best climate change mitigation policies.

As late as 2016 UBEM was referred to as a 'nascent field' by Reinhart and Cerezo Davila [2016] who, in their review of UBEM, laid out what remains a typical, data-intensive process for building out a city building stock model. In essence, this typical process relies on having detailed building data (including hourly energy use) for a large segment of the buildings in a city, clustering these by some process (in the beginning it was often done by manual judgement; now machine learning tools are more common, as shown in Deru et al. [2011], Reinhart and Cerezo Davila [2016]) to create data-driven archetypes, and filling in any gaps with constructed archetypes (archetypes built from the building codes, such as the U.S. DOE archetypes). This process also shows why so little study has been given to UBEM: the data sets simply do not exist in the vast majority of cases, especially in North America. Europe has several data projects which have provided material for case-studies of UBEM; unfortunately these are not generalisable as they are tied to the datasets used. [Ali et al., 2019, Cerezo et al., 2017, Reinhart and Davila, 2019, Swan et al., 2009, Pasichnyi et al., 2019, Deru et al., 2011, Mata et al., 2014]

However, in the last few years there have been advances in parallel fields in computer science, providing a suite of machine learning concepts and tools for inferring and tuning models from very little data. These tools are just beginning to be applied to UBEM for the construction of stock models, usually by calibrating an existing archetype set. Notably, Nagpal et al. [2019] and Nagpal and Reinhart [2018] developed a calibration technique that works on city blocks or large buildings. Tardioli et al. [2020] recently took this work further, doing work with building location in GIS as well as using Bayesian inference techniques to improve data-driven archetypes. Unfortunately, these techniques use a large amount of data as their initial base — in essence what has been developed is a better way of filling in the gaps and building out a data-driven model and not a method for working in a data-sparse environment and filling in the gaps in constructed archetypes. [Ali et al., 2019, Cerezo et al., 2017, Reinhart and Davila, 2019, Nagpal and Reinhart, 2018]

Some of the most recent work in this field, though, carried out by Roth et al. [2020b] takes the calibration ideas in Nagpal et al. [2019] to the next logical step, using them to refine a mix of constructed and data driven archetypes. This work shows it is possible to take a mix of highly specific building data for only part of city, general archetypes, and a relatively data-sparse city with open data and calibrate a UBEM stock model from this data. While their paper relied on having a rich data source for validation and cross-checks, now that the concept and technique has been proved, it is of interest how much of such data is necessary — the less data needed, the more generally applicable the technique. Furthermore, because they were uncertain if the concept would work, they used a multi-faceted method to test several different ways of performing calibration; this process, while effective, could prove a bar to wide spread deployment. [Nagpal and Reinhart, 2018, Nagpal et al., 2019, Tardioli et al., 2020]

And wide spread deployment is highly desirable — detailed may provide municipalities with the tools to develop targeted evidence based policies to lower carbon emissions. But, because such data sets are the result of years of work, often contain confidential information, and, if developed by a company, are usually proprietary, these detailed building stock models are rare, forcing cities to use rough estimates (such as multiplying the square footage of building types by the relevant archetypes, refered to later in this paper as the 'scaled' method) to predict the impact of their building policies. [Nagpal and Reinhart, 2018, Reinhart and Cerezo Davila, 2016, Swan et al., 2009, Cerezo et al., 2017, Mata et al., 2014]

Fortunately, most cities can obtain basic building information (building heights, footprint areas, and general uses) that could form the base of a more generic archetype-based model. Most of the methods used in Roth et al. [2020b] can be separated from the data-rich baseline; in place of data-driven archetypes a more generic archetype can be used. City-scale aggregate electricity use data (for tuning) is relatively easy to request, as it offers no privacy issues in the way building-by-building data would. [Swan et al., 2009, Nagpal and Reinhart, 2018, Nagpal et al., 2019, Kristensen et al., 2018, Deru et al., 2011, CanmetENERGY]

Therefore, on the basis of this past work, this paper seeks to prototype a simpler, more portable method of archetype calibration for an UBEM stock model. This method we propose uses a minimum of specialised data: data used will be limited to open and common data, such as municipal GIS data and easily requested aggregate electricity use. Because of this, it will focus on 'bottom-up' methods, starting with assumptions and refining on the basis of data, rather than the 'top down' method more generally employed, starting with data and using assumptions to fill in the gaps. Rather than attempting to build something perfect, this paper will focus on 'good enough', striving for simple methods that are reasonably accurate. Most municipalities are facing difficult decisions with no tools, and this paper seeks a method to fill in this gap, to find the minimum amount of data and model parameters that can be used to develop a UBEM stock model.

Methods

The methods deployed in this paper comprise three distinct stages:

1. Build: Create archetypes: select base archetypes and input data in preparation for the next two stages.
2. Fit: Generate building stock options, map them to the archetypes created in phase 1, and select of parameters for tuning and fitting a surrogate model to each archetype to speed up computation of energy use in the genetic algorithm.
3. Tune: Use a genetic algorithm to tune the parameter values selected in 2 to fit the real-world time sequence.

The goal of this process is a set of parameters for the input archetypes which create a daily energy time series which matches the actual time series from BC Hydro.

Input Data Selection

For this study, we use various different data made available by the City of Victoria and BC Hydro. The data sets can be put into two categories. The first is building size, use, and classification from the City of Victoria. The second is the total electricity use of the downtown core in the form of hourly time series data.

The first set of data was taken from City of Victoria open data portal [City of Victoria] , which has a tremendous amount of information. The data set of interest to us is the Building Rooflines 2019 data set (the Rooflines dataset), with information on the building use (allowing sorting into archetypes), and building size and shape (allowing scaling of energy use).

The second set of data — energy use data — was requested from BC Hydro. This data is sufficiently aggregated that it was easy to request — there are no privacy issues with electricity use data from a large area, as it is impossible to de-aggregate to individual buildings. It contains aggregated hourly data of every commercial building in the City of Victoria.

The last input needed is the archetypes. These were selected from the Building Technology Assessment Program (BTAP) [CanmetENERGY], a Canadian version of the U. S. Department of Energy (DOE) standard reference buildings produced by Natural Resources Canada (NRCAN). To these archetypes a 'No Energy' archetype was added, having no energy use at any time, for vacant buildings and parking lots. [Deru et al., 2011]

For this study, the BTAP 2011 National Energy Building Code (NEBC 2011) implementation was used as base buildings, as they represented a compromise position: while there are many older buildings in Victoria's downtown core, 2011 was the earliest code implemented in BTAP. These archetypes were assigned to the buildings in the downtown core using the 'Actual Use' given in the Rooflines data set, and, in the case of buildings with multiple sizes, storeys. [CanmetENERGY]

As the BTAP archetypes are commercial only, this study is limited to commercial data only.

Generation of the Building Stock Model

To generate the building stock we will translate the building stock data extracted from the Rooflines data set to BTAP archetypes. First of all, each actual use type — the City's classification of the building by its use — is translated into a building type. Then these building types are assigned BTAP archetypes. While this may seem redundant, as several building types may have the same BTAP archetype, in later tuning steps these building types will have unique deviations from the base BTAP archetype.

This division into building types and assignment into archetypes is done by engineering judgement. Where there was a need to determine if a building was small, medium, or large, the number of storeys was used, such as for office buildings.

There are two obvious ways to assign the buildings into building types, and both were tried: straight assignment into archetypes (where BTAP archetypes plus the "no energy" archetype become building types, so there are only 13 building types matching the 13 base archetypes), and straight assignment of building types by actual use type (where the City's actual use type categories become the building types.)

After refinement of parameters and the addition of light and plug load, a third, simplified, assignment was tried, between these two extremes, both to reduce the number of variables in the GA and to better reflect reality. For example there were several categories of small office in the actual use type set, ranging from a generic small office to a government building, that were the same type of building type — a small office building used for desk work. Such building types could be profitably consolidated into one and were in this simplified actual use type run.

As the BTAP models are electric heat, the percent of buildings using gas heat was located in the NRCan statistics for building stock in Canada, and overall energy use was reduced by this amount, 76.7%. [Government of Canada, 2020]

Parameterisation and Energy Use

Parameters were decided upon based on previous research into archetypes and tuning [Swan et al., 2009, Reinhart and Cerezo Davila, 2016, Ali et al., 2019, Cerezo et al., 2017, Reinhart and Davila, 2019, Swan et al., 2009, Pasichnyi et al., 2019, Deru et al., 2011, Mata et al., 2014], with the parameters that had the consistently highest impact on energy use used:

- Heating Set Point – Overall heating set point. In later runs this was changed for weekday only, during the day.
- Cooling Set Point – Overall cooling set point. In later runs this was changed for weekday only, during the day.
- Insulation Value – value of the wall insulating materials in RSI.

- Light and Plug Load – average sum of all lighting and plug loads in the building, on a schedule determined by the archetype.

It is noted that these parameters oversimplify; often archetypes have, for instance, different set points for weekend and weekday which are not taken into account in the initial or final heating and cooling set point setup. However, tuning all set points often leads to an excessive number of variables being tuned; in the case of the actual use type tuning it is in the thousands of variables (69 actual use types, some with as many as 40 variables) so simplification must be done.
Light and plug load was added after runs the first set of runs, in an attempt to further improved the archetypes.
Once these parameters were decided, it was relatively easy to parameterise the archetypes and determine energy use. However, as EnergyPlus (EP) runs are quite slow, and each run of the genetic algorithm will need many simulation runs, it was decided to train surrogates in place of EP for use in the genetic algorithm. Each surrogate model is based on a regression neural network method. All surrogate models were constructed using TensorFlow with input parameters proportional to the building type division and 365 output parameters with a learning rate of 0.001 using 4000 epochs. The model additionally has four hidden layers with the first having twice the size of the input parameter nodes, the second 183 nodes, and the third and fourth 365. The inputs and outputs are normalized using the training data, which consists of a subset 80 percent of 50 EP runs. The input parameters for these EP runs are based on random set points produced by Latin hypercube sampling, while the outputs are a year's electricity use time series data. The surrogate model showed high R2 values on the test data in the range of 0.99, due to the simplicity of the model.

Genetic Algorithm Tuning

To tune the buildings, a genetic algorithm was used. Time series energy use for the city, as predicted by the input parameters, a list of the buildings in the city, and the building type models, was compared to the actual time series energy use of the city using cumulative RMSE. This error was minimised, as it was desired to have as little difference between the predicted and actual energy time series.
See table 3.1 for a breakdown of which parameters were used by which runs. Note, this table does not show the scaled-only run as it was not put through the GA.

Run Name ((Y)es or (N)o) ((Y)es or (N)o	Building Type Division Lights and Plugs	Weekday Set Points Only	
Archetype	Archetype	N	N
Actual Use Type	actual use type	N	N
Four Parameter Archetype	Archetype	Y	Y
Four Parameter Actual Use Type	actual use type	Y	Y
SAU	Simplified Actual Use Type	Y	Y

Table 3.1: Setup for Each Genetic Algorithm Run

Common values to all runs are:

- Heating Set Point Range: 5-15°C
- Cooling Set Point Range: 25-35°C
- Insulation Value Range: 0-10°C
- Light and Plug Load (for runs used, see table 3.1): 5-30 W/m^2
- Genetic Algorithm Population: 20
- Genetic Algorithm Evaluations: 600
- Number of GA runs: 20

Results Interpretation and Error Calculation

To gain a larger sample of parameters and prove convergence, the GA will be run 20 times and the mean value for each parameter calculated. This mean value will be used to predict a final daily energy time series. Errors will be quantified using the root mean square error (RMSE), showing how far the predicted series deviates from the actual (i.e. the spread of the residuals) and the mean bias of the predictions (showing over or under prediction.) Additionally, scatter plots will be plotted of predicted vs actual results, allowing easy visualisation and comparison of the over and under prediction of each run.

Results

Results of all runs are in fig. 3.1, which shows the predicted energy uses and the actual energy uses. Errors fig. 3.3, which shows the mean root mean square error (RMSE) (showing how far the predicted series deviates from the actual, i.e. the spread of the residuals) and the mean bias of the predictions (showing over or under prediction) (ideally both of these are zero), and in fig. 3.2 which shows the SAU time series, which was the best time series calibrated. Convergence for the SAU run is shown in fig. 3.6. To further quantify over- and under-prediction, fig. 3.4 was plotted, showing the predicted vs actual values. The red line in each plot is the line of equality; ideally the scatter plot would be concentrated along this line. The rows are method (straight scaling, three parameter, and four parameter, from top to bottom), and the rows are the building type division employed (archetype, actual use type, and simplified actual use type, from left to right.)

The parameter values for the four parameter actual use and the SAU runs are compared in fig. 3.5; these are the two best runs and have very similar output time series and identical errors, making a detailed comparison of their output desirable.

Discussion

While precise results were not arrived at, several useful conclusions can be drawn. The process was started with with the baseline case of straight scaling of archetypes, then progressed through tuning archetypes and building types, with steady improvements. A final improvement was obtained by refining parameters, and the interpretation of results was improved by creating the simplified actual use building type. The base case of scaling can be seen in fig. 3.1 (the orange line; the blue line is the actual energy use.) It can be seen this technique is sub-par; it vastly under predicts, though it does maintain a reasonable weekday/weekend relationship. Therefore, you cannot just scale the energy use by floor area and buildings using electric heat, as was done to generate the orange line, but rather need to adjust the actual underlying values.

The next stage was to tune one building type per archetypes for all the buildings. i.e. splitting the city up into 13 building types directly corresponding to the archetypes (12 of these are BTAP archetypes, 1 is the 'No Energy' Archetype.) This is the green line fig. 3.1. As shown in fig. 3.3, this is extremely inaccurate, having both high bias

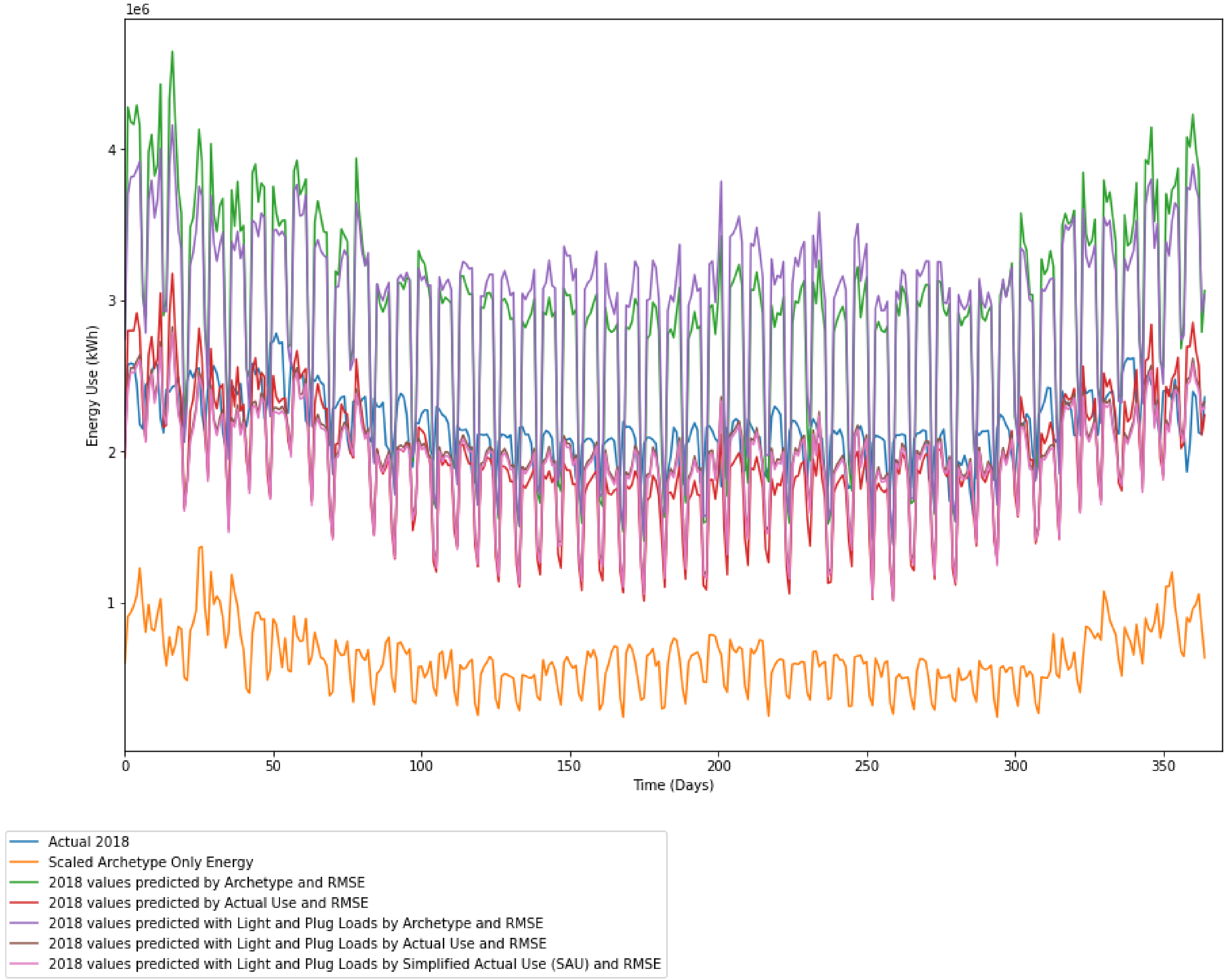


Figure 3.1: All BTAP Archetype Based Energy Prediction Series

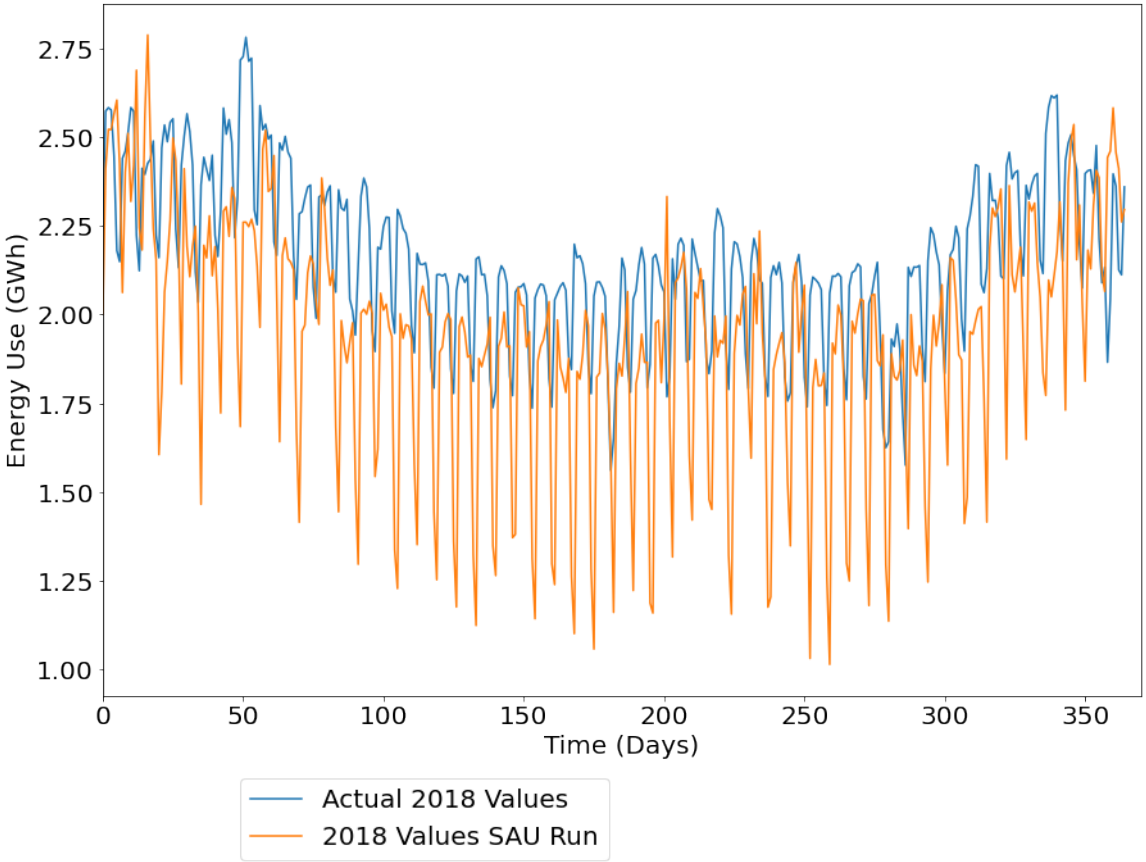


Figure 3.2: SAU Energy Series

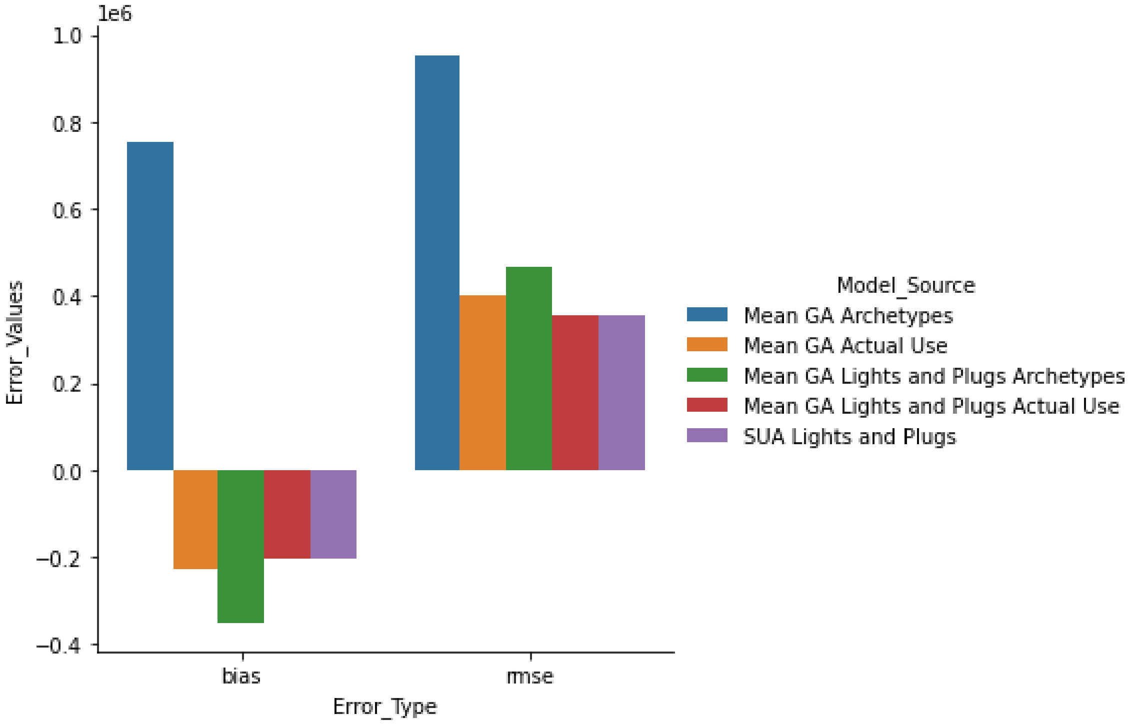


Figure 3.3: Bias and Root Mean Square Error for BTAP Archetype Based Predictions

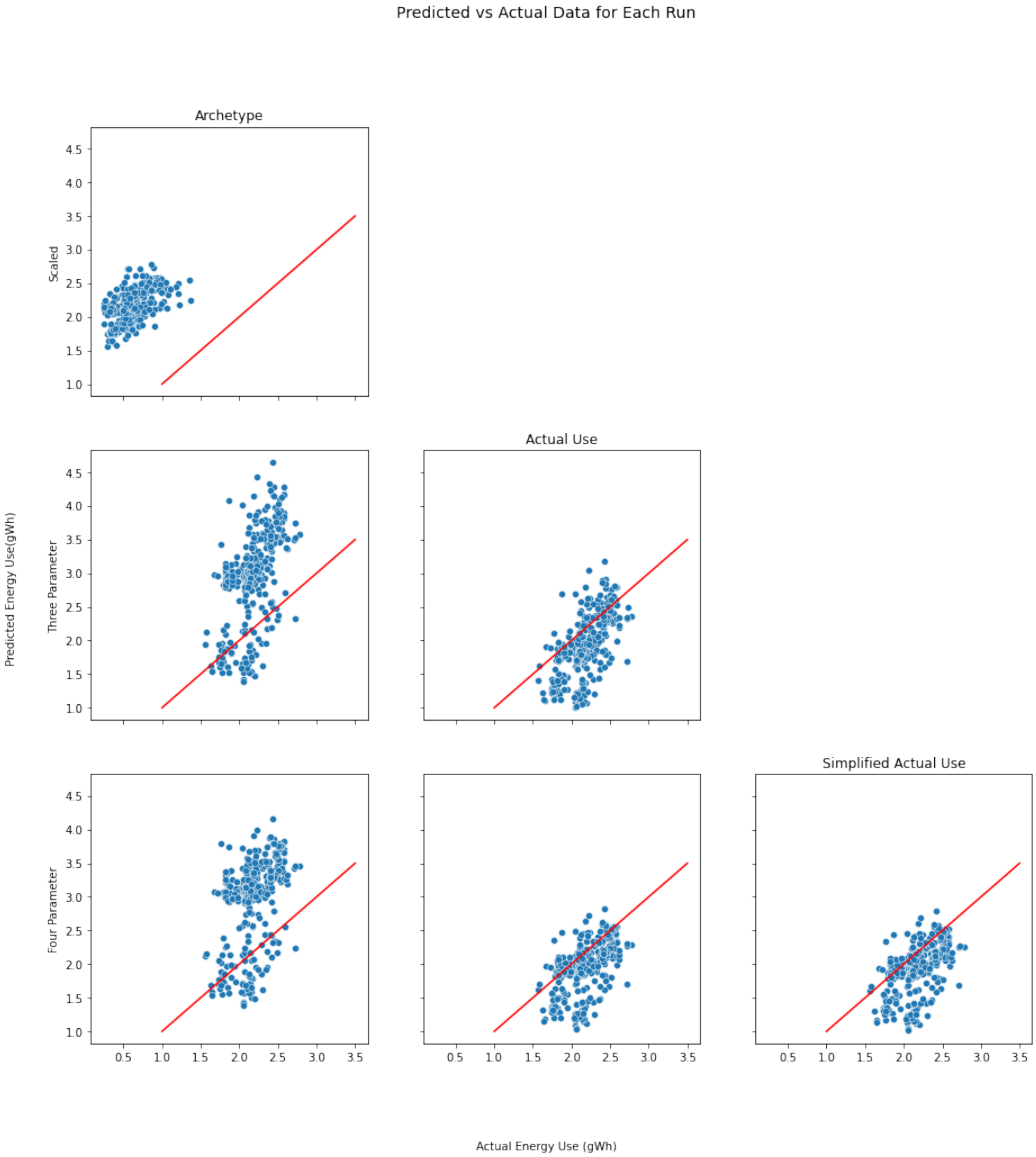


Figure 3.4: Predicted vs Actual Energy Use

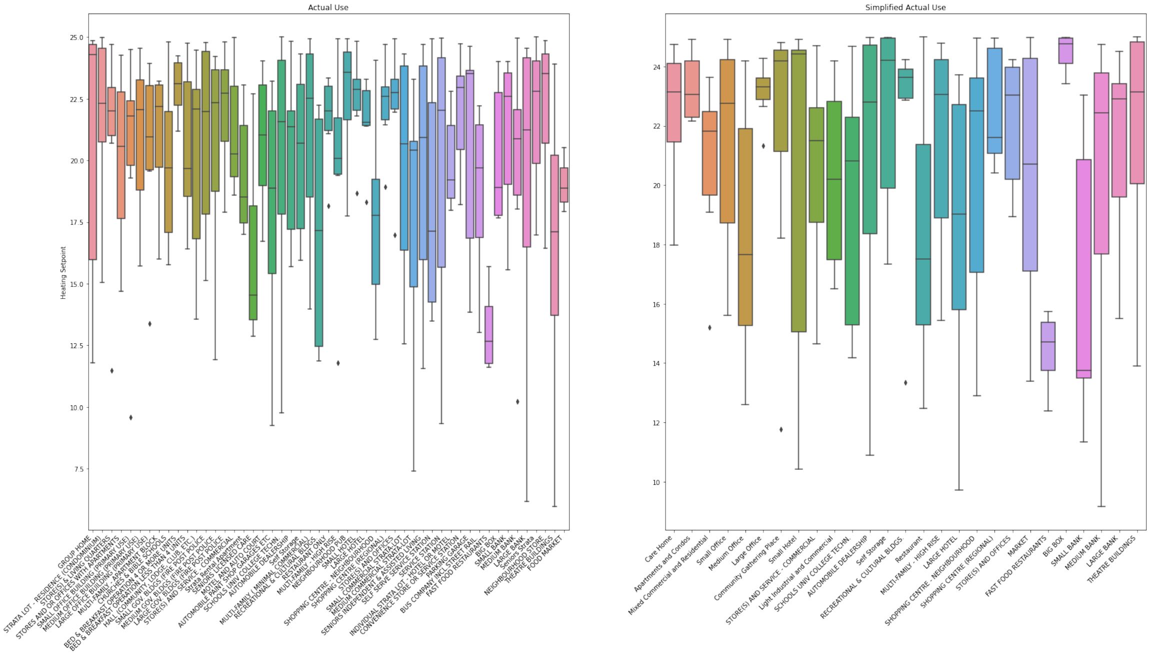


Figure 3.5: Actual Use Type and SAU Run Variable Results by Parameter for Heating Setpoint

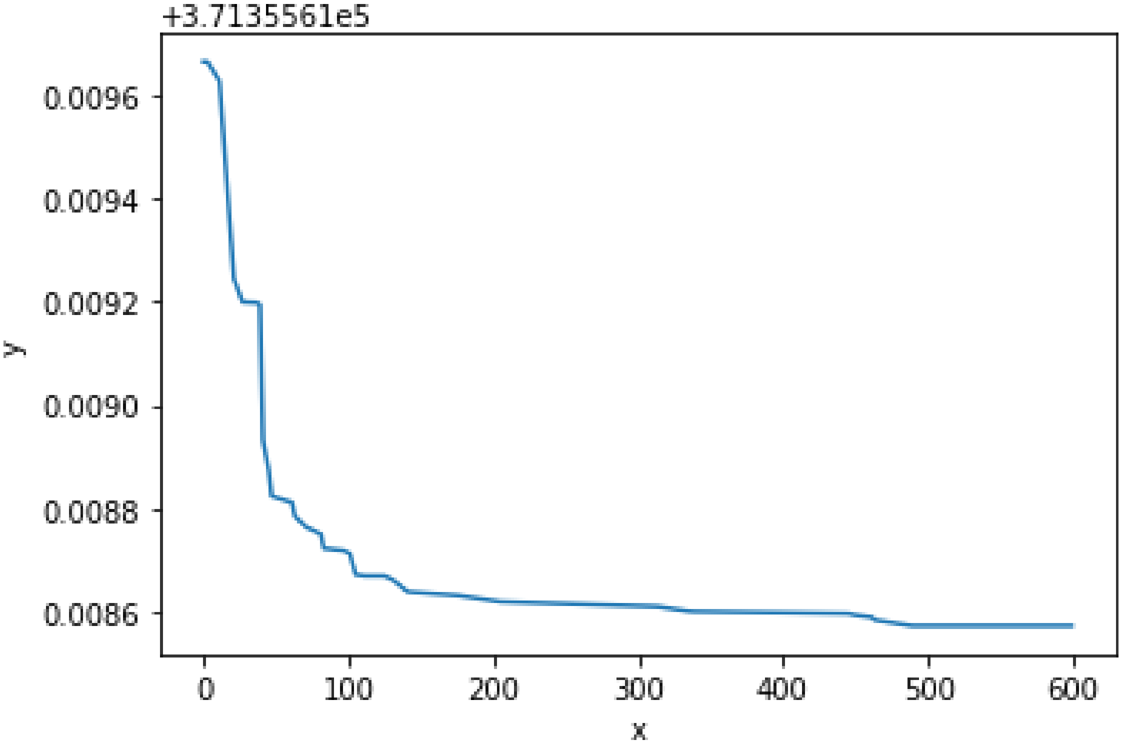


Figure 3.6: SAU Run Convergence

and high RMSE values, due to this method's over prediction of energy use, as shown in fig. 3.4.

To improve the results, the City of Victoria Roofline data set actual use types were used as building types, creating 41 types; note six of these have a base 'No Energy' archetype, and will have an energy use of zero. Each building type was assigned a base archetype, but each building type was tuned individually, giving the GA 105 parameters to tune (compared to the 36 used in the archetype division.) Both these parameter sets exclude the 'No Energy' archetype building types (whose energy use is zero).

The results of this actual use building type division is much better than the straight archetypes; as shown fig. 3.3 and in fig. 3.1 the time series (the red line) is much closer than one for straight archetype scaling. This is due to essentially eliminating over prediction, as shown in fig. 3.4 and fig. 3.3; unfortunately, as also shown in these figures there is a pronounced tendency to under predict, mostly on the weekends.

It was hypothesized this was due to issues with the base load, and two changes were made. One, instead of using a universal heating and cooling set point, only the weekday heating and cooling set points were changed; and two, light and plug load was introduced. For the sake of completeness, this was computed using archetype divisions, but (as expected), this was a poor prediction. However, it is notable that these changes did improve the significantly improve the prediction from the previous, three parameter, archetype prediction — as shown in fig. 3.4 the over prediction was consolidated, and the errors shown in fig. 3.3 were much reduced. Unfortunately, the improvements in the actual use type building division prediction using four parameters were more modest; while the predicted vs actual plot in fig. 3.4 shows a lessening of the under prediction, the error plots in fig. 3.3 show that the overall improvement was only slight.

Furthermore, this actual-use tuning actually divides the buildings too much, creating a situation where some categories only had a few buildings in them, too few for good tuning by the GA or statistical analysis. Hence, at this stage, the simplified actual use building types were created. This set has fewer building types than actual use type (by, for example, merging various kinds of small stores together), but more categories than pure archetype binning (which had poor results due to having too few building types for the GA to have a sufficient number of variables to tune.) It was possible to reduce the city to 23 building types, of which only one was No Energy, leaving 22 building types for a total of 66 parameters.

The simplified actual use type did not improve the errors as shown in fig. 3.4 and fig. 3.3, but as shown in fig. 3.5 it did improve the overall quality of the results — there are fewer outliers and generally smaller bars with shorter whiskers with simplified actual use type compared to actual use building types, making results from the simplified actual use more precise.

While it was briefly attempted to increase the heating and cooling set point divisions, to allow for a weekend daytime heating set point, the preliminary results were quite bad, showing errors in excess of the simplified actual use runs, and this work was finished there, as it was felt that the limits of the accuracy of the method with the current data had been reached.

Potential improvements in this method are to be found in either more accurate base archetypes (for instance archetypes with gas heating and tuning with a gas time series as well as an electric one), or in using a detailed data set of a subset of buildings (such as Roth et al. [2020b] did. However, Roth et al. [2020b] is a top-down approach, using assumptions to fill in the gaps, as opposed to our bottom-up approach, which uses data to refine assumptions, and hence is not a method that can be used in a truly data-poor area.) This work does, however, show the potential viability of a bottom up approach, as the opposed to the mostly top-down approach used in previous papers. It also shows the need for at least some detailed building data to flesh out the assumptions and basic, publicly available, data in a bottom-up approach. Determining the amount of detailed data needed to produce an acceptable model in a bottom-up approach is left for future work.

Conclusion

While a straight scaling of generic archetypes is inaccurate, it is possible to create a time series which is close to accurate with very little data and a set of generic archetypes, proving the viability of a bottom-up, data-poor, approach. However, a truly acceptable bottom-up approach will require at least some detailed building information to allow final refinements of the archetypes.

Chapter 4

A Practical Process for Determining the Impacts of Residential Retrofits From Limited Data

This paper presents an example of the third way of dealing with data-poor environment, approximations. It focuses on the practical development and uses of archetypes, using a less than perfect, but still rich, data source, which is typical of the frequently available 'good' data sources. It demonstrates the proper techniques for eliminating machine learning for archetype creation and for moving to a deterministic process to generate archetypes, and how such relatively imprecise techniques may yield usable results.

4.1 A Practical Process for Determining the Impacts of Residential Retrofits From Limited Data

Garrett E. S. Therrien[1], *Rachel Barton* [1], *Dr. Ralph Evins*[1]
[1] *University of Victoria, Victoria, Canada*

Abstract

Retrofit studies are fairly common, as the need to reduce the carbon and energy footprint of the building stock is well established. However, most of these studies operate in an ideal data environment (such as Dineen and Ó Gallachóir [2017]) or are extremely specific (such as Jermyn and Richman [2016]) If, however, the data falls between these two extremes — well labelled, detailed, data for multiple buildings or extremely specific building surveys — what can, practically, be done? This question demands an answer, as many municipalities are struggling to implement building policy with less than perfect information. This study will demonstrate a practical analysis of a building survey data set for Victoria B.C., including analysis of current retrofit policies and future retrofit analysis.

4.2 Introduction

As more and more emphasis in municipal policy shifts to reducing carbon emissions, and the emissions reduction target dates become closer, there is more and more interest in modelling building stock retrofits to select municipal building policies to reduce emissions. Unfortunately, traditional methods of building modelling and larger urban simulation are data intensive, requiring rich data sources with specialised data which is not generally collected by municipalities. Municipalities require a way to use existing data sets to model their building stock in a way sufficient to set policy. This method need not be precise or detailed: it merely has to provide insight into the existing stock, and where improvements may best be found, in greater detail than generic 'best-practice' retrofit measures, which may or may not suit the actual building stock at hand.

These methods should blend urban building energy modelling (UBEM) with retrofit modelling to provide a picture of the overall municipal building stock, or a targeted slice of that stock. The most obvious division for a targeted slice is between residential and commercial building stock, and many data sets available reflect this division. One example is the data set from the EnerGuide building retrofit program, a Canadian program for providing residential single family energy audits and house retrofit suggestions. The EnerGuide data also provides additional analysis opportunities, as it includes the results of retrofitting the houses (if any retrofit was performed), so it is possible to see how home owners choose to retrofit their buildings, and how the

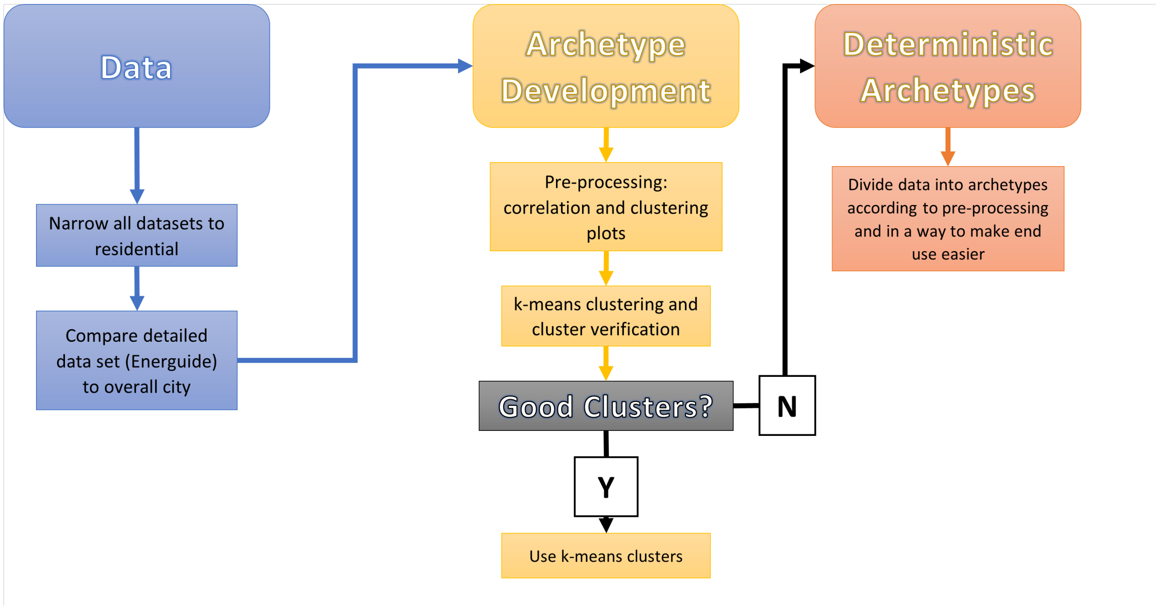


Figure 4.1: Archetype Development Process

great the typical retrofit impact is. While this data set has good information on year built, insulation and construction, unfortunately, this data set is not labelled: there is no way to tell what kind of house is involved. The size of houses in this data set is also an issue: a heated floor area is given, but no storeys or floor layout.

UBEM techniques, such as Roth et al. [2020b], assume better labeling of data and a broader spectrum of buildings than are available in the EnerGuide data set, making these techniques unfeasible. On the other hand, classic focused retrofit papers, such Jermyn and Richman [2016] work on only one specific archetype. The EnerGuide data has a broader spectrum of buildings, making these techniques unworkable as well.

There is a need to develop a technique halfway between a limited UBEM and a detailed retrofit case study. Machine learning should be considered, but the practicality and quality aspects also have to be considered: the end goal is policy-applicable information, so archetypes that cannot be applied to easily identifiable classes of houses and used to draft policy will not be usable.

4.3 Methods

To determine how the residential building stock will respond to various levels of retrofit, analysis will be divided into four stages:

- Unretrofitted buildings as a base case (pre-retrofit case)
- Typical retrofit from the data (performed case)
- maximum practical retrofit (maximum case)
- best case deep retrofit (recommended case)

The analysis will be based on the EnerGuide data set, which contains the results of several thousand building audits, the retrofit advice given by the building auditor, and the results of a follow-up building audit when retrofit measures were applied.

This data is the result of HOT2000 building modelling program energy advisor reports; because of this, the data does not contain complete information, for instance about windows, because the report are intended to provide an overview. Additionally, HOT2000 uses many assumption to simply modelling.[Canada, 2018]

Data for both pre-retrofit and the performed case are found in the EnerGuide data set, but the maximum and recommend case retrofits will be determined from existing industry guides, standards, and literature. The maximum case represents a halfway point between the performed and the recommend case. The recommend case can be considered to be a full deep retrofit. Energy will be considered a proxy for emissions.

4.3.1 Data Analysis

Data analysis will be conducted to determine the typical retrofits done to buildings, the fit of the EnerGuide data set to the city of Victoria residential stock, and the typical energy use improvement.

Additional data analysis will be done to test for correlation and clusters.

4.3.2 Clustering and Archetypes

As the data is unlabeled, unsupervised methods must be used. The most common and popular method is k-means, which will be used by this paper as well. If k-means

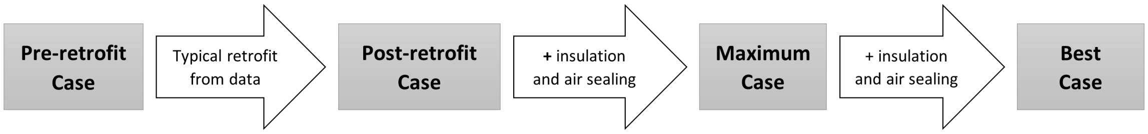


Figure 4.2: Retrofit Flow Diagram

Fuel Type	Carbon Factor (kg/GJ)
Oil	67.42
Natural Gas	49.46
Electricity	1.12

Table 4.1: Carbon factors by fuel type

does not produce high-quality clusters (based on silhouette score, a measure of how well the data divides into clusters), a literature based method will be used, dividing by year and then heat source. This will be verified by the correlation and clustering analysis carried out in the data analysis portion. [Mata et al., 2014]
The process for the creation of archetypes is laid out in fig. 4.1

4.3.3 Existing Retrofit Analysis

The retrofit performed data in the EnerGuide data will be examined for most common retrofits performed, and the energy improvement impact of these retrofits. This stage will also be modelled as part of the further retrofit modelling and analysis.

4.3.4 Retrofit Modelling

Retrofit can be divided into two parts: the post-retrofit case which represents the retrofits actually done for which we have data, a maximum practical retrofit (maximum case), representing the step up from the post-retrofit scenario, and a best case deep retrofit (recommend case.) The retrofit steps are shown in fig. 4.2.
The same software will be used for modelling as the data came from, HOT2000. HOT2000 comes with certain assumptions built in, covering some of the holes in data. [Canada, 2018] Of interest is relative improvements, not absolute numbers — we are looking for retrofits likely to significantly enhance performance, as opposed to precise numbers. Carbon will be computed using figures from the B.C. government,

found in Strategy and noa [2014], and given table 4.1.
General assumptions:

- The weather will be the "Victoria University" setting;
- The house will be assumed to be a detached, square, one floor wood frame house with flat ceilings and a full basement.
- As the house is assumed square, the required length and width of the house will be calculated as the square root of the area;
- the foundation will be assumed to have a concrete wall and floor;
- each side of the house will be assumed to have two windows;
- and for heating systems of a given fuel the default will be assumed; however for gas and oil the efficiency from the data will be used.

There will be three stages of modelling, post-retrofit, maximum, and recommend case, as shown in fig. 4.2, and values used are in table 4.2. Additionally, oil and gas archetypes will be electrified at the maximum and recommend case steps, to investigate the potential energy impacts of fully electrifying the city.

4.3.4.1 Post Retrofit Case

For this case the EnerGuide data set provides post retrofit information. As air sealing and window improvements are common (see fig. 4.8), these will be improved as well in the simulation, though the data is not present in the EnerGuide data set.

4.3.4.2 Maximum and Recommend Case

It is assumed that post-retrofit represents spray foam and similar 'easier' retrofit measures, while the recommend case retrofit represents a full deep retrofit, irregardless of cost or difficulty. Therefore, the challenge is defining an appropriate 'in between' step for maximum retrofit. One measure that is possible for improving the insulation of a house is the addition of exterior sheathing. As long as the house has siding, and the insulation board used not too thick, this is a relatively straightforward retrofit.

Therefore, this was decided to be the maximum retrofit. Insulation value was determined from a one inch XPS board (thin enough to be easily installed, thick enough to be R-5), however there are thinner, non-XPS, panels available. (Wei et al. [2018], Zhivov et al., noa [e], Canada, Soprema)

The recommend case retrofit was taken from B.C. Housing's recommendations for Zone 4, including Victoria. [noa, a]

At each of these steps, window quality and air tightness will be further improved, to the maximum given in B.C. Housing's recommendations. [noa, a]

4.4 Results

The EnerGuide data set is a reasonable and reasonably large (approximately 80%) sample of the City of Victoria's residential stock. Overall, there was a 72.4% retrofit rate. However, most retrofit packages applied are not what is recommended by the EnerGuide advisors; instead, a subset of retrofits is applied (see fig. 4.9.) The most commonly applied retrofits are air sealing and window improvements (see fig. 4.8.) After first stage improvements, an average of 15% to 25% energy improvement is seen (see fig. 4.11). Carbon outcomes are given in fig. 4.12, which shows electrified archetypes produce almost no carbon, whereas oil archetypes produce the most.

4.4.1 Archetypes

As shown in fig. 4.4, K-means produced mediocre clusters with silhouette scores ranging between .5 and .6. Ideally, the clusters scores would be close to 1, as 1 indicates perfect clusters. Additionally, these clusters would have been difficult to apply for policy, as they often grouped a broad spread of non-coherent years.

Instead, division was by time period and fuel type, similar to Mata et al. [2014] and Djebbar et al. [2019]. The time periods chosen were pre-1940, 1940-1980, post 1980, based on the scatter plots of pre-retrofit properties (see fig. 4.5 to fig. 4.7.) Figure 4.5 shows that insulation increases as year increases; however three distinct shading regions are visible, corresponding to the three time period divisions. As a proxy for window quality, fig. 4.6 plots window and door retrofit recommendations against year built and floor area. There is a distinct region post-1980 where the retrofit suggestion changes from recommending retrofit to not recommending retrofit; at approximately

	Archetype	Fuel Type	Retrofit Status	Attic/Ceiling RSI	Foundation Wall RSI	Furnace Efficiency	Floor Area m^2	Main Wall RSI	HOT2000 Annual Energy Use (GJ)	Air Tightness (ACR)	Carbon Emitted (kg)
0	1940-1980 Electricity	Electricity	Pre	3.08	0.915	100.0	199.0	1.58	101.0	6.06	113.120
1	1940-1980 Natural Gas	Natural Gas	Pre	3.10	0.943	81.2	207.0	1.40	134.0	6.06	6627.640
2	1940-1980 Oil	Oil	Pre	3.09	0.916	75.5	208.0	1.50	126.0	6.06	8494.920
3	Post 1980 Electricity	Electricity	Pre	4.13	1.180	100.0	248.0	2.32	97.4	4.11	109.088
4	Post 1980 Natural Gas	Natural Gas	Pre	4.70	1.640	82.6	313.0	2.43	131.0	4.11	6479.260
5	Post 1980 Oil	Oil	Pre	3.45	1.030	77.8	263.0	1.96	118.0	4.11	7955.560
6	Pre-1940 Electricity	Electricity	Pre	2.46	0.886	100.0	221.0	1.21	124.0	9.03	138.880
7	Pre-1940 Natural Gas	Natural Gas	Pre	2.37	0.931	81.2	259.0	1.08	180.0	9.03	8902.800
8	Pre-1940 Oil	Oil	Pre	2.37	0.740	75.3	249.0	1.09	173.0	9.03	11663.660
9	1940-1980 Electricity	Electricity	Post	4.48	1.360	99.9	199.0	1.78	90.1	4.54	100.912
10	1940-1980 Natural Gas	Natural Gas	Post	4.65	1.380	85.6	207.0	1.71	113.0	4.54	5588.980
11	1940-1980 Oil	Oil	Post	4.34	1.220	89.1	208.0	1.67	101.0	4.54	6809.420
12	Post 1980 Electricity	Electricity	Post	5.02	1.430	100.0	248.0	2.29	91.5	3.08	102.480
13	Post 1980 Natural Gas	Natural Gas	Post	4.96	1.650	91.2	313.0	2.45	131.0	3.08	6479.260
14	Post 1980 Oil	Oil	Post	4.11	1.000	93.9	263.0	2.01	116.0	3.08	7820.720
15	Pre-1940 Electricity	Electricity	Post	3.71	1.430	99.8	221.0	1.68	103.0	6.77	115.360
16	Pre-1940 Natural Gas	Natural Gas	Post	3.67	1.350	86.5	259.0	1.57	140.0	6.77	6924.400
17	Pre-1940 Oil	Oil	Post	3.40	1.300	88.8	249.0	1.49	126.0	6.77	8494.920
18	1940-1980 Electricity	Electricity	Max	5.38	2.220	99.9	199.0	2.68	77.1	3.03	86.352
19	1940-1980 Natural Gas	Natural Gas	Max	5.55	2.360	85.6	207.0	2.61	95.9	3.03	4743.214
20	1940-1980 Oil	Oil	Max	5.24	2.210	89.1	208.0	2.57	84.7	3.03	5710.474
21	1940-1980 Electricity	Electricity	Recommended	7.00	3.500	99.9	199.0	3.50	73.1	4.00	81.872
22	1940-1980 Natural Gas	Natural Gas	Recommended	7.00	3.500	85.6	207.0	3.50	91.1	4.00	4505.806
23	1940-1980 Natural Gas	Natural Gas - Electrified	Max Electrified	5.55	2.360	100.0	207.0	2.61	78.2	3.03	87.584
24	1940-1980 Oil	Oil - Electrified	Max Electrified	5.24	2.210	100.0	208.0	2.57	79.1	3.03	88.592
25	1940-1980 Oil	Oil	Recommended	7.00	3.500	89.1	208.0	3.50	79.1	4.00	5332.922
26	1940-1980 Natural Gas	Natural Gas - Electrified	Recommended Electrified	7.00	3.500	100.0	207.0	3.50	74.3	4.00	83.216
27	1940-1980 Oil	Oil - Electrified	Recommended Electrified	7.00	3.500	100.0	208.0	3.50	74.3	4.00	83.216
28	Post 1980 Electricity	Electricity	Max	5.02	2.290	100.0	248.0	3.19	81.5	2.06	91.280
29	Post 1980 Natural Gas	Natural Gas	Max	4.96	2.690	91.2	313.0	3.35	107.0	2.06	5292.220
30	Post 1980 Oil	Oil	Max	4.11	2.020	93.9	263.0	2.91	92.0	2.06	6202.640
31	Post 1980 Electricity	Electricity	Recommended	7.00	3.500	100.0	248.0	3.50	77.8	3.00	87.136
32	Post 1980 Natural Gas	Natural Gas	Recommended	7.00	3.500	91.2	313.0	3.50	104.0	3.00	5143.840
33	Post 1980 Oil	Oil	Recommended	7.00	3.500	93.9	263.0	3.50	84.0	3.00	5663.280
34	Post 1980 Natural Gas	Natural Gas - Electrified	Max Electrified	4.96	2.690	100.0	313.0	3.35	89.4	2.06	100.128
35	Post 1980 Oil	Oil - Electrified	Max Electrified	4.11	2.020	100.0	263.0	2.91	87.4	2.06	97.888
36	Post 1980 Natural Gas	Natural Gas - Electrified	Recommended Electrified	7.00	3.500	100.0	313.0	3.50	86.9	3.00	97.328
37	Post 1980 Oil	Oil - Electrified	Recommended Electrified	7.00	3.500	100.0	263.0	3.50	80.0	3.00	89.600
38	Pre-1940 Electricity	Electricity	Max	4.61	2.460	99.8	221.0	2.58	86.1	4.51	96.432
39	Pre-1940 Natural Gas	Natural Gas	Max	4.57	2.340	86.5	259.0	2.47	115.0	4.51	5687.900
40	Pre-1940 Oil	Oil	Max	4.30	2.140	88.8	249.0	2.39	102.0	4.51	6876.840
41	Pre-1940 Electricity	Electricity	Recommended	7.00	3.500	99.8	221.0	3.50	77.6	4.00	86.912
42	Pre-1940 Natural Gas	Natural Gas	Recommended	7.00	3.500	86.5	259.0	3.50	102.0	4.00	5044.920
43	Pre-1940 Oil	Oil	Recommended	7.00	3.500	88.8	249.0	3.50	87.9	4.00	5926.218
44	Pre-1940 Natural Gas	Natural Gas - Electrified	Max Electrified	4.57	2.340	100.0	259.0	2.47	93.7	4.51	104.944
45	Pre-1940 Oil	Oil - Electrified	Max Electrified	4.30	2.140	100.0	249.0	2.39	93.5	4.51	104.720
46	Pre-1940 Natural Gas	Natural Gas - Electrified	Recommended Electrified	7.00	3.500	100.0	259.0	3.50	83.1	4.00	93.072
47	Pre-1940 Oil	Oil - Electrified	Recommended Electrified	7.00	3.500	100.0	249.0	3.50	81.7	4.00	91.504

Table 4.2: Archetype Values

1980 the quality of installed windows changes. Lastly, heating systems were examined in fig. 4.7. This includes all three systems, natural gas, oil, and electricity (which has 100% efficiency). Efficiency has a tendency to increase (as does the adoption of natural gas, if plotted in a similar manner), until the 1980s when efficiency becomes largely 100% due to the adoption of electric systems. Propane and wood burning eliminated as heating fuel type as very few houses (10 or less) per time period used these sources.[Djebbar et al., 2019, Mata et al., 2014]

4.4.2 Retrofits

The kinds and results of retrofits are shown in fig. 4.8 to fig. 4.12. Figure 4.8 details the frequency individual retrofits were recommended and performed; fig. 4.9 and fig. 4.10 package the retrofits recommended for each house into group and show the frequency those packages were recommended and then performed (fig. 4.9), and the frequency of retrofit packages being performed compared to how often those packages were recommended (fig. 4.10), to give a picture of how people are choosing to retrofit their houses compared to what upgrades are being recommended for their houses. For fig. 4.9 packages were only displayed if they were recommended in more than 1% of cases; similarly, for fig. 4.10 packages were only displayed if they were performed in more than 1% of cases.

Energy and carbon improvements are addressed in fig. 4.11 and fig. 4.12. fig. 4.11 shows the distribution of percent energy improvement in 5% increments after the post-retrofit stage from the real world data in the EnerGuide data set. fig. 4.12 uses the developed archetypes and shows both absolute and successive percent improvements in carbon as successive retrofit measures are applied.

4.5 Discussion

4.5.1 Data Sets

Three data sets were in use: the EnerGuide data set, the BC Assessment data set filtered for single family residential housing (BC Assessment data set) and the City of Victoria Rooflines 2019 data set, also filtered for single family residential housing

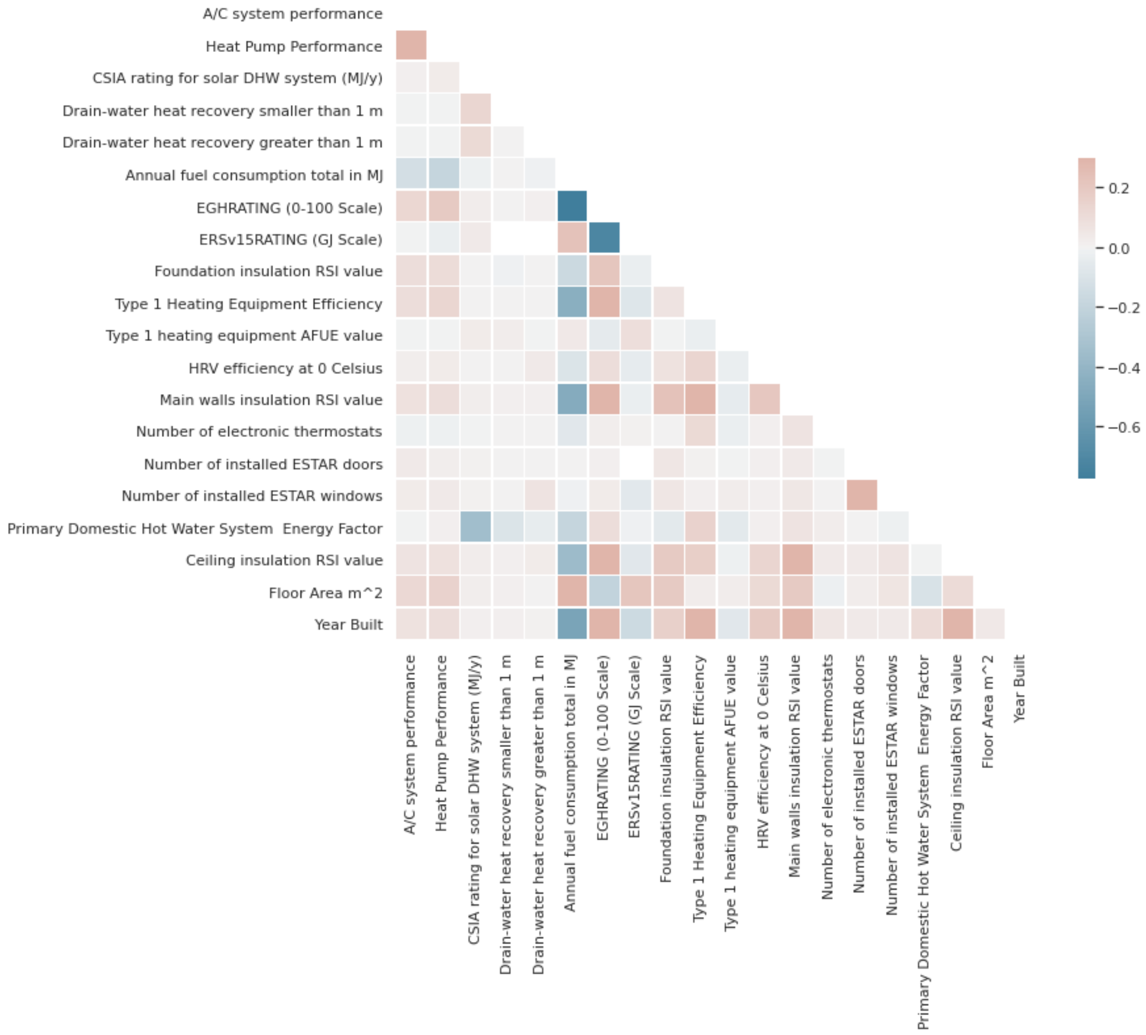


Figure 4.3: Correlations in the Data Set

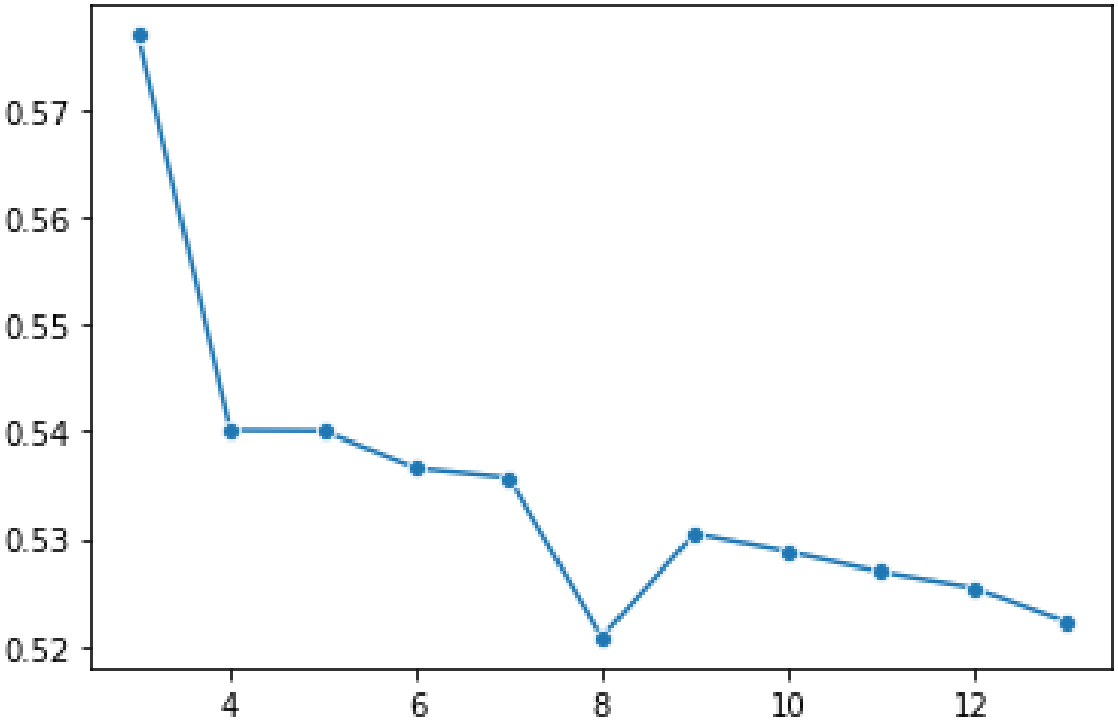


Figure 4.4: Silhouette Score of k-means over all variables

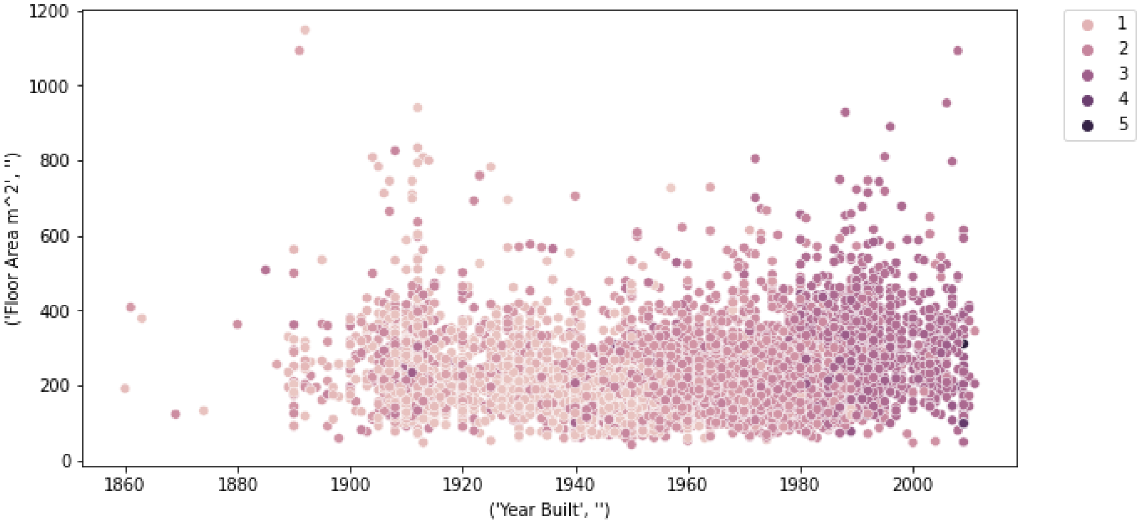


Figure 4.5: Wall Insulation RSI against Floor Area and Year Built

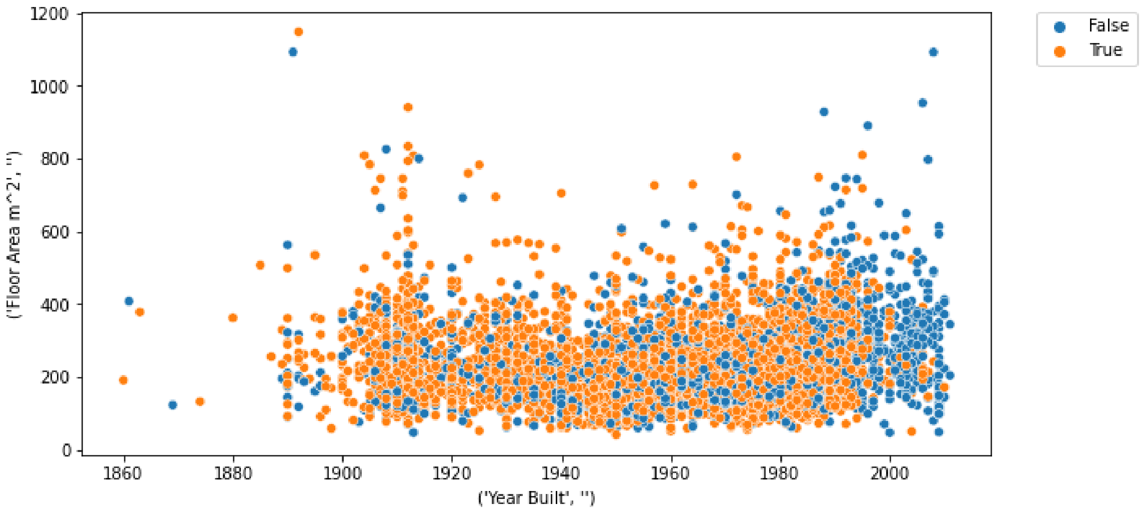


Figure 4.6: Window and Door Retrofit Recommended against Floor Area and Year Built

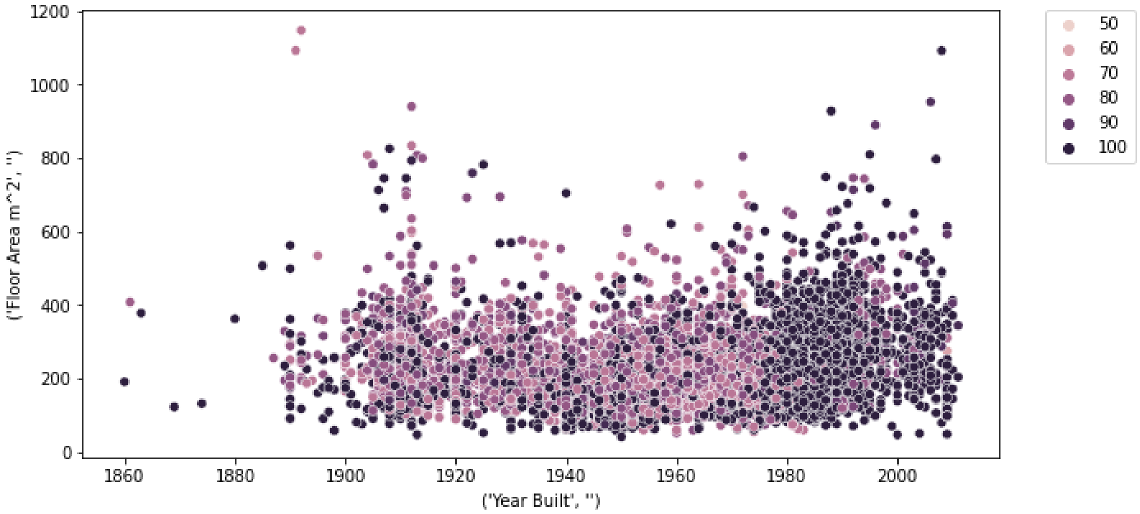


Figure 4.7: Furnace Efficiency against Floor Area and Year Built

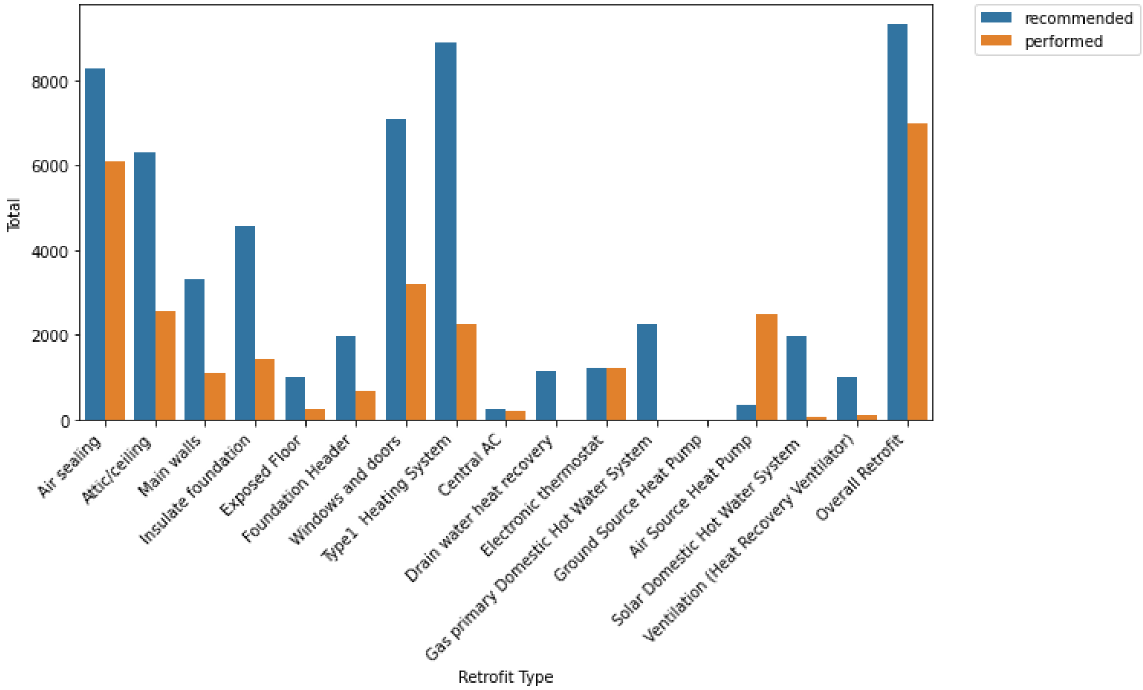
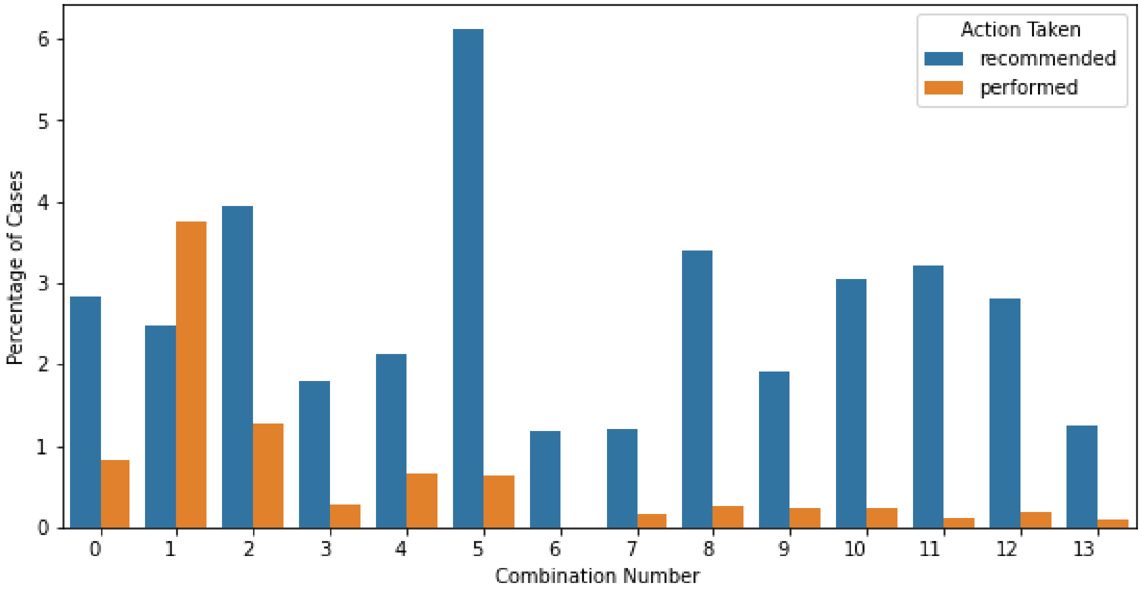
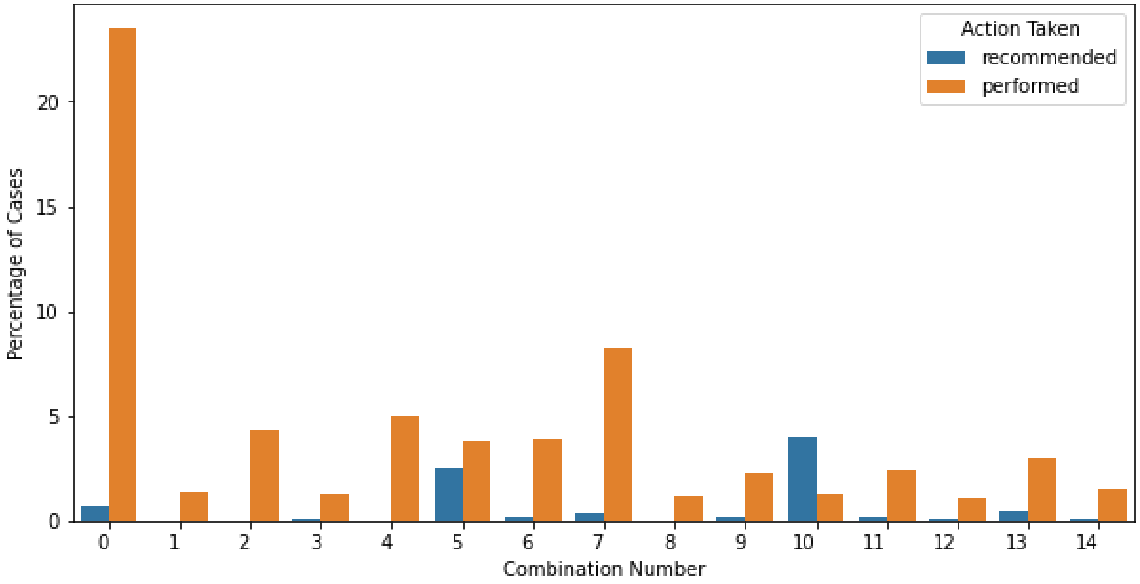


Figure 4.8: Overall Retrofits Performed by Type



Combination Number	Retrofits
0	(Type1 Heating System,)
1	(Air sealing, Type1 Heating System)
2	(Air sealing, Windows and doors, Type1 Heating System)
3	(Air sealing, Insulate foundation, Windows and doors, Type1 Heating System)
4	(Air sealing, Attic/ceiling, Type1 Heating System)
5	(Air sealing, Attic/ceiling, Windows and doors, Type1 Heating System)
6	(Air sealing, Attic/ceiling, Windows and doors, Type1 Heating System, Gas primary Domestic Hot Water System, Solar Domestic Hot Water System)
7	(Air sealing, Attic/ceiling, Insulate foundation, Type1 Heating System)
8	(Air sealing, Attic/ceiling, Insulate foundation, Windows and doors, Type1 Heating System)
9	(Air sealing, Attic/ceiling, Insulate foundation, Foundation Header, Windows and doors, Type1 Heating System)
10	(Air sealing, Attic/ceiling, Main walls, Windows and doors, Type1 Heating System)
11	(Air sealing, Attic/ceiling, Main walls, Insulate foundation, Windows and doors, Type1 Heating System)
12	(Air sealing, Attic/ceiling, Main walls, Insulate foundation, Foundation Header, Windows and doors, Type1 Heating System)
13	(Air sealing, Attic/ceiling, Main walls, Insulate foundation, Exposed Floor, Foundation Header, Windows and doors, Type1 Heating System)

Figure 4.9: Retrofit packages recommended and frequency performed



Combination Number	Retrofits
0	(No Retrofit)
1	(Air Source Heat Pump,)
2	(Electronic thermostat,)
3	(Type1 Heating System, Air Source Heat Pump)
4	(Air sealing, Air Source Heat Pump)
5	(Air sealing, Type1 Heating System)
6	(Air sealing, Type1 Heating System, Air Source Heat Pump)
7	(Air sealing, Windows and doors)
8	(Air sealing, Windows and doors, Air Source Heat Pump)
9	(Air sealing, Windows and doors, Electronic thermostat)
10	(Air sealing, Windows and doors, Type1 Heating System)
11	(Air sealing, Attic/ceiling)
12	(Air sealing, Attic/ceiling, Electronic thermostat)
13	(Air sealing, Attic/ceiling, Windows and doors)
14	(Air sealing, Attic/ceiling, Main walls)

Figure 4.10: Retrofit packages performed and frequency recommended

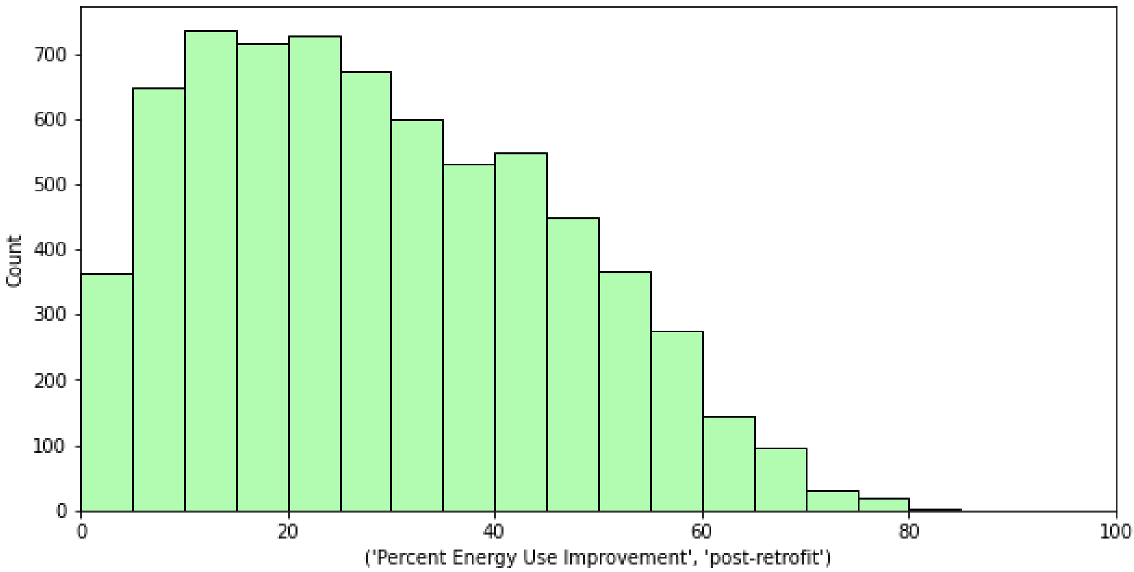


Figure 4.11: Percent Energy Improvements after First Retrofit

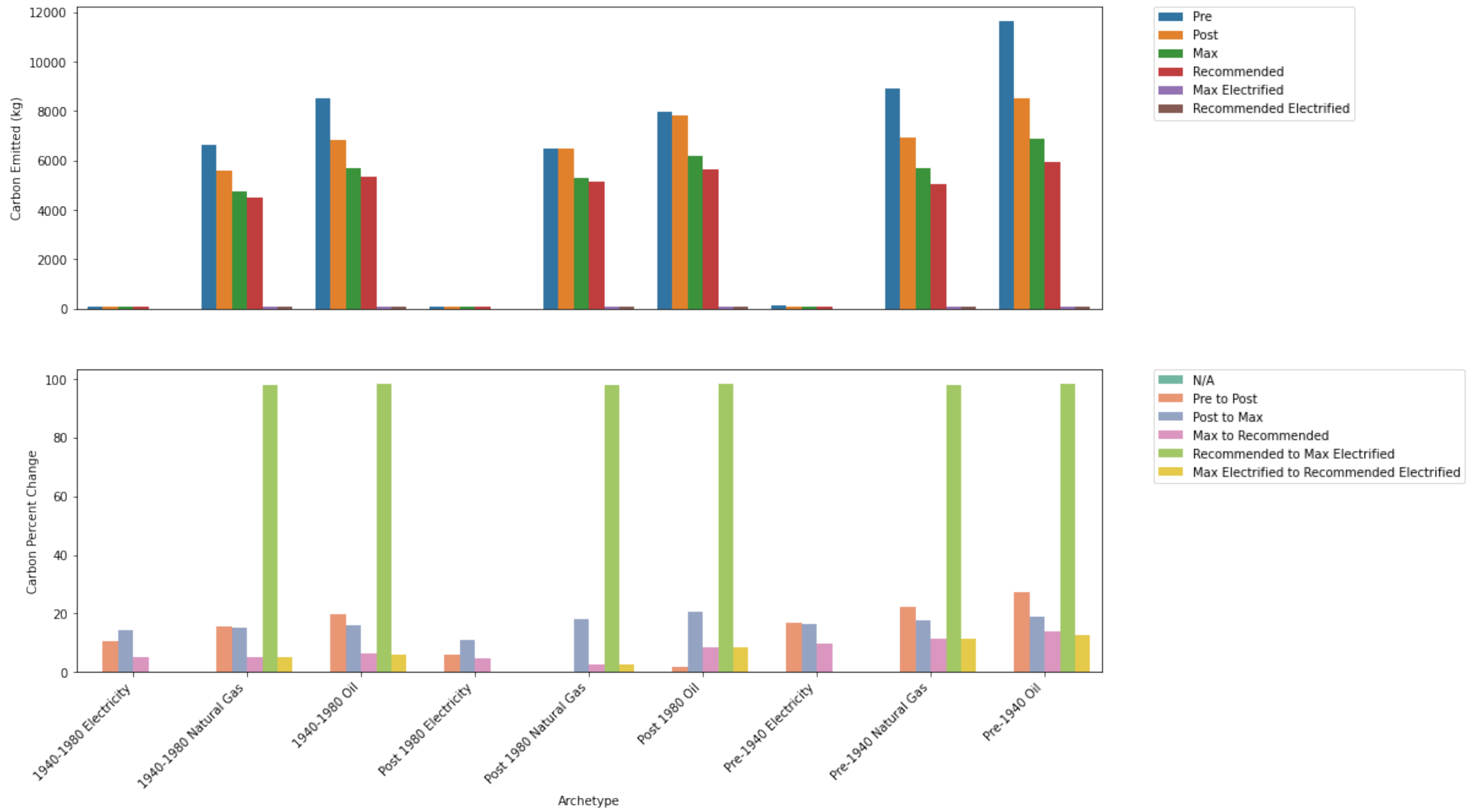


Figure 4.12: Carbon Emitted By Archetype and Retrofit Stage. Top is absolute improvements, bottom is percent improvement

(Rooflines data set.) The floor area distribution does not perfectly match between the three different data sets due to different types of floor area being measured. The BC Assessment data set contains taxable area, the Rooflines data set contains overall area, and the EnerGuide data set contains heated floor area. The EnerGuide data set is within the same range as the other two, and shows similar characteristics, so we can conclude that it is a reasonable representation.

The EnerGuide data set is also quite large; approximately 80% of the size of the BC Assessment and Rooflines data set. Hence, we can consider the results of the EnerGuide data set to be a reasonable approximation of the overall residential single family building stock. This means the EnerGuide dataset can be used by itself to predict the impacts of retrofits on the building stock, as opposed to using it as a basis for quantifying a data set such as the Rooflines one.

4.5.2 Correlations

As part of preparing the EnerGuide data set, correlations between various building properties and the year built and floor area were considered (see creffigure: correlations.) These two properties – year built and floor area – are common in all available data sets, and it was hoped that building properties could be predicted using these from the EnerGuide data. Unfortunately, as seen in fig. 4.3 there are no significant positive or negative correlations between any of the properties in the EnerGuide data.

4.5.3 Clustering

As the data is unlabeled, unsupervised clustering techniques must be used. Initially k-means was considered and run over all variables as it is the most common unsupervised technique, but it created groupings with scattered years and a wide cluster spread, as shown in fig. 4.4. A silhouette score of between .5 and .6 means the clusters are somewhat spread out and hence mediocre (1 is perfect clusters.)

When the relative impractically of the k-means (it is desirable to have continuous years in the clusters for making policy) and the mediocre silhouette score were combined, it was decided to use a deterministic archetype method using period built and heating furnace type. This clustering method, while crude, maps well to the clusters in fig. 4.5 to fig. 4.7. After examining this figure and the results of the k-means unsupervised clustering, three periods were decide on: pre-1940, 1940-1980 (mid-century), and post-1980. This also reflects the history of Victoria's construction of residential housing stock: a post World War 2 boom and the increasing stringency of building codes through the 90s and 2000s, as reflected by increasing values of main wall insulation (seen in fig. 4.5.) This is also reflected in fig. 4.6, where we see a sharp change from recommending window and door upgrades to not recommending them — the quality of the windows and doors has changed sufficiently that there is no longer a need to retrofit them. Figure 4.7, showing the percent efficiency of the heating system, also shows a change in the 1980s, showing a dramatic increase in the installation of electric systems which are the only ones with a 100% efficiency. The median values in the EnerGuide data set for each period and heating type were taken and used as HOT2000 input.

4.5.4 Retrofits

Overall, the greatest improvements are generally seen at the first step, the performed retrofits, except for post-1980 buildings, where the greatest impact was seen moving to the maximum case. For the pre-1980 archetypes, reasonable gains were also seen moving to maximum case retrofit. There is not a lot of difference when moving from maximum to recommend case in all scenarios, because of the focus on wall insulation and air sealing, two of the more common retrofits, across all categories.

Also note that wood burning was eliminated; while these houses were very few, they may have disproportionate impact on air quality. [Wolf et al., 2020]

The post-1980 electric archetype showed the least energy use overall, and the least energy use improvements between steps and overall, and probably should be excluded from most retrofit incentives as there is little to gain.

4.5.4.1 Performed Retrofits

Performed retrofits generally showed a 15% to 25% decrease in energy use, despite people choosing not to follow all of the EnerGuide advisor's recommendations, as shown in fig. 4.9. However, as show in in fig. 4.8 and fig. 4.10, people did perform at least some of the recommended upgrades. Though 'no retrofit' (0) in fig. 4.10 appears to be the most common, the sum of the other retrofit packages is greater than this bar.

As shown in fig. 4.8 the most common retrofits performed and recommended were air sealing, attic insulation, heating system upgrades, and window upgrades. In fact, examining fig. 4.10 the retrofit package of air sealing and heating system upgrades was performed more often than recommended (probably because every other common retrofit package included these upgrades, and they were 'cherry picked' by owners to perform.) Interestingly, as shown in fig. 4.10 heat pump retrofits were performed more often than recommended by EnerGuide advisors, probably because rebates of up to $5000 are available specifically for heat pumps, showing the power of municipal policy. [noa, d]

For post-1980 buildings, we see very little impact in energy use at this stage (see fig. 4.12).

4.5.4.2 Carbon Impacts

Overwhelmingly, the greatest carbon savings came from electrifying natural gas or oil. For both 1940 to 1980 archetypes and post 1980 archetypes there was little gain to be had pushing to a full deep retrofit (the recommended case) from the maximum case. Pre-1940 archetypes, however, saw reasonable gains pushing to the recommended case.

Overall, the post 1980 archetypes saw the least carbon reductions (apart from moving natural gas or oil to electricity.) Note also in fig. 4.12 the retrofit improvements between post 1980 natural gas pre and post cases was very small; the carbon improvement was less than 1% and because of this a bar does not show up on the percentage graph for this scenario.

Therefore, it is desirable to focus on electrification and encouraging greater retrofit of pre-1980s houses; houses post-1980 need little improvement.

4.6 Conclusions

Surprisingly, heat pumps have been retrofitted more than recommended, due to municipal policies. Analysing carbon impacts showed the greatest impact is to push electrification; after electrification there is little need to modify houses built after 1980. However, pre-1980s houses can benefit greatly from more aggressive retrofits, especially ones which increase wall R-value and air tightness. Building which predate

1940 show the largest gains even after being retrofitted, and should be aggressively targeted for upgrades.

The method demonstrated in this paper shows meaningful insight can be extracted from less than ideal data sources, without the need to worry about precise and accurate figures.

Chapter 5

Conclusions

This thesis has shown methods of navigating the significant difficulties in data poor UBEM, including inference and approximation, as well as distilling best practices for data driven archetypes from the literature.

In chapter 2 a best practices technique for creating data driven archetypes (see fig. 2.5) was developed. Additional insights from the literature included k-means as the most popular clustering algorithm and the relative lack of machine learning verification of clustering results.

Chapter 3 demonstrates inference of building properties using the combination of surrogate modelling and genetic algorithms; while this demonstration was not completely successful, the technique has promise. With some specific data to further refine the base archetypes, this technique could be further refined. Bearing this out, Roth et al. [2020b] demonstrate a similar technique using both inference and a small, detailed, data set to further refine their base buildings.

Lastly, practical techniques for working with a detailed but less than ideal data set are shown in chapter 4. K-means clustering is properly eliminated from consideration, and deterministic archetypes are developed and used to produce policy insights by examining relative (as opposed to absolute) energy improvements to eliminate the need for precise numbers, as the objective is quantify retrofits as more effective or less effective, not reach a fixed energy target.

Overall, the methods and ideas explored in this this thesis have filled in the gaps in the framework shown in fig. 1.1, as shown in fig. 5.1. Options have been provided for both the previously unexplored branches; an inference technique was developed and tested, and the process for creating rigorous deterministic archetypes was demonstrated. This gives both a framework for further exploration of data driven archetypes

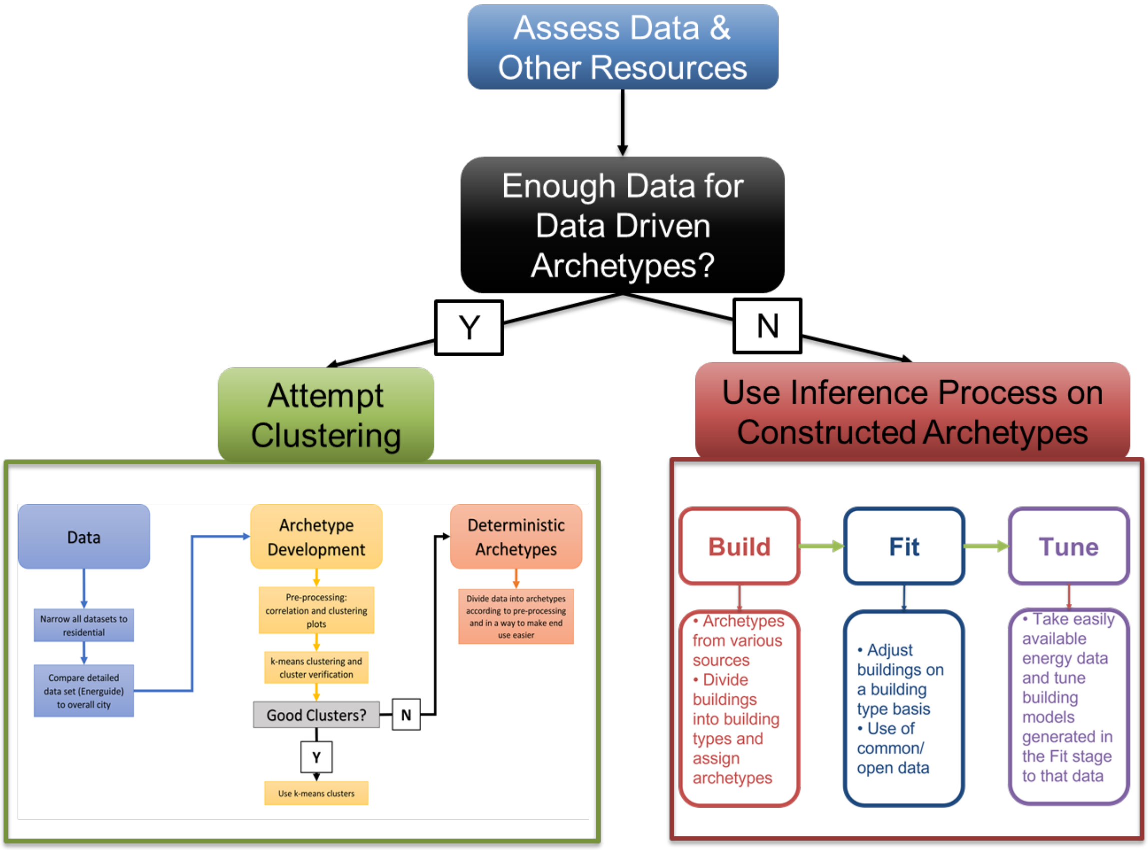


Figure 5.1: Final overview of UBEM Methods for Archetype Creation

in a data poor environment and solutions to some of the data gaps causing issues in building energy policy.

5.1 Future Work

Future work should focus on combining techniques, such as using transfer learning to create the base archetypes used as input to an inference system such as the one demonstrated in chapter 3. As inference methods did not prove as simple as expected, the utility of transfer learning should be re-thought. Perhaps transfer learning can be used within a city, as a way of deploying smaller, detailed, data sets more broadly. Additionally, broader uses of machine learning, such as those used in Westermann et al. [2020b], where surrogate models are used for weather, should be investigated as part of developing the recommended hybrid systems. To aid these works, a detailed sensitivity analysis of building parameters should be performed.

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