RETAIL ELECTRIC PROVIDER SELECTION FOR PROSUMERS WITH LOCAL DISTRIBUTED ENERGY RESOURCES AND PLUG-IN ELECTRIC VEHICLES USING DATA MINING TECHNIQUES

by

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An oral defense of this thesis took place on 18 January 2021 in front of the following examining committee:

Examining Committee:

Chair of Examining Committee	Dr. Ying Wang
Research Supervisor	Dr. Walid Morsi Ibrahim
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Thesis Examiner	Dr. Miguel Vargas Martin, FBIT

The above committee determined that the thesis is acceptable in form and content and that a satisfactory knowledge of the field covered by the thesis was demonstrated by the candidate during an oral examination. A signed copy of the Certificate of Approval is available from the School of Graduate and Postdoctoral Studies.

Abstract

In a deregulated retail electricity market, the residential customers typically have the liberty to choose an electricity service plan from a list of retail electric providers (REPs) that best matches their monthly energy consumption. This process is called “retail choice”. The selection of a suitable REP plan creates uncertainty for the residential customer, especially when numerous plans with various rate structures exist. The customers who intend to become prosumer (producers and consumers of electric power) face an expected change in their monthly energy consumption. This builds on the uncertainty of purchasing local distributed energy resources (L-DERs) and/or plug-in electric vehicles (PEVs) that are feasible for their REP plan and may result in savings on their energy bills. Therefore, this thesis designs and implements a personalized tool to guide residential customers and those who intend to become prosumers in selecting a suitable REP plan that maximizes their energy bill savings. In this study, 48 annual home profiles from the Pecan Street dataset and 24 REP plans with both time-invariant and time-variant plans, from the state of Texas, were evaluated. A feature-based approach was used to create the monthly energy bills from which a suitable REP plan could be selected for a customer. Additionally, the residential customers who intend to become prosumers are considered through clustering the profiles of rooftop solar photovoltaic (PV), home battery energy storage system (HBESS) and/or PEV and finding the representative profiles, which are then used to identify the most feasible combination of resources and plan to maximize their energy bill savings. The results revealed that the presence of PV is essential in achieving significant savings on the energy bills. Furthermore, if the customer plans on adding a HBESS and/or PEV, the solar PV capacity installed should be at a high capacity so to achieve savings on the energy bill. The results have also revealed that time-invariant plans are more suitable for customers with high energy usage that exceeds 1,000 kWh/month while time-variant and time-invariant plans may be suitable for customers with energy usage that is under 1,000 kWh/month to help them achieving significant savings on their energy bills.

Keywords: Retail electric providers; distributed energy resources; electric vehicles; energy bill savings; net metering

Author's Declaration

I hereby declare that this thesis consists of original work of which I have authored. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Statement of Contributions

The contributions that accompany this thesis include an accepted paper in the IEEE Electric Power & Energy Conference (EPEC) organized by the IEEE Power and Energy Society (PES) and a journal paper that is currently in the preparation stage, respectively. These are described in further detail below.

1. Referred Conference Proceedings

D. J. Mabuggwe and W. G. Morsi, "Representative Profiling of Prosumers with Local Distributed Energy Resources and Electric Vehicles Using Unsupervised Machine Learning," *in Proc. IEEE Electric Power & Energy Conference, Edmonton, AB, Canada, 2020*.

In this work, the author conducted representative profiling of the annual generation/consumption profiles of rooftop solar photovoltaic (PV), home battery energy storage system (HBESS) and plug-in electric vehicle (PEV) from the Pecan Street dataset. A systematic approach was proposed using K-means clustering, principal component analysis and K-nearest neighbor. The approach extracted 17 representative profiles from 123 PV, HBESS and PEV generation/consumption profiles. This work is identified in Chapter 4 and is under consideration for publication.

2. Referred Journal Proceedings

D. J. Mabuggwe and W. G. Morsi, "A New Selection Tool of Retail Electric Provider for Prosumers with Local Distributed Resources and Plug-in Electric Vehicles," *in preparation for Journal submission*.

In this work, the author designed and implemented a new selection tool to identify suitable retail electric provider plans for prosumers with local distributed energy resources

(L-DERs) and plug-in electric vehicles (PEVs). The methodology employed a feature-based approach for retail electric provider plan selection; a knowledge base for L-DER and/or PEV decision support; and the necessary calculations for personalized energy bill savings. This was implemented on the MATLAB App Designer platform with interactive graphical user interfaces for both residential customers and prosumers. Part of this work is presented in Chapters 5, 6 and 7, which has been submitted and is under review.

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Firstly, I would like to thank God almighty for giving me the wisdom to complete this Master's thesis. Despite the challenges I faced, I was able to overcome them through His unfailing guidance.

"For I know the plans I have for you, declares the Lord, plans to prosper you and not to harm you, plans to give you hope and a future."

Jeremiah 29:11

Secondly, I would like to thank Dr. Walid G. Morsi for his support as my research supervisor and my research teammates within the Smart Grid & Electric Vehicles Research Laboratory. Dr. Morsi consistently reviews my progress, even remotely, during the ongoing COVID-19 pandemic. The engagement in exchanging ideas, refining drafts and presenting findings, provided me with clarity to finalize my write up. I greatly appreciate all the time he had invested.

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Nomenclature

A	Annual Energy Bill
a	Average Distance of a Data Observation Relative to others in the Cluster
ASC	Average Silhouette Coefficient
B	Monthly Energy Bill
b	Minimum Average Distance of a Data Observation Relative to Others in Different Clusters
B_C	Monthly Base Charge
C_R	Promotional Credit Offered by Retail Electric Provider Plan
c	Cluster Centroid
DER	Distributed Energy Resource
d	Euclidean Distance Measurement
E	Vector of Monthly Energy Features
ERCOT	Electric Reliability Council of Texas
e	Electricity Sold
eGauge	Electrical Gauge
F	Vector of Monthly Fixed Cost Features
F_C	Monthly Fixed Charge
GUI	Graphical User Interface
HBESS	Home Battery Energy Storage System
H	Vector of Annual Home Profiles with Monthly Generation/Consumption Features
$\widehat{H}$	Normalized Vector of H
$\widehat{H}_{PC}$	Principal Components of $\widehat{H}$
I	Initial Investment
i	Number of Cluster Centroid
j	Residential Customer Group
K	Number of Clusters
K-NN	K Nearest Neighbor
k	Current Dimension of Data Observation
kWh	Kilowatt-hour

kW	Kilowatt
L-DER	Local Distributed Energy Resource
l	Index of Data Observation for Silhouette Coefficient
m	Monthly Generation/Consumption Feature
min	Minimum Function
N	Number of Annual Home Profiles
N_U	Monthly Net Energy Usage
n	Total Number of Dimensions of Data Observation
ONCOR	Oncor Delivery Service Company
PCA	Principal Component Analysis
PC	Principal Components
PEV	Plug-in Electric Vehicle
PUCT	Public Utility Commission of Texas
PV	Rooftop Solar Photovoltaic
p_w	Wholesale Electricity Rate
REP	Retail Electric Provider
r	Retail Electricity Rate
S	Energy Bill Savings
s	Silhouette Coefficient
SSE	Sum of Squared Errors
S_G	Monthly Generation from Rooftop Solar Photovoltaic
TDU_1	Transmission and Distribution Rate
TDU_2	Fixed Transmission and Distribution Charge
TOU	Time of Use
TOU_D	Monthly Energy Usage During the Day Time
TOU_N	Monthly Energy Usage During the Night Time
TOU_{WD}	Monthly Energy Usage During the Weekday
TOU_{WE}	Monthly Energy Usage During the Weekend
t	Index of Monthly Energy Bill Type

U.S.	United States of America
V	Vector of Monthly Variable Cost Features
VOS	Value of Solar Credit Rate
w	Auxiliary Cost of Electricity
x	First Data Observation in Euclidean Distance Measurement
y	Second Data Observation in Euclidean Distance Measurement
\$	United States Dollars
∂	Partial Change in a Quantity
τ	Delivery Cost of Electricity
μ	Mean/Average of Data Observations
σ	Standard Deviation of Data Observations

Chapter 1: Introduction

1.1 Background

The deregulation of the traditional electricity market in the United States of America began in the early 1990s, where the core business of electric utilities experienced significant transformation [1]. The business structure was a monopoly consisting of three sectors namely: 1) generation, 2) transmission & distribution and 3) retail, and the source of revenue was predominantly commodity-driven i.e., electricity sales [2]. Since then, the deregulation policies were introduced to develop specialization and market competition in each sector. The retail electricity market in some states in the United States of America began to participate in the business of "retail electricity choice", where end-users were given the liberty to choose competitive retail rates that were different from the standard electricity whole-sale rates [3]. Significant revenue was attained in this market, however over the past 30 years retail rates in the United States of America have been volatile; decreased by 4% in 2002 and increased by 15% in 2006 [4]. Despite this volatility, the State of Texas managed to maintain a successful retail electricity market in the United States of America, with 95% participation (residential and non-residential) in "retail electricity choice" [5].

Smart grids were developed as a way to integrate automation and communication into the electric utility. Prior to this, traditional electrical networks faced challenges such as late fault detection, premature damage to electrical assets, wide-spread customer blackouts and ultimately revenue loss. Due to this, active pilot projects were initiated globally to study the performance of smart grids at the residential level as a test-bed for larger systems [6], [7]. More specifically, case-studies involving roof-top solar photovoltaic (PV), home battery energy storage systems (HBESS) and plug-in electric vehicles (PEV) integration. The economic driver from residential customers for such resources has also accelerated the investigation of their effect on the smart grid. In the past decade, the average annual growth of residential PV installations, that are typically coupled with BESS, in the United States of America was 57% [8]. Similarly, the average annual growth of PEVs sales since 2011 was 55% [9]. This implies an inevitable evolution in the role of residential customers from being consumers to also local producers of electricity, known as prosumers [10]. The key question then is: how will the retail electricity choices of residential customers be affected when they plan on adding as local distributed energy resources (L-DERs) and/or PEVs and hence becoming prosumers?

1.2 Problem Statement and Motivation

Electricity suppliers that sell electric energy to the retail customers at a competitive retail rate are known as retail electric providers (REPs) [11]. Their main responsibilities entail: 1) purchasing whole sale electricity, 2) purchasing delivery services of electricity over the transmission and distribution network, 3) establishing a competitive retail rates for customers and 4) providing monthly billing and daily customer service [11]. These REPs make use of the electrical infrastructure (transmission and distribution) owned by the electric utility, which are typically compensated for utilizing their assets in their retail rate. However, the retail rate is only a part of the group of cost features offered by the REP. The remaining features are listed in the REP plan that has various designs and incentives for different customer needs [12]. The six key features of the REP plan that could influence a customer’s monthly energy bill, are shown in Figure 1.1. The rate structure of the retail rates are further subdivided into time-invariant and time-variant rates [13], as shown in

Figure 1.2, where the rates are independent or dependent on the time during which the electric energy is used, respectively. Therefore, seven features (including the two rate structures) may possibly impact the outcome of a customer's monthly energy bill; introducing a dilemma as to which REP plan is best suited for a customer.

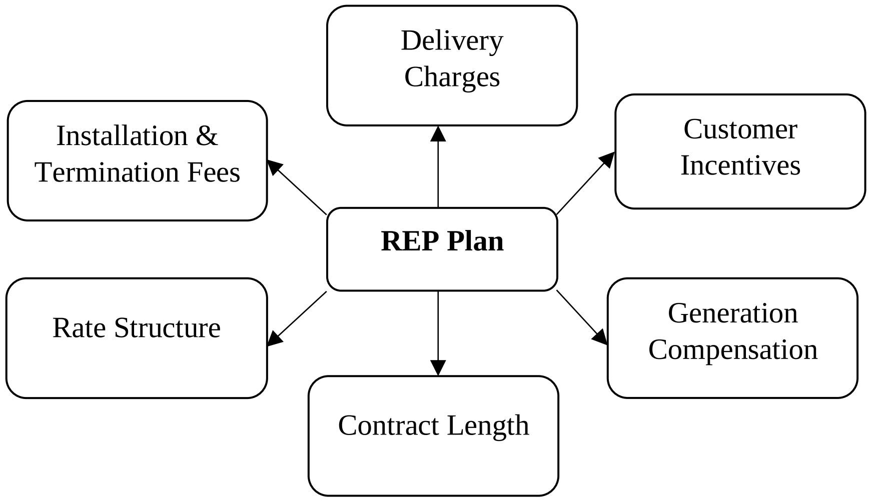


Figure 1.1: Features of a REP Plan [12]

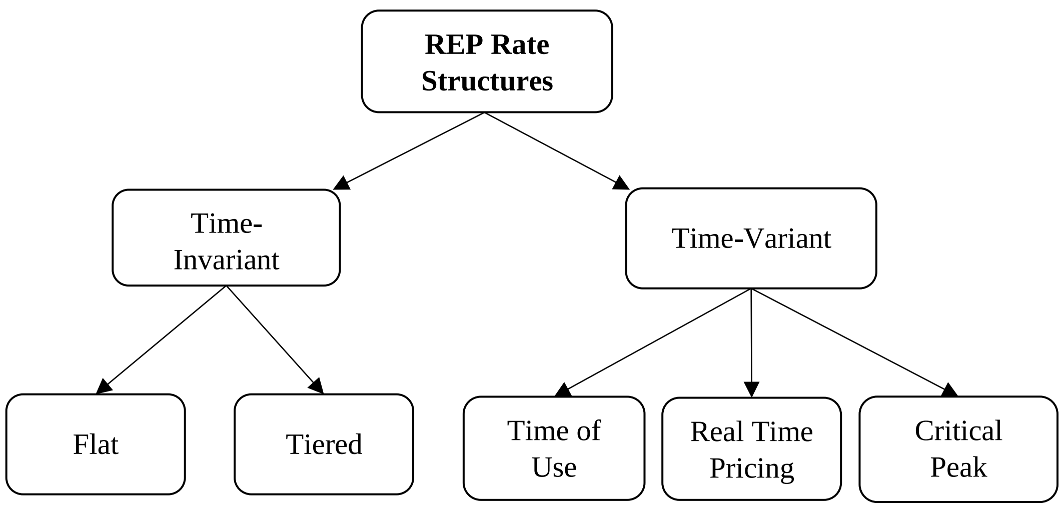


Figure 1.2: REP Rate Structures and Subtypes [13]

The energy bill of a residential customer is also influenced by the monthly energy usage. However, the residential customer are typically known to have different energy consumptions patterns that are dependent on their usage behaviors and seasonal variations

[14]. In the United States of America, three of the top energy consumption regions for residential customers occur in the South Atlantic, East South-Central and West South-Central regions [15]. In the West South-Central region, Texas homes had an average energy consumption of 1,176 kilowatt hours per month in 2018. It is also the state with a 95% customer participation in the retail electricity market [5]. Consequently, the selection of various REP plans would reflect more significantly on their energy bills compared to other states with low energy consumption. Hence, a technique for suitable REP plan selection is essential for such residential customers to help them lowering the cost of their energy bills.

In the literature, which will be presented in Chapter 2, the techniques for mapping residential customers to suitable REP plans has been limited. A key limitation has been the lack of analysis in mapping the residential customers with added L-DERs and/or PEVs to the ideal REP plans. Considering the growth of these resources in the residential market makes this a relevant investigation. Furthermore, the existing personalized selection tools have broken ground in offering web-based guidance to customers in selecting REP plans [16], [17] and [18], however they too are yet to incorporate the decision support for choosing suitable L-DER and/or PEV capacities as well as estimate the energy bill savings acquired when a residential customer chooses to add any combination of these resources.

In summary, it is evident that a problem exists in the retail electricity sector in mapping the residential customers, specifically those with added L-DERs and/or PEVs, to economically suitable REP plans. Furthermore, the personalized selection tools that also offer decision support and estimated the bill savings for prospective prosumers are scarce. This prompted the current study to establish a solution for these customers in a rapidly advancing smart grid.

1.3 Research Question

How can a personalized selection tool map the monthly energy features of the residential customer who intend to install L-DERs and/or PEVs, to a suitable REP plan that minimizes their energy bill?

1.4 Thesis Objectives

The main objectives of this thesis are the following:

1) Develop a personalized selection tool for prospective prosumers that will map their monthly energy features to a suitable REP plan that achieves a minimum energy bill.
2) Present an approach for extracting L-DER and PEV representative profiles from time-series energy data.
3) Present a REP selection approach that uses the key features from the residential customers as well as the residential prosumers and the REP plans.
4) Develop decision support and energy bill savings estimation for the customers who want to add different L-DER and PEV combinations to their existing profiles.

1.5 Thesis Contributions

The main contributions of this thesis include the following:

1) Development of a personalized selection tool for mapping monthly energy features of residential customers with L-DERs and PEVs to suitable REP plans that minimizes their monthly energy bill.
2) A systematic approach for representative profile extraction of L-DER and PEV profiles using unsupervised learning techniques. These representatives will be added to the existing customer profiles for forecasting REP plans for prosumers.

3) A REP selection approach for finding the most economical REP plan for customers and prosumers. This approach incorporates an energy billing design for extraction of the monthly energy features from the times-series residential data and the monthly cost features (fixed and variable) from the REP plans.
4) Development of a knowledge base that provides decision support to the customers in choosing L-DER and PEV combinations that maximize their estimated energy bill savings.

1.6 Thesis Organization

The organization of this thesis from chapter 2 – 8 is described as follows:

Chapter 2 reviews the previous studies related to mapping the residential customers to the retail electric providers, the economic impacts of residential L-DERs and PEVs on energy bill savings, and the methods for extracting the representative L-DER and PEV profiles from the residential time-series datasets.

Chapter 3 provides an overview of the retail electric provider rate design and the energy billing process under different metering schemes at the residential level and the generation compensation mechanisms that accompany these schemes. Additionally, the Pecan Street household database with various metered resources are described.

Chapter 4 proposes a systematic approach that uses unsupervised learning techniques to extract the representative L-DER and PEV profiles from the time-series residential data. A comprehensive list of representative PVs, HBESS and PEV profiles with various consumption and generation levels is the outcome of this approach.

Chapter 5 proposes an approach for REP selection using a feature-based energy billing design that uses the monthly features from the residential customer, the prospective prosumer and the REP plans. The datasets of the existing residential customers and the list of REP plans used in the study are also presented.

Chapter 6 presents the expected energy bill savings of households with different L-DER and PEV combinations using the proposed REP selection approach. This is to understand the relationship between the following: 1) the average monthly net usage, 2) the expected energy bill savings and 3) the REP plan selection.

Chapter 7 presents the design of the personalized selection tool that guides residential customers in selecting the suitable REP plans as well as L-DER and/or PEV combinations. Additionally, a knowledge base is developed using a rule-set to recommend L-DER and PEV combinations to the prospective prosumers that maximize their energy bill savings. This tool consists of four graphical user interfaces implemented on the MATLAB App Designer platform.

Chapter 8 concludes the work in this thesis and provides recommendations for future work.

Chapter 2: Literature Review

2.1 Introduction

In this chapter relevant previous work to the mapping of the residential customers to the suitable retail electric provider (REP) plans, and the approaches utilized are reviewed. Since the main objective is usually to minimize the costs for the residential customers, the economic impact of the local distributed energy resources (L-DERs) and the plug-in electric vehicles (PEVs) on the energy bill savings is also reviewed, to identify which resource combinations are ideal for maximizing the savings. Furthermore, the effective strategies for representative the profiling of the high granularity time-series data is reviewed to extract a group of L-DER and PEV profiles that statistically represents the large residential energy datasets. Finally, at the end of the chapter the research gaps are identified and are summarized.

2.2 Mapping Residential Customers to Retail Electric Provider Plans

The Public Utility Commission of Texas (PUCT) defines a residential customer as an end-user that consumes electrical energy for household activity and does not sell it [19]. It also defines a REP as a seller of electrical energy to such customers [19]. These two entities are related through the retail choice of customers to specific REP service plans. In [20], the three benefits of customer's retail choice intend to: 1) reduce retail electricity prices, 2) broaden the selection of services for customers, and 3) promote the growth of distributed energy resources (DERs).

Previous work on retail choice has not considered the mapping of the residential customers with added local distributed energy resources (L-DERs) and plug-in electric vehicles (PEVs) [22]-[25],[28]-[29]. Additionally, the personalized selection tools with decision support and estimated energy bill savings for such customers i.e. prosumers, are limited, leading to suboptimal retail choices [28]-[29]. An overview of mapping a residential customer to a REP is first explained, then the various approaches used for mapping are discussed.

2.2.1. Overview of Customer-Supplier Mapping in the Energy Market

An ideal framework for mapping was developed in [21] to describe the engagement of a residential customer and a supplier in an energy market, which also include REPs. This framework was based on the best practices observed in the United Kingdom, Texas and Ireland. As illustrated in Figure 2.1, mapping occurs in three stages when a customer: 1) joins, 2) uses and 3) changes an energy supplier.

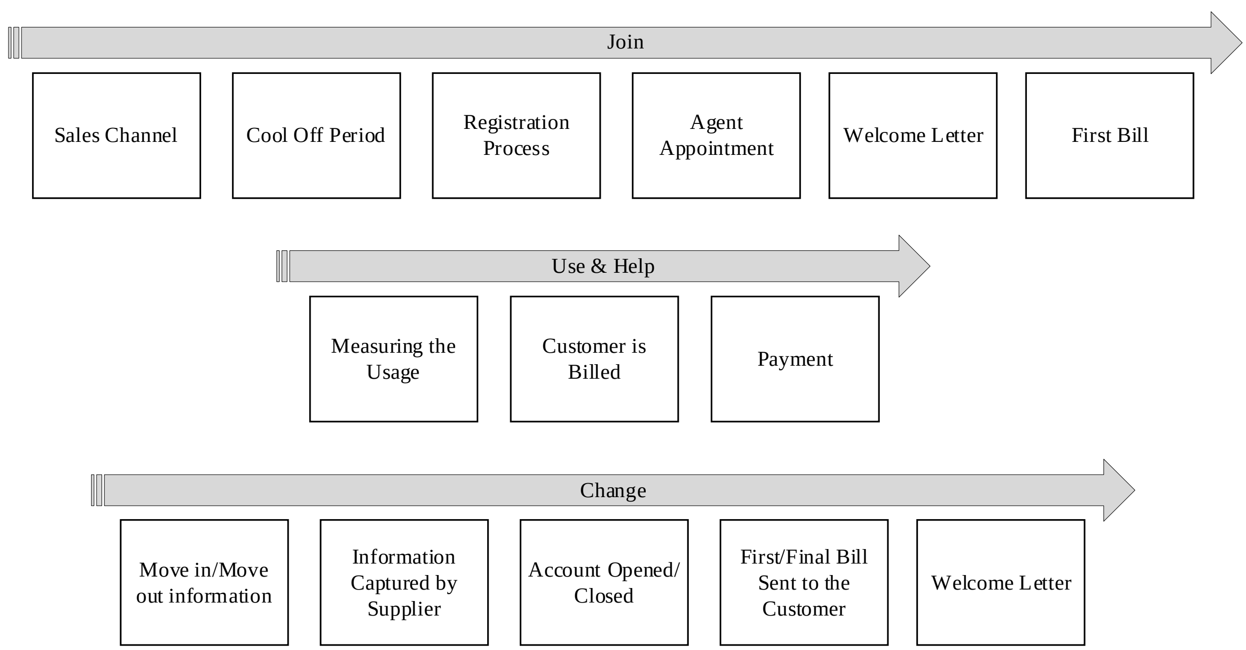


Figure 2.1: Framework for Customer-Supplier Mapping in an Energy Market [21]

In the “join” stage, a customer approaches a sales channel to compare and select a REP and a particular service plan. Then, they undergo a registration process where customer-supplier information is exchanged and an agent is appointed to establish the service connection for the energy metering. At the end of this stage, the first energy bill is communicated to the customer. In the “use” stage, metering takes place on a monthly basis to bill the customer based on their energy consumption from the REP. This is also were the daily customer service issues are addressed. Lastly, in the “change” stage the customer informs the REP of when they plan to move out or when a new tenant is due to move in. This way the REP captures the usage information in advance, exchanges the customer-supplier information, undergo a closure or registration process and provide the last or first bill to a departing or new customer. The following subsection looks into the different approaches used to map the residential customers to REPs.

2.2.2. Previous Work on Customer-Supplier Mapping Approaches

Nafka et al. [22] applied the unsupervised machine learning techniques using K-means clustering, hierarchical clustering and self-organizing maps to 197 residential customers and three REP plans. The data mainly consist of 91 consumption features were extracted from the hourly consumption profiles of the customers. The three REP plans had various rate structures; one plan with a time-invariant rate and two plans with time-variant rates. The clustering results showed that 81% of the customers benefited from mapping to the time-variant rates instead of the time-invariant rates (flat). However, the study was limited to only one retail rate with no analysis to the numerous REP plan features listed in [12]. This made the results highly dependent on the consumption of each customer. Furthermore, the addition of L-DER and/or PEV profiles were not considered to estimate the selection of REP plans for prosumers.

Zhou et al. [23] proposed a three-stage Stackelberg game model to optimize the pricing of REP plans based on the decision of the residential customers. The residential customers were given three time-invariant plans, including: a flat rate, tiered rate and a lump-sum fee to choose from. The REP plan that maximized the pay-off of a customer according to its consumption and demand was the ideal plan selection. The REP then optimized the pricing of each plan, based on the customer's selection, to maximize the profits. It was found that the flat rate plans are optimal for the low energy consumption customers and the lump-sum fee plans are ideal for the high consumption customers. This study did not consider the impact of the time-variant rates on the customer REP plan selection. Additionally, this study did not consider the residential customers with L-DER and/or PEV profiles. Furthermore, the energy bill savings that the individual customers would achieve from choosing an ideal plan were not evaluated.

The studies in [24] and [25] proposed a probabilistic approach to determine the likelihood of residential customers choosing a specific REP plan. In [25], 192,000 residential customers and six REP plans were evaluated using a two-stage logit probability model. The monthly consumption profile of each customer was evaluated. The six REP plans consisted of one incumbent plan and five alternative plans that each had an average retail rate of 1,000 kWh. It was found that 19% of the customers are likely to seek alternative REP plans annually, typically in summer months, when the energy bills are the highest. The monthly consumption of the customers is expected to vary, so an average retail rate centered at 1,000 kWh would lead to estimated energy bills. Additionally, the exclusion of the other REP plan features made the results highly dependent on the monthly energy consumption. In [24], 1022 residential customers were evaluated with a logit probability model. Although, in this case the information was collected on the customer's awareness of alternative REPs and their annual consumption, it was found that 47% of customers are unlikely to seek alternative REPs because of the barriers that exist in joining a new REP, such as customer loyalty to existing suppliers and uncertainty of the economic viability of various plans. This study however, did not incorporate the customer's decision support or the estimated bill savings to overcome such barriers and increase the interest of customers to map to alternative REPs. Furthermore, both studies did not evaluate the residential customers with added L-DER and/or PEV profiles.

2.2.3. Previous Work on Customer-Supplier Personalized Mapping Tools

More recently, the personalized tools have become a useful approach in guiding the residential customer decisions for suitable mapping to REP plans. Fan et al. [26], mentioned that the personalization is broadly used in many sectors, where it aims to tailor customer needs and build healthy customer-supplier relationships. They identified that the implementation of the personalization should consist of three dimensions, namely: 1) information being personalized, 2) target of personalization and 3) initiator performing the personalization, as shown in Figure 2.2.

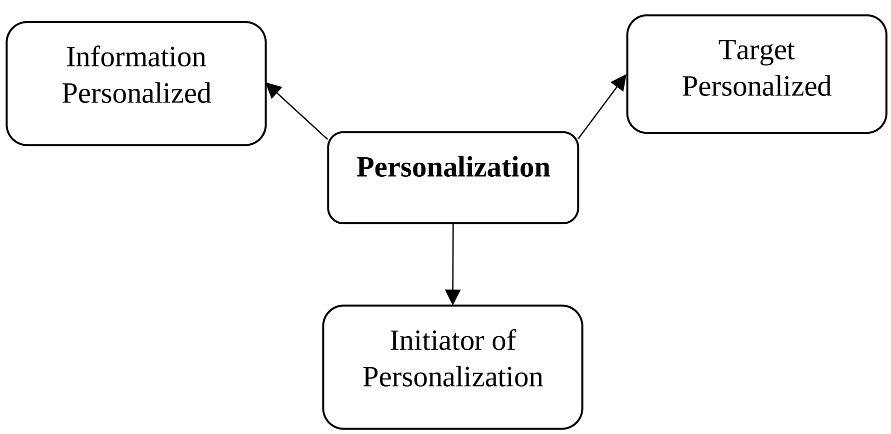


Figure 2.2: Concept of Customer Personalization [26]

Meuer et al. [27], also support the concept of personalization from the perspective of the retail electricity market. They argue that relevant customer information can be analyzed with advanced machine learning techniques to arrive at a personalized offer or plan for the customers. Some web-based personalized tools include [16],[17],[18], which collect the customer consumption profiles, compare retail rates, estimate energy bills for various plans and recommend the most suitable plan. However, these tools are typically targeted towards the existing customers and not those that anticipate introducing L-DERs and/or PEVs to their existing consumption profiles. The studies that used personalized tools for mapping are discussed further.

Belton et al. [28], applied logistic regression models to determine the likelihood of 145 residential customers selecting the cheapest of four types of rates given two price comparison interfaces. The first comparison interface displayed the cost of each rate based on an average annual consumption of 4,000 kWh. The second comparison interface allowed a customer to input their personal consumption profile, which is then used to calculate the cost of each rate. The cheapest rate was identified with 92% success rate when customers input their personal consumption profiles in the second comparison interface. Conversely, when the first comparison interface was used, the cheapest rate was identified with a 65% success rate. The benefit of the personalization was therefore shown in this study to accurately map the existing customers to the suitable rates. However, the expected savings in choosing the cheapest rate were not explicitly stated in the study. Furthermore, the addition of L-DERs and/or PEVs profiles for the existing customers and their estimated savings were not included.

Li et al. [29] used clustering and a collaborative filtering algorithm, to create a personalized recommendation system that identifies a small group of suitable plans for the customers. The framework for this system was adopted from a popular web-based personalized tool used by PUCT – "Power-to-Choose" [18]. The evaluation included 100 REP plans from 15 retailers and the consumption profiles of 90 residential customers. It was found that the top recommendation reduces a sampled customer's total electricity cost by 30%. However, similar to the previously mentioned studies, the only REP plan feature used was the retail rate. Additionally, the recommendations were based on the daily consumption that does not account for the seasonal consumption behaviors. More so, the results from [25] suggest that the customers rarely seek alternative retailers at a daily frequency. Furthermore, the customers that anticipate introducing L-DERs and/or PEVs are not considered in this personalized recommendation system.

A summary of these studies and their key features are presented in Table 2.1. The research gaps are annotated by "✗" and the areas that have been investigated are annotated by "✓".

Table 2.1: Summary of Studies on Mapping the Residential Customers to the Retail Electric Provider Plans

Study Reference	Method	Customer Features	REP Plan Features	Personalized Tool	L-DER and/or PEV profiles	Estimated Bill Savings
[22]	Hierarchical, K-means clustering and Support Organizing Maps	Daily Consumption	Time-invariant and Time-variant rates	✗	✗	✗
[23]	Stackelberg Game Model	Random Variable for Consumption	Time-invariant	✗	✗	✗

[24]	Logit Probability Model	Annual Consumption	-	✗	✗	✗
[25]	Logit Probability Model	Monthly Consumption	Average rates	✗	✗	✓
[28]	Logistic Regression Model	Weekly Consumption	Time-invariant and Time-variant rates	✓	✗	✗
[29]	DBSCAN clustering and Collaborative filtering	Daily Consumption	Time-variant rates	✓	✗	✓

2.3 Impact of L-DERs and PEVs on the Energy Bill Savings

Due to the advancements in the smart grid, smart homes with L-DERs such as rooftop solar photovoltaic (PV) and home battery energy storage systems (HBESS) were introduced [30]. Also, in the transportation sector, the electric vehicles became an appealing option for the governments to reduce their carbon footprint through local charging [31]. The addition of these rooftop solar PV, HBESS and PEV profiles directly impact the consumption profiles of the existing customers, thus influencing the expected energy bills they receive from REPs. A positive or negative saving may influence the retail choice of these residential prosumers. Therefore, the relationship between different L-DER and PEV profiles and the expected energy bill savings is reviewed in this section.

Previous work on the energy bill savings were found to have a strong relationship with the retail rate structure (time-invariant or time-variant), generation compensation mechanism (net metering or feed-in tariff) and the capacity of L-DERs [13], [32]-[35]. The retail rate structure was observed to have the most significant impact on savings, where the time-invariant rates were more feasible for rooftop solar PV adoption and conversely time-variant rates were more feasible for HBESS or PEV adoption. Furthermore, the combination of rooftop solar PV, HBESS and PEV introduce a dilemma as to which retail rate structure to select for maximizing energy bill savings. The following subsection will discuss these different studies.

2.3.1. Previous Work on the Impact of Rooftop Solar Photovoltaic on the Energy Bill Savings

Thakur et al. [13], investigated the impact of increasing rooftop solar PV penetrations on the energy bill savings of the net metered residential customers. Both time-invariant and time-variant rates were evaluated for 97 residential customers. The value of the savings was found to be significant for high energy usage customers that use flat or tiered rates. Additionally, the study found that the value of these savings ($/kWh) diminishes for higher rooftop solar PV penetration levels, because the capacity of PV generation is inversely proportional to the retail rate of electricity. Therefore, the appropriate PV sizing is imperative for the net metered customers, which should at most support 90% of the household load [13]. This reduces the issue of diminishing the bill savings and avoids the annual exhaustion of excess generation bill credits. The study in [32] identified that tiered rates quadruple the value of the electricity bill savings for the residential customers when they add rooftop solar PV. The use of the net metering, as a generation compensation mechanism, was also found to contributor significantly to the electricity bill savings in comparison to the feed-in tariff, which does not allow for the self-consumption of local generation.

2.3.2. Previous Work on the Impact of Rooftop Solar PV and Home Battery Energy Storage Systems on the Energy Bill Savings

Shen et al. [33], determined the optimal sizing of HBESS for a residential rooftop solar PV and HBESS combination that was the most feasible for customers. An approach of self-consumption maximization was compared against an operational optimization approach, that uses the least costly time-of-use rates to coordinate the battery charging and the discharging events. The solar PV capacities evaluated were between 2 to 10 kW peak. The operational optimization approach was found to be the most feasible; resulting in minimum annual costs and significant returns on investment. The optimal sizing of HBESS, for a solar PV capacity of 8 kW-peak, was 3.45 kWh with a return on investment of 28.93% for the operational optimization. In comparison, the self-consumption maximization had an optimal HBESS sizing of 1.49 kWh with a return on investment of 4.38%. Therefore, the time-variant rates can increase the sizing of HBESS and the value of the energy bill savings. Ren et al. [34] evaluated the impact of PV and HBESS systems on three residential locations. They identified that the households in each location benefit from significant energy bill savings with critical peak pricing that has a time-variant rate structure. In this study, the generation compensation mechanism used was the feed-in tariff, which is the rate that the generation is sold back to the grid for the customer to receive credit. Shen et al. [33], argues that since the value of this feed-in tariff has decreased globally, local storage is becoming a more feasible option because of the time-variant retail rate structures.

2.3.3. Previous Work on the Impact of Rooftop Solar PV, Home Battery Energy Storage Systems and Plug-in Electric Vehicles on the Energy Bill Savings

Schwarz et al. [35], investigated the impact of retail rates on PEV charging and the adoption of residential PV and HBESS from 2005 to 2030. They found that PEV charging is highly sensitive to the retail rate structure. Tiered rates were suitable for PV adoption, but led to an increase in the evening load due to the arrival of residential customers from work. Time-of-use rates were suitable for HBESS adoption but led to over-coordinated charging by attempting to shift most PEV loads to off-peak hours, which also increased the late evening load. Hourly rates reduced the evening load by shifting the PEV charging to midday, which was suitable for both PV and HBESS adoption. However, the success of the hourly rates was based on the assumption that the PEV owners have access to public charging infrastructure, where a portion of their charging capacity can be met before they arrive home. Therefore, residential PEV customers are advised to control their charging with time-variant rates and public charging to support the contribution of the energy bill savings from PV and HBESS. A summary of the studies related to the impact of PVs, HBESSs and PEVs on the energy bill savings and the ideal retail rate structures are illustrated in Table 2.2. The various combinations are annotated by "×" for L-DERs and/or PEVs that are excluded and "✓" for those that are included in the study.

Table 2.2: Summary of Studies on the Impact of L-DERs and PEVs on Energy Bill Savings

Study Reference	PV	HBESS	PEV	Generation Compensation Mechanism	Ideal Retail Rate Structure
[13]	✓	×	×	Net Metering	Flat or Tiered

[32]	✓	×	×	Net Metering	Tiered
[33]	✓	✓	×	Net Metering	Time-of-Use
[34]	✓	✓	×	Feed-in Tariff	Critical Peak Pricing
[35]	✓	✓	✓	Net Metering	Hourly

2.4 Representative Profiling of Residential Customers

Residential load profiles in distribution systems have a high level of variability that is influenced by the seasonal changes, the customer's behavior and the combination of the resources in a home [14]. Automatic meter readings through smart meters have made it possible to record large volumes of energy data in short intervals to understand the residential consumption patterns [30]. However, processing this raw energy data raises challenges of information quality that has different measurement precisions, granularities and embedded noise [36]. The introduction of L-DERs and PEVs at residential level add to this challenge, as new sources of energy data are recorded that require processing to extract consumption and generation characteristics of prosumers. Representative load profiling is a useful approach for grouping and classifying the customers profiles with similar behavioral patterns by employing clustering techniques [37]. In this way a small representative set of L-DER and PEV profiles, with key characteristics, can be chosen to be superimposed onto the existing customer profiles to determine the REP plan mapping and possible energy bill savings of these prospective prosumers. Previous work in the literature on representative load profiling use systematic approaches to extract the representative profiles [38]-[43] and [45]. They also employ different metrics to evaluate the quality of these representatives, which are further discussed in this section.

Li et al. [38], proposed a three-stage approach to predict the profiles of unmonitored low-voltage substations using the representatives of monitored substations in the same region. From 800 low-voltage substations, 10 representative substations were identified. The stages consisted of: 1) clustering, 2) classification and 3) scaling. In the clustering stage load profiles were normalized, to extract the load profile shape, then grouped using hierarchical and K-means clustering algorithms. The representative profile was the average of the load shapes within each cluster. In the classification stage, a multinominal logistic regression model was used to predict the ideal representative profile for the unmonitored substations based on fixed substation properties of each cluster. Lastly, in the scaling stage the representative profile magnitude is re-established.

The work in [39], identified 9 low-voltage customer representatives from a total of 165 customers. The study applied the first two stages suggested by [38] but incorporated a self-organizing map, before applying K-means clustering, to reduces the dimensionality of the clustered features. Thereafter, a decision tree and rule set were applied to classify new customer load profile shapes to the representative profiles. Shaker et al. [40], conducted a similar study on rooftop solar profiles using a hybrid approach that consisted of principal component analysis and K-means clustering. It was found that from 405 rooftop solar profiles, 15 representative profiles were extracted. The representative profiles in each cluster were based on the observations with the highest principal component ranking and the closest distance to the cluster centroid. The closest observation to the cluster centroid, as a representative, is argued by [41] to be more indicative of an actual dataset sample compared to the average of the profiles in a cluster. This was conducted using the K-nearest neighbor to extract the closest observation to the cluster centroid.

The quality of representative clusters was assessed in [42], which emphasize the importance of selecting the appropriate type and quantity of clustered features. The study applied a finite mixture model to cluster 3,622 residential customers, where 10 representative clusters were found from 7 features. It was concluded that the type of features should capture the most significant variance in the dataset and the quantity of features should be decent enough to avoid high computational costs. Rasanen et. al [43], followed a similar method and extracted 7 key statistical features from 1,035 residential customers where 16 representative clusters were found.

In each of the above mentioned studies, the optimal number of representative clusters is determined using metrics that measure the cohesion and separation of observations within and between clusters, respectively [44]. A common metric used in the studies is the sum of squared errors (SSE) that measures the cohesion of observations within clusters. However, this metric solely does not describe the interaction between the clusters and requires a supplementary metric to measure the cluster separation such as the cluster dispersion index [39], average silhouette coefficient (ASC) [41] or the Davies-Bouldin index [43]. A summary of the related studies on the representative profiling of residential customers is shown in Table 2.3.

Table 2.3: Summary of Studies on Representative Profiling of Residential Customers

Study Reference	Method	Dataset	Data Sample Rate	Cluster Evaluation Metrics	Representatives
[38]	Hierarchical and K-means clustering	800 LV substations	10 min	SSE	10 LV substations
[39]	Self-organizing map and K-means clustering	165 LV customers	15min	Cluster Dispersion Indicator and Mean Index Adequacy	9 LV customers
[40]	Principal component analysis and K-means clustering	405 Rooftop solar sites	1 hour	-	15 Rooftop solar sites
[41]	Principal component analysis, K-means clustering and K-nearest neighbor	365 Days of peak load	1 hour	SSE and ASC	15 Days of peak load
[42]	Finite mixture model	3622 Residential customers	30 min	Bayesian Information Criterion	10 Residential customers
[43]	K-means clustering	1035 Residential customers	1 hour	Davies-Bouldin Index	16 Residential customers
[45]	K-means clustering	365 Days of solar irradiance and temperature	1 hour	SSE	9 Days of solar irradiance and temperature

2.5 Research Gaps

The following represents the main research gaps in this literature:

- The design of a personalized tools for mapping residential customers with L-DERs and/or PEVs to REP plans is limited. Additionally, the estimation of the energy bill savings is not adequately represented for individual prosumers.
- Existing personalized selection tools also do not provide decision support as to which combinations of L-DERs and/or PEVs are the most feasible for "new" prosumers and what retail rate structure is the most suitable for them.
- The application of the representative profiling is more focused towards residential customers without L-DERs and/or PEVs. A systematic approach, using unsupervised machine learning, to find representative profiles for customers with PV, HBESS and PEV is therefore necessary.

2.6 Summary

This chapter presented the previously published literature related to the mapping of the residential customers to the REP plans and the various approaches used to do so. The concept of customer personalization for optimal REP plan selection was discussed. Then, the chapter reviewed the impact of L-DERs and PEVs on the customer energy bill savings. Lastly, the chapter reviewed the established techniques for representative profiling of residential loads with large datasets of energy data. From this the research gaps were identified that will be addressed in the proposed work of this thesis.

Chapter 3: Retail Electric Providers and the Energy Billing

3.1 Introduction

This chapter presents a model for the retail electricity rates and the structuring of these rates as advertised in the retail electric provider (REP) plans. The residential customers or the prosumers then select a REP plan based on the "retail choice". Through using the services of a REP plan, the users are given an energy bill at the end of the billing cycle. Therefore, the various energy billing schemes and the compensation mechanism for the local generation will also be discussed in this chapter. In addition, the annual consumption and generation profiles from the Pecan Street home dataset, specifically those with local distributed energy resources (L-DERs) and plug-in electric vehicles (PEVs), are described. Finally, the list of REP plans in the jurisdiction of the residential data are presented with various retail rate structures.

3.2 Retail Electric Provider Electricity Rate

In a competitive electricity market, the retail electricity rates of the REPs are unbundled into deregulated and regulated rates. Each retail electricity rate consists of three costs that include: 1) energy costs, 2) transmission and distribution costs and 3) auxiliary costs as shown in Figure 3.1 [46].

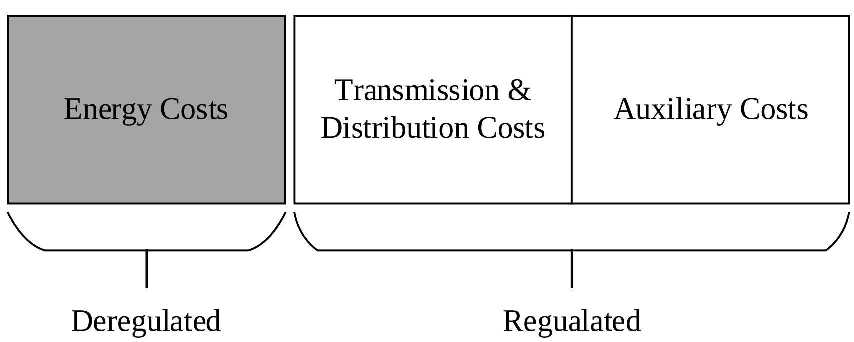


Figure 3.1: Composition of a Retail Electricity Rate [46]

The energy costs are related to the value of the commodity – electricity. The transmission and distribution costs are related to the delivery of the electricity from a generation source to the residential customers. Furthermore, the auxiliary costs account for all other overhead costs, such as taxes, supply regulation, customer service and metering [46]. From these three costs, the REP has the liberty to design its own energy costs to create a competitive retail electricity rate, while maintaining transmission, distribution and auxiliary costs. These costs are itemized in a customer's energy bill, where the deregulated rate (REP) is "separate" or unbundled from the regulated rate (electric utility). The modeling and the structuring of the retail electricity rates are further elaborated in the following subsection.

3.2.1. Retail Electricity Rate Model

A mathematical model is presented in [47] that describes the design of a retail electricity rate for a group of residential customers. This model follows the value chain of a REP business from the acquisition of electricity at a generation source to the final delivery of electricity to the customers. Along this value chain, the REP must make a series of purchases before establishing an optimal rate. Firstly, the REP purchases electricity from a generation source (renewable or non-renewable) at a wholesale electricity rate. Secondly, the REP purchases the transmission and distribution services to enable the delivery of electricity to customers. Lastly, the REP pays for any auxiliary costs that need to be met for regulated services. Therefore, the established retail electricity rate (r_j) for a group of residential customers (j) is a combination of the wholesale electricity rate, marginal delivery and auxiliary costs. This is shown in Equation 3.1 below.

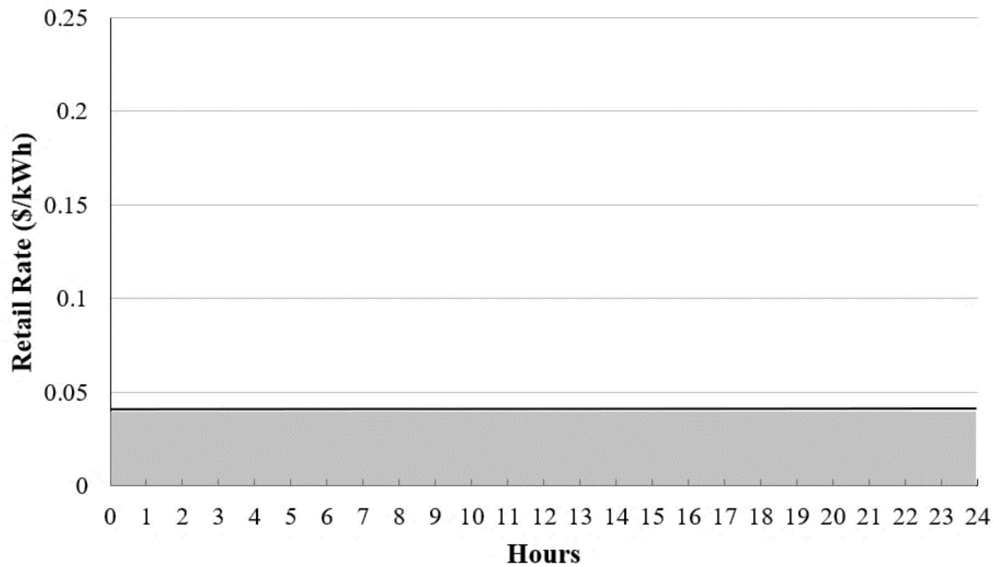
$$r_j = p_w + \frac{\partial \tau}{\partial e_j} + \frac{\partial w}{\partial e_j}\ ; where\ j \geq 1 \tag{3.1}$$

Where r_j is the retail electricity rate (\$/kWh) of the j^{th} customer group, p_w is the wholesale electricity rate (\$/kWh), e_j is the electricity sold (kWh) to the j^{th} customer group, $\frac{\partial \tau}{\partial e_j}$ is the marginal delivery cost of electricity (\$/kWh) and $\frac{\partial w}{\partial e_j}$ is the marginal auxiliary cost of electricity (\$/kWh).

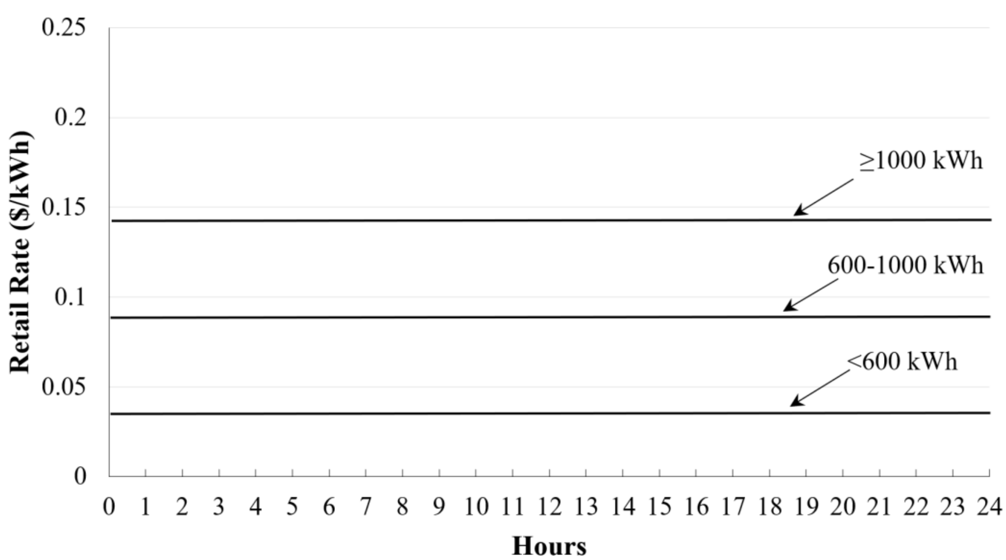
It is evident from this model that many retail electricity rates are possible from a single REP business based on the customer's demand, the generation wholesale rate, and the regulated costs of the transmission and distribution network. Consequently, this introduces a dilemma for residential customers who want to select the most feasible REP rate for their pattern of consumption. Furthermore, the complexity of retail choice is increased with retail rate structures, that introduce the concept of electricity pricing over time.

3.2.2. Retail Electricity Rate Structures

At a higher level, retail electricity rates are organized into different pricing structures that are used to bill customers for their consumption on a periodically i.e. monthly period. These retail rate structures occur in two categories, namely: 1) time-invariant rates and 2) time-variant rates [13]. The time-invariant rates remain constant within the season of a customer's consumption. Conversely, the time-variant rates vary based on the time of the day, the day of the week or season of a customer's consumption. Some examples of time-invariant rates and time-variant rates, for a typical summer weekday, are illustrated in Figures 3.2 - 3.3 [48]. The illustrated retail rates in $/kWh are not associated with any specific REP but do represent the overall profile of each retail rate structure within a 24-hour period.



(a)



(b)

Figure 3.2: Time-invariant Rate Structures – (a) Flat Rates and (b) Tiered Rates [48]

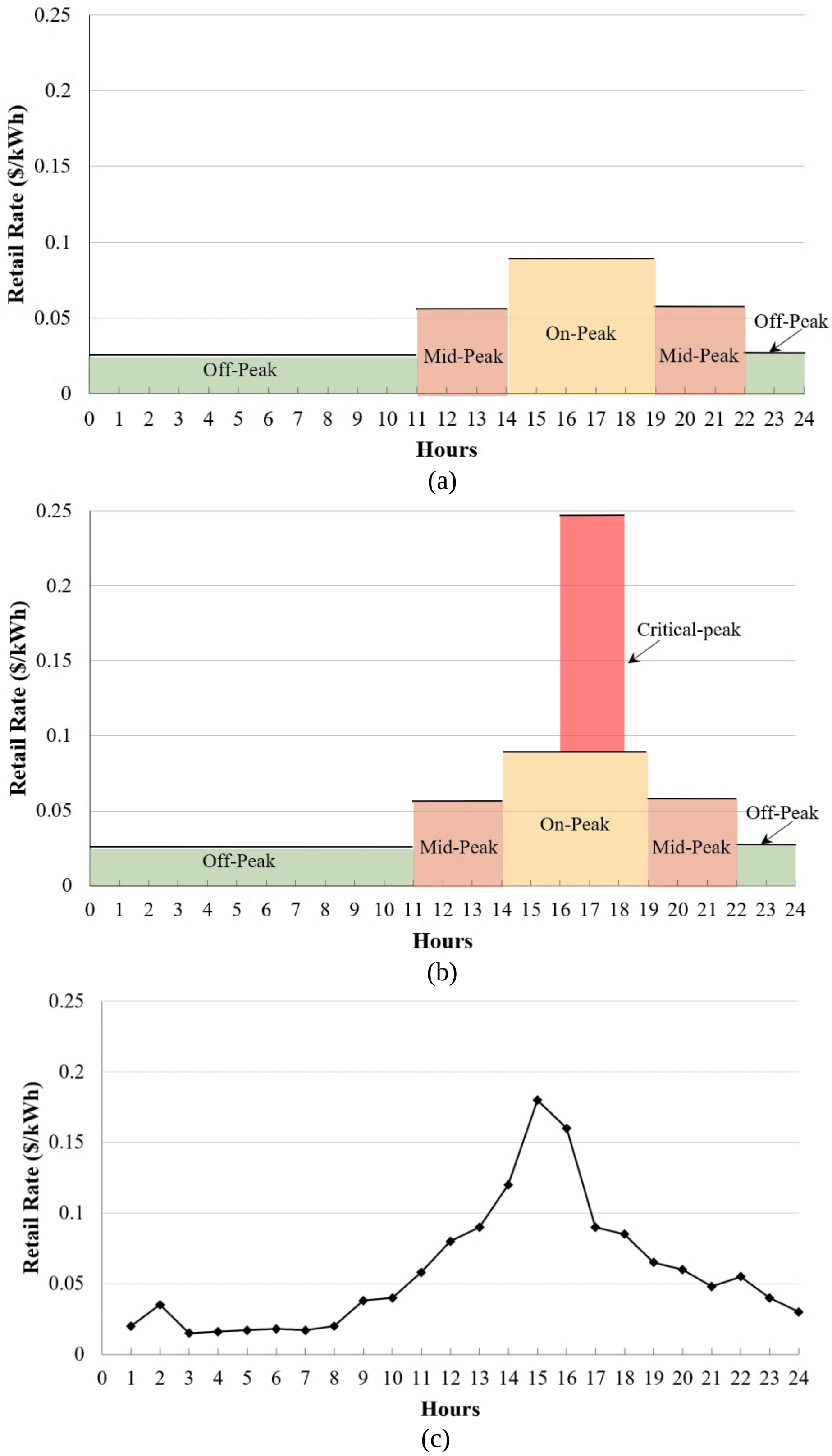


Figure 3.3: Time-variant Rate Structures – (a) Time-of-use Rates, (b) Critical Peak Pricing and (c) Real-Time Pricing [48]

3.2.2.1. Time-invariant Rate Structures

The two common types of time-invariant rates are the flat and the tiered rates, as illustrated in Figure 3.2 (a) and (b) respectively. Flat rates remain fixed irrespective of the customer's aggregated consumption, whereas tiered rates are composed of different flat rates for specific ranges of aggregated consumption i.e. <600 kWh, 600 – 1000 kWh or ≥1000 kWh. This is the simplest form of rate structure for residential customers, because they can easily anticipate their monthly energy bills. However, the risk factor of maximizing REP profits is increased because the time-invariant rates do not reflect the short-term changes in the wholesale rate.

3.2.2.2. Time-variant Rate Structures

The three common types of time-variant rates are the time-of-use rates, the critical peak pricing and the real-time pricing, as illustrated in Figure 3.3 (a) - (c). The time-of-use (TOU) rates typically segment the day into three rates, namely: 1) off-peak, 2) mid-peak and 3) on-peak [48]. These rates represent the level of demand from customers throughout the day, where off-peak rates are for periods of low demand; on-peak rates are for periods of high demand and mid-peak rates are for the periods in-between. This rate structure is applied to weekdays, but on weekends, only the off-peak rate is used. Additionally, depending on the season (summer or winter) the mid-peak rate and the on-peak rate are exchanged. Critical peak pricing is similar to TOU, but only applies to the on-peak rate. It is a short-term high retail rate announced a day ahead by the electric utility for a maximum of 15 times per season [48]. Real-time pricing is the most complex retail rate structure that varies hourly based on the wholesale rate [48]. Time-variant rates reduce the risk factor of maximizing REP profits, as retail rates reflect the trend of wholesale rates. However, from the perspective of the customer the uncertainty of anticipating the energy bills increases. A REP can maximize the profits from the residential customers by using multiple retail rate structures. These are advertised as individual service plan, where customers can choose to enter into a contractual agreement with a REP to receive a secure electricity supply. The customer then makes the monthly payments for their plan based on their monthly energy bill.

3.3 Residential Energy Billing

An energy bill outlines a residential customer's consumption and/or generation, if they are a prosumer, and itemizes each cost in a monthly statement. In a home, one or two electric meters are installed to measure the flow of the electrical power between the electric grid and the customer. This electric meter aggregates the energy consumed and/or generated by the user in a month, which the REP uses to create an energy bill, as illustrated in Figure 3.4. Based on the configuration of the electric meters, two types of billing schemes are possible, namely: 1) net metering scheme and 2) net billing scheme [49]. The compensation mechanisms for the local generation is different in each billing schemes, which benefit the residential prosumers in different ways. In the United States, mandatory state-wide policies for the energy billing exist for most distribution networks. However, in some states, such as Texas and Idaho, there is no mandatory policy for energy billing [50] which makes it specific to the policy of the REP.

Figure 3.4: Residential Energy Billing Process

3.3.1. Net Energy Metering Scheme

In this scheme, a single electric meter measures the bi-directional flow of electrical power between the electric grid and the prosumer, as illustrated in Figure 3.5 [49]. A smart meter is typically used, due to its capability of measuring the bi-directional power flow and its ability to perform automatic meter readings [30]. This electric meter records the net usage in kWh, which is the difference between the imported electricity and the local generation. Prosumers in this scheme are compensated for their local generation through direct self-consumption or excess generation. Only the excess generation is exported to the electric grid, which is the residual generation left after self-consumption. A positive net usage, at the end of a billing month, implies that more electric energy was imported from the electric grid than the locally generated energy. Therefore, the prosumer is charged by the REP at the retail electricity rate. A negative net usage, at the end of a billing month, implies that less electric energy was imported from the electric grid than the locally generated energy. This excess generation is credited to the prosumer at the retail electricity rate. Lastly, a zero-net usage, at the end of the billing month, implies that the electricity imported was equal to the local generation. Here, the prosumer is not charged an energy cost but is required to pay other regulated costs. Furthermore, the credit for excess generation is not always guaranteed for prosumers on some REP plans. This is because not all REPs purchase excess generation [51] and therefore the prosumers need to strategically size the local distributed resources to capitalize on self-consumption.

3.3.2. Net Billing Scheme

In this scheme, two electric meters are used to measure the inflow of the electrical power from the electric grid to a prosumer and the outflow of the generated power from the prosumer to the electric grid. Each electric meter is unidirectional, operating in opposite directions, as illustrated in Figure. 3.6 [49]. The prosumers export all their generation, without the capability of self-consumption. At the end of a billing month, the imported electricity from the electric grid is charged to the prosumer at the retail electricity rate. In addition, the exported generation is credited/compensated to the prosumer at a feed-in tariff. This feed-in tariff is either equal to, more than or less than the retail electricity rate [49]. However, the global trend of feed-in tariffs is gradually decreasing and therefore the prosumers need to seek alternative ways to directly use the local generation through the home battery energy storage [33].

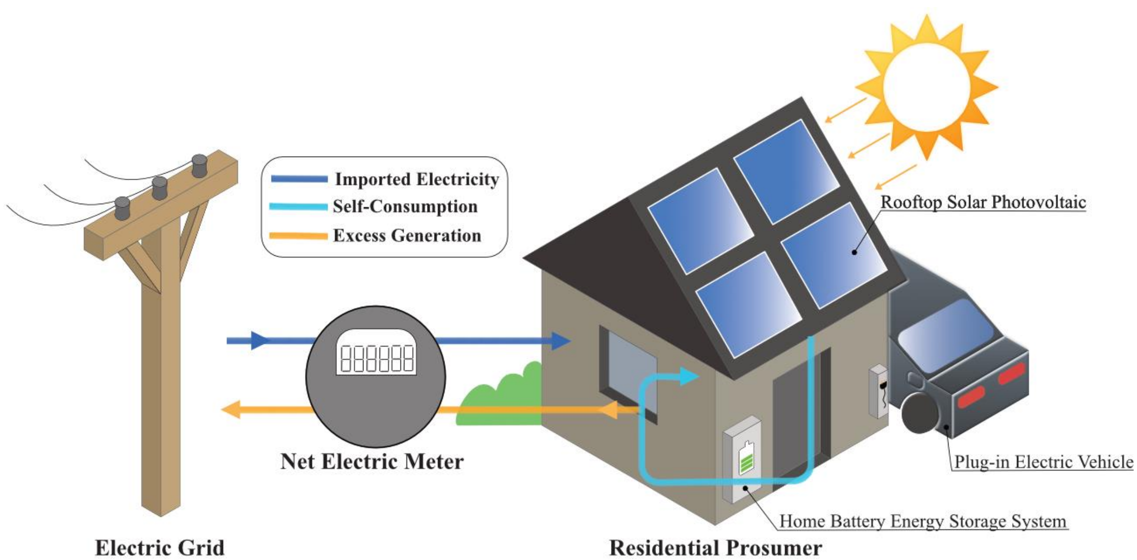


Figure 3.5: Residential Net Metering Scheme

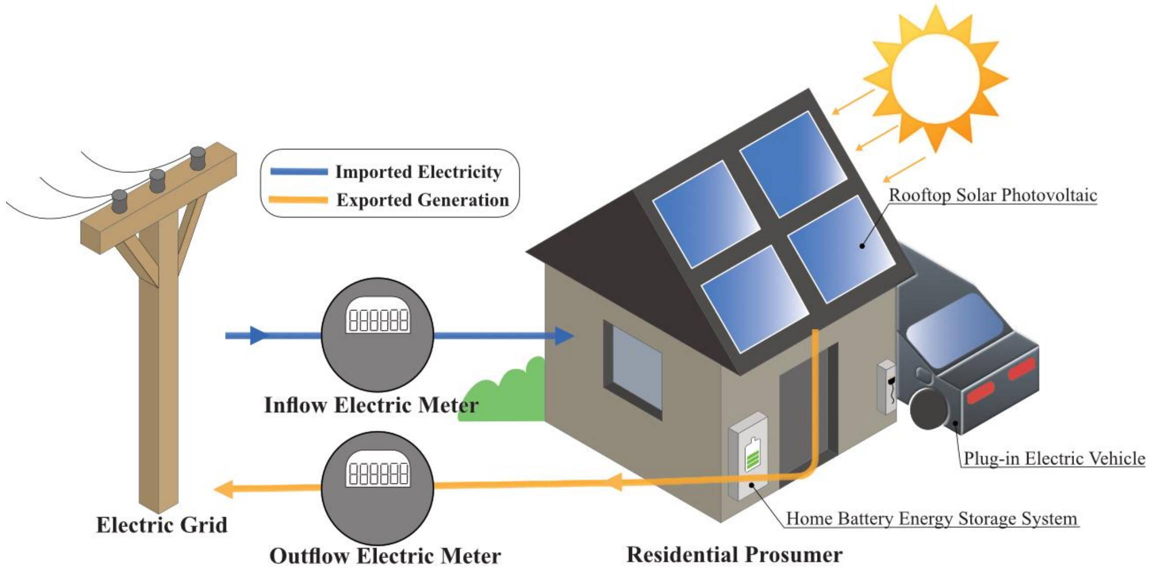


Figure 3.6: Residential Net Billing Scheme

3.4 Residential Consumption and Generation Profiles

The energy consumption and generation profiles are needed from the residential customers and the prosumers to establish the energy bills. A dataset of the annually metered homes, from Pecan Street [6], was therefore used in this study. The homes are located in Mueller, Austin, Texas, where Oncor Electric Delivery Company provides the electricity delivery services and the Electric Reliability Council of Texas is the independent system operator [12]. An aerial view of this community is shown in Figure 3.7. The homes in this dataset were chosen for three reasons, namely: 1) the active retail electricity market location [5] and [52], 2) the monthly variability of L-DER and PEV profiles and 3) the high granularity residential data. This meets the experimental requirements in this study of finding a suitable REP plan for the residential customers with various L-DERs and/or PEVs profiles. The following subsection describes the Pecan Street home dataset in more detail.

Figure 3.7: Aerial View of Pecan Street Homes in Mueller, Austin, Texas [53]

3.4.1. Pecan Street Home Dataset

There are 940 homes monitored by Pecan Street in Austin, Texas, between 2011 and 2019, according to the metadata in [6]. Within each home, there are up to 77 electric gauges that collect power data from various household appliances, rooftop solar photovoltaic (PV), home battery energy storage systems (HBESS) and plug-in electric vehicles (PEV); if they are present in a home. These electric gauges are similar to the electric meters but have a more frequent sampling rate of 1 minute. The main electric meter in the home can measure the bi-directional power flow (net usage), which implies that the net metering is used for the energy billing. This home dataset is unique because there is diversity in the make, rating and capacity of L-DERs (PV and HBESS) and PEVs, as shown in Table 3.1. Furthermore, since the residential customers typically receive the monthly energy bills, the monthly variability in PV generation, the HBESS discharge and the PEV charging is explored for a sample of the annual profiles in subsections 3.4.2 – 3.4.4.

Table 3.1: Manufacturers, Rating and Capacity of PVs, HBESSs and PEVs in Dataset [6]

L-DER/PEV	No. of Homes	Manufacturer	Rating (kW)	Capacity (kWh)
PV	232	Specific to home	2 - 10	-
HBESS [54],[55]	7	Tesla Powerwall	5	14
		LG Chem RESU 10H	5	9.8
PEV [56]	126	Tesla Model S	-	60 – 100
		Nissan Leaf		24 – 40
		Chevrolet Volt		16.5 – 18.4
		Mitsubishi i-MiEV		16
		Ford Fusion		7.6

3.4.2. Residential Customers with Roof-top Solar Photovoltaic

The annual generation is measured from the PV electric gauge of the residential customer. A total of 74 annual profiles were sampled, between 2016 – 2019, and their monthly average peak generation (kW) was plotted as shown in Figure 3.8. It can be observed that 99.3% of the profiles have a monthly average peak generation between 2 – 7.5 kW.

3.4.3. Residential Customers with Home Battery Energy Storage Systems

The annual charging and discharging are measured for the HBESS electric gauge of residential customers. A total of 5 annual profiles were sampled, in 2019, and their monthly aggregated profile (kWh) was plotted as shown in Figure 3.9. The monthly aggregated profile fluctuates between the range of 0 – 500 kWh as customers charge and discharge the battery. The residential customers with HBESS only featured in the Pecan Street dataset in January 2019, when this study was conducted, which explains the limited number of annual profiles. Despite this limitation they are still included in the study to investigate their impact on REP plan selection.

3.4.4. Residential Customers with Plug-in Electric Vehicles

The annual charging is measured for the PEV electric gauge of residential customers. These PEVs are charged from Level 2 charging infrastructure (3.3 – 19.2 kW) at each home [6]. A total of 44 annual profiles were sampled, between 2018 – 2019, of the three most observed PEV makes, namely: 1) Tesla Model S, 2) Nissan Leaf and 3) Chevrolet Volt. The monthly aggregated charging in kWh was plotted as shown in Figure 3.10. It can be observed that 99.3% of the profiles have a monthly charging energy between 0 – 450 kWh.

From exploring samples of the annual PV, HBESS and PEV profiles in this dataset, the monthly variability is evident. This also implies that the monthly energy bills from the prosumers will vary, which is necessary for testing the REP plan selection approach in Chapter 5.

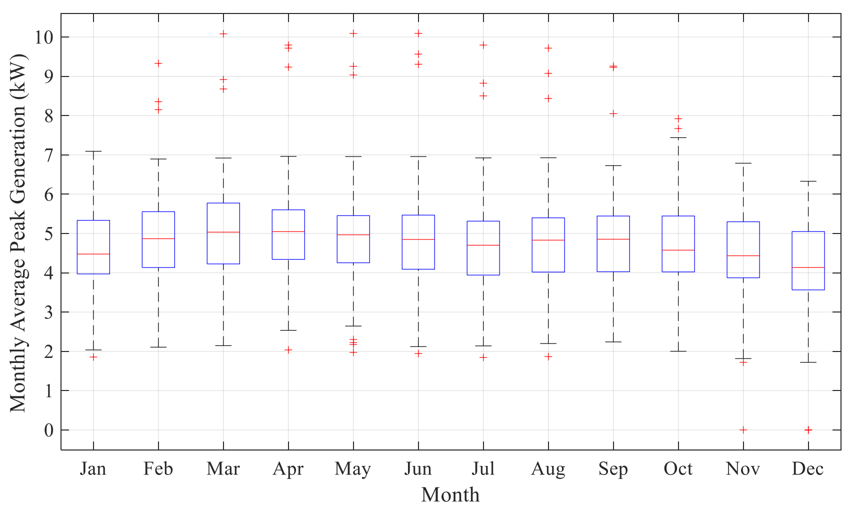


Figure 3.8: Monthly Average Peak Generation for Residential Customers with PV (74 Samples)

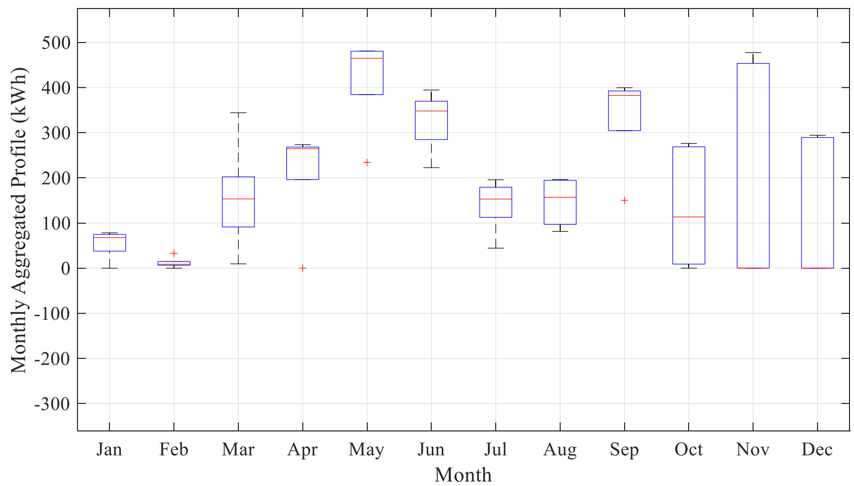


Figure 3.9: Monthly Aggregated Profile for Residential Customers with HBESS (5 Samples)

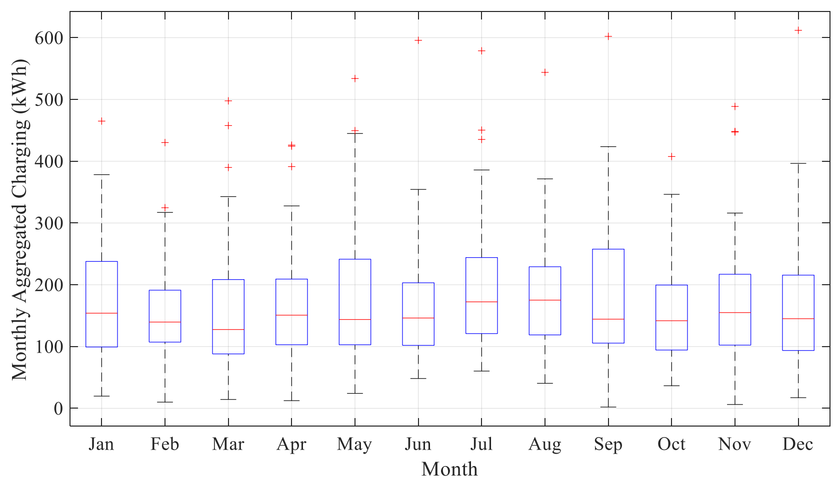


Figure 3.10: Monthly Aggregated Charging for Residential Customers with PEV (44 Samples)

3.5 Retail Electric Provider Plans

The last component needed to establish the energy bills for the residential customers or the prosumers are the REP plans. Based on the location of a customer, a specific variety of the REPs and the service plans are available. Therefore, the zip-code of the homes in the Pecan Street dataset was used to identify a list of REP plans that have a mixture of time-invariant and time-variant rates. A total of 5 REPs were chosen with 24 service plans. The rate structures of these REP plans consisted of 14 tiered rates, 8 flat rates and 2 TOU rates, as shown in Table 3.2. The retail rates advertised in these plans were based on 2019 costs.

In addition, the fixed and the variable delivery costs specified by the Oncor Electric Delivery Company in October 2019, are shown in Table 3.3. These will be used to formulate the REP plan selection approach for the residential customers and the prosumers in Chapter 5.

3.6 Summary

This chapter presented a model for the retail electricity rates and the various rate structures employed in REP plans. Then, the two common residential energy billing schemes were discussed, together with the compensation mechanism used for the local generation. Next, the chapter presented the Pecan Street home dataset with the annual consumption and the generation profiles that have the monthly variability. Finally, the list of the REPs and the service plans to be used in this study, was presented. The following chapter presents a systematic approach for the representative profiling of the residential customers with L-DERs and/or PEVs using the unsupervised machine learning techniques. This is necessary for extracting a set of prosumers with the representative characteristics from high granularity time-series data.

Table 3.2: Retail Electric Provider List and Plans in Mueller, Austin, Texas

REP Name	REP Plan	REP Plan Abbreviation	REP Plan Electricity Rate Structure
4 Change Energy[57]	Budget saver 12	Budget S	Tiered
	ECO saver plus 12	ECO S	Tiered
	Generous saver plus 12	Generous S12	Tiered
	Helpful saver 24	Helpful S	Tiered
	Generous saver plus 36	Generous S36	Tiered
	Generous saver monthly	Generous SM	Tiered
Acacia Energy[58]	Free Night	Free N	TOU
	Valtricity	-	Flat

	Free Weekend	Free W	TOU
	2 Month Free	-	Flat
Frontier Utilities[59]	Straight Power 12 ONC	Straight P	Tiered
	Beat the Heat 12	Beat H	Flat
	Friends & Family 24+	Friends F24	Flat
	Friends & Family 12+	Friends F12	Flat
	Accident Forgiveness	Accidental F	Flat
	Easy Bill O A	Easy B	Tiered
Infinite Utilities[60]	48- month Smart	Smart 48	Tiered
	36-month Smart	Smart 36	Tiered
	24-month Nest Cam Rate	Nest CR24	Flat
	24-month Nest Rate	Nest R24	Flat
	Classic 12-month	Classic 12	Tiered
Austin Energy[61]	Standard Austin Energy	Standard AE	Tiered
	Green Choice	Green C	Tiered
	Community Solar	Community S	Tiered

Table 3.3: ONCOR Transmission and Distribution Costs per Residential Customer [62]

Transmission and Distribution Costs	ONCOR Rates
Fixed Cost ($)	3.42
Variable Cost ($/kWh)	0.038447

Chapter 4: Representative Profiling of Local Distributed Energy Resources and Plug-in Electric Vehicles

4.1 Introduction

This chapter presents a systematic approach for representative profiling of the residential customers with local distributed energy resources (L-DERs) and/or plug-in electric vehicles (PEVs). The purpose of this is chapter is to extract the common consumption/generation characteristics from the prosumers in an existing community. Therefore, the customers who intend to add L-DERs and/or PEVs can estimate their future profiles by superimposing the representatives profiles, which exist in the surrounding community. This approach incorporates three well-known unsupervised machine learning techniques that include: 1) principal component analysis, 2) K-means clustering and 3) K-nearest neighbor to find the representative clusters for the residential rooftop photovoltaic (PV), home battery energy storage systems (HBESS) and PEV using their monthly features of variability. Furthermore, the outcome of this approach will be compiled into a comprehensive list of representative profiles to be used in the REP plan selection.

4.2 Overview of the Proposed Methodology

This proposed method consists of five processes, starting from pre-processing the L-DER and PEV consumption/generation profiles to finally extracting the representative profiles, as shown in Figure 4.1. The following method was adopted from [38] but includes an additional process of quantifying the monthly variability of PV, HBESS and PEV consumption/generation profiles. Furthermore, in the clustering process two cluster evaluation metrics namely the sum of squared errors and the average silhouette coefficient are used to determine the optimal number of clusters.

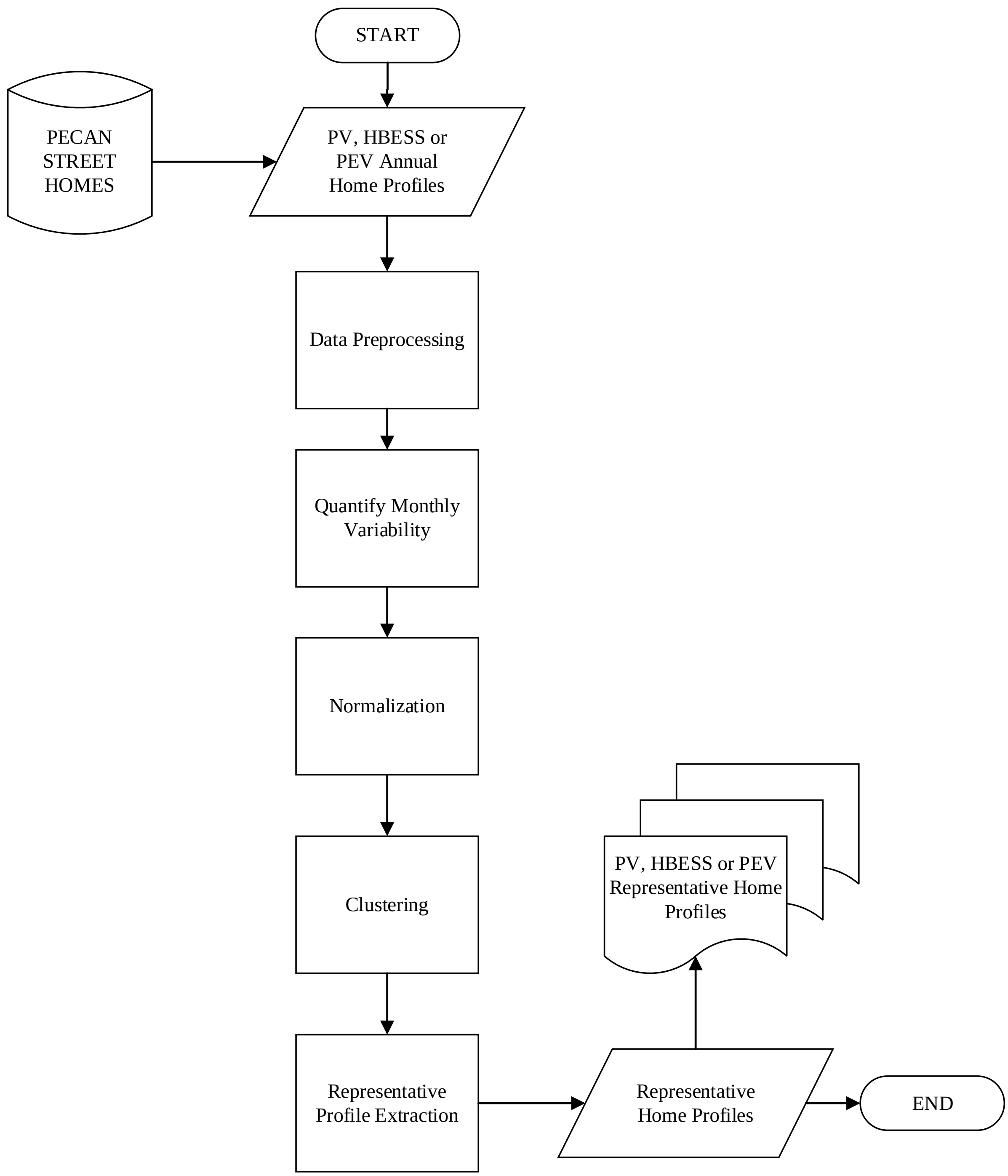


Figure 4.1: Flowchart of Proposed Methodology for Representative L-DER and PEV Profile Extraction

Finally, K-nearest neighbor is used to extract the individual home profiles instead of the aggregation of home profiles in a cluster, as suggested by [41]. The remaining sections will explain each of these processes as outlined in Figure 4.1.

4.3 Data Preprocessing

In this process, the PV, the HBESS and the PEV generation/consumption profiles, sampled at 1-minute intervals, are pre-processed to address the issues of: 1) missing data entries and time stamps and 2) duplicate times stamps. Given a profile of 365 days × 1440 minutes/day and assuming a one year of data, the missing data entries are replaced with a value of zero. Then, the missing time stamps are eliminated due to the uncertainty of the time of the sampled data. Next, the time stamps are sorted in ascending order i.e. 1 January 00:00 to 31 December 23:59. This addresses the first issue of the missing data entries and the time stamps. The second issue is the duplicate time stamps, which are addressed by taking the mean of these data entries to simplify into a single time stamp. Lastly, the time series data is resampled in 15-minute intervals, which produces a profile of 365 days × 96 minutes/day. The representation of the data in 15-minute intervals is to remain consistent with the sampling rate of the existing smart meters [30]. Furthermore, the steps for data pre-processing are presented in Algorithm 4.1.

Algorithm 4.1: Data Preprocessing Algorithm

```
Input: PV, HBESS or PEV Profile in 1-minute intervals
Replace missing data entries with a value of zero
Eliminate missing time stamps
Sort data in ascending time stamps
Replace data entries of duplicate time stamps by their mean value
Resample data to 15-minute intervals
Output: Preprocessed PV, HBESS or PEV Profile
```

4.4 Quantification of the Monthly Variability

In this process the monthly variability of PV, HBESS and PEV generation/consumption profiles that were discussed in subsections 3.4.2 – 3.4.4, are quantified to extract the key features from the pre-processed 15-minute data. The monthly features are quantified because the residential customers are typically billed on a monthly basis. For the residential customers with PV, the monthly average peak generation output (kW) of rooftop solar panels is quantified. For the residential customers with HBESS, the monthly aggregated profile (kWh) of the battery is quantified. Additionally, for the residential customers with electric vehicles, the monthly aggregated charging (kWh) is quantified. This is used to develop 12 months (January – December) of features for each annual PV, HBESS and PEV generation/consumption profile. This is expressed in (4.1), where H is a vector of a group of N annual home profiles (PV, HBESS or PEV) each with 12 months of generation/consumption features.

$$H = \begin{bmatrix} H_1 \\ H_2 \\ H_3 \\ . \\ H_N \end{bmatrix} = \begin{bmatrix} Jan_1 & Feb_1 & Mar_1 & . & Dec_1 \\ Jan_2 & Feb_2 & Mar_2 & . & Dec_2 \\ Jan_3 & Feb_3 & Mar_3 & . & Dec_3 \\ . & . & . & . & . \\ Jan_N & Feb_N & Mar_N & . & Dec_N \end{bmatrix}, where\ N \geq 1 \qquad (4.1)$$

4.5 Element-based Z-Normalization

In this process, the group of N annual home profiles (PV, HBESS or PEV) with monthly features are normalized to capture the profile shape in preparation for clustering. The technique used is element-based z-normalization [63], where each month (columns of H) are normalized to have a mean (μ) of zero and a standard deviation (σ) of unity across the group of N annual home profiles. This is expressed in (4.2), where $\widehat{H}(m)$ is the normalized form of a monthly feature (m) for a group of N annual home profiles. This normalization process is repeated for all 12 months of features.

$$\widehat{H}(m) = \frac{H(m) - \mu}{\sigma}, where\ 1 \le m \le 12 \quad (4.2)$$

4.6 Principal Component Analysis, K-means Clustering and Evaluation Metrics

In this process, the normalized monthly features $\widehat{H}(m)$ of the group of N annual home profiles (PV, HBESS or PEV) undergo the principal component analysis (PCA) and K-means clustering. There are 12 months of features in total, which means that 12-dimensional clustering is required. This is difficult to visualize and is computationally expensive. Therefore, PCA is used to reduce the dimensionality of the feature space from 12-dimensions to 2 or 3 dimensions that explain at least 60% of the variance in the dataset [64]. A correlation matrix of all the features is also analysed in Appendix C for each dataset. The original set of features ($\widehat{H}(m)$) are transformed to an orthogonal set of axes, known as principal components (*PCs*). These *PCs* are the eigenvectors of the original set of features, whereas the corresponding eigenvalues are the explained variance in the group of N annual home profiles. This is expressed in (4.3) for the first two principal components (PC1 and PC2) of $\widehat{H}(m)$), which is represented as $\widehat{H}_{PC}$.

$$\widehat{H}_{PC} = \begin{bmatrix} PC1_1 & PC2_1 \\ PC1_2 & PC2_2 \\ PC1_3 & PC2_3 \\ \cdot & \cdot \\ PC1_N & PC2_N \end{bmatrix}, where\ N \ge 1 \quad (4.3)$$

After reducing the dimensionality of features, through PCA, the N annual home profiles (PV, HBESS or PEV) are ready for clustering in the PCA domain. The technique used for clustering in this study is K-means clustering [44]. This clustering technique is preferred for the unsupervised machine learning, where the number of clusters in the data is unknown. It is based on the Euclidean distance, expressed in (4.4), for the measurement of cohesion and separation of data observations within and between clusters [44].

$$d(x, y) = \sqrt{\sum_{k=1}^{n} (x_k - y_k)^2} \tag{4.4}$$

Where d is the Euclidean distance between two data observations (x and y), k is the current dimension of the data observation and n is the total number of dimensions of the data observation.

The algorithm for K-means clustering [65] accepts an initial value for the number cluster (K), which are equivalent to the number of cluster centroids (c_i). It then finds K clusters in the data based on the distance (d) between data observations and the cluster centroids. A range of K values between 1 and 10 were evaluated to determine the optimal number of clusters for each group of N annual home profile observations. Clustering metrics were used in each iteration of the clustering algorithm to measure the optimal value for K. These two cluster evaluation metrics were: 1) sum of squared errors (SSE) and 2) average silhouette coefficient (ASC). Furthermore, since the K-means clustering algorithm is stochastic [65], this cluster evaluation process is repeated a large number of times to converge towards a reliable solution. Therefore, the process was iterated 300 times, which is 200 iterations more than recommended in [44].

The first cluster evaluation metric is the SSE, which measures the cohesion of data observations within each cluster, using (4.5) [44].

$$SSE = \sum_{i=1}^{K} \sum_{x \in C_i} d(c_i, x)^2 \tag{4.5}$$

Where x is the data observation within a cluster, c_i is the i^{th} cluster centroid, and K is the total number of clusters. The optimal number of clusters for a given dataset is identified at the "knee" of the SSE plot, which is the point where the value of SSE does not change significantly for any further increase in the values of K. In order to identify this "knee" more accurately, the gradient of this metric with respect to K is used instead. Therefore, when the gradient of the SSE (with respects to K) tends towards zero it is apparent that the change in the SSE value tends towards a constant value. This is expressed in (4.6) as:

$$SSE\ Gradient = \frac{\partial SSE}{\partial K} \tag{4.6}$$

The second cluster evaluation metric is the ASC, which measures the cohesion of data observations within a cluster and the separation of data observations between clusters. The silhouette coefficient (s_l) of each data observation is calculated using (4.7) [44].

$$s_l = \frac{(b_l - a_l)}{\max{(a_l, b_l)}} \tag{4.7}$$

Where a_l is the average distance of the l^{th} data observation relative to others in the same cluster and b_l is the minimum average distance of the l^{th} data observation relative to others in different clusters. The average of all the silhouette coefficients (ASC) is calculated for the N annual home profile observations using (4.8). The optimal number of clusters is determined by the value of the ASC, which is bound between (-1,1). An ASC of 1 well-separates the clusters and -1 symbolizes poorly separated clusters.

$$ASC = \frac{1}{N}\sum_{l=1}^{N} s_l \tag{4.8}$$

The complete clustering process to find the optimal number of clusters for a group of N home profile observations (PV, HBESS or PEV) is summarized in Algorithm 4.2.

Algorithm 4.2: Optimal Clustering Algorithm

Input: Dataset ($\widehat{H}_{PC}$) of N Annual Home Profiles with PV, HBESS or PEV
for trials = 1 to 300
    for K = 1 to 10
        Apply K-means Clustering Algorithm
        Calculate and plot SSE and ASC metric values
    end for
end for
Determine optimal number of clusters from SSE and ASC plots → K
Output: Optimal number of clusters for $\widehat{H}_{PC}$

4.7 Optimal Number of Clusters

The results for the optimal number of clusters are presented in this section using the cluster evaluation metrics listed in the mathematical expressions (4.5) – (4.8). The number of the annual home profile observations for PV, HBESS and PEV are specified in each case.

4.7.1. Optimal Clusters for Homes with Rooftop Solar Photovoltaic

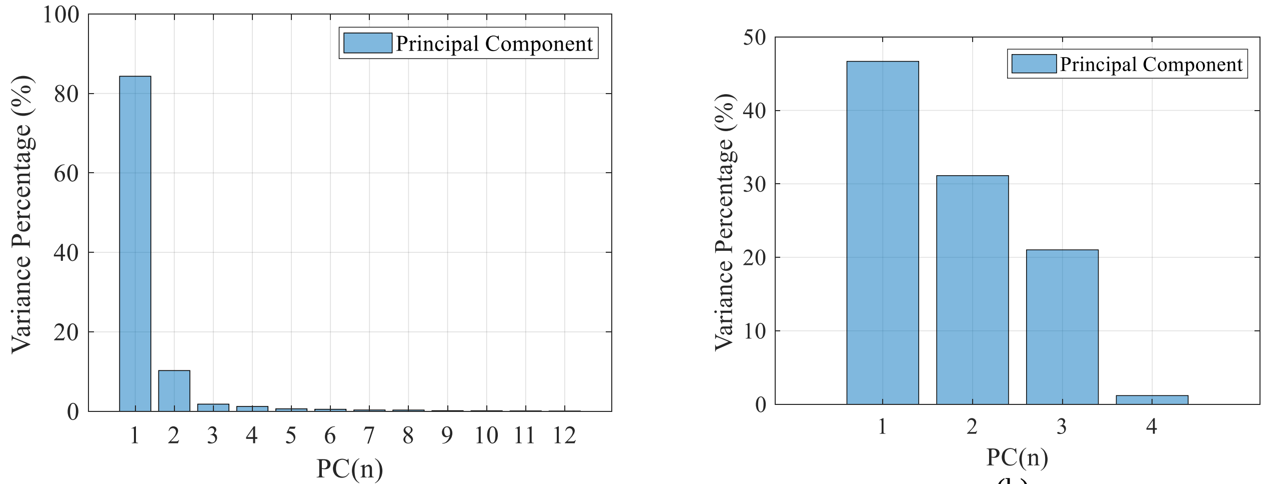
A total of 74 annual generations profiles for the residential customers with PV were observed between 2016 and 2019. After applying PCA, it was observed that 94% of the explained variance exists in the first two principal components (PC1 and PC2), as illustrated in Figure 4.2 (a). Therefore, clustering in 2-dimensions would be sufficient as more than 60% of the explained variance is captured from the original data. From visual inspection of Figure 4.3 (a), it is observed that the median value of SSE gradient (for 300 iterations) decreases towards zero for increasing values of K. This occurs because as the number of clusters increase, the data observations tend to be closer to the cluster centroids, hence the SSE value decreases. Specifically, for $K > 4$ the gradient of SSE does not decrease significantly (less than -39.4 per cluster), which means that the "knee" point is established at K = 4. From visual inspection of Figure 4.3 (b), the median value of ASC fluctuates between 0.58 and 0.64, with a local maximum at K = 4. This implies that 4 clusters are the optimal number of clusters for the 74 observations of PV annual generation profiles.

4.7.2. Optimal Clusters for Homes with Home Battery Energy Storage

A total of 5 annual profiles for the residential customers with HBESS were observed in 2019. After applying PCA, it was observed that 78% of the explained variance exists in the first two principal components (PC1 and PC2), as illustrated in Figure 4.2 (b). From observing Figure 4.4 (a) the median value of the SSE gradient decreases less significantly (less than -3. 25 per cluster) for $K > 3$. This means that the "knee" point is established at K = 3. From visual inspection of Figure 4.4 (b), the median value of ASC increases from 0.72 to 1. This occurs because they are a few observations and as the number of clusters increase, the singular clusters will be developed rapidly. A cluster with a single observation defeats the purpose of the clustering algorithm. Therefore, a median ASC value at K = 3 (0.83), which coincides with the "knee" of the SSE gradient plot, was selected as the optimal number of clusters from 5 observations of HBESS annual profiles.

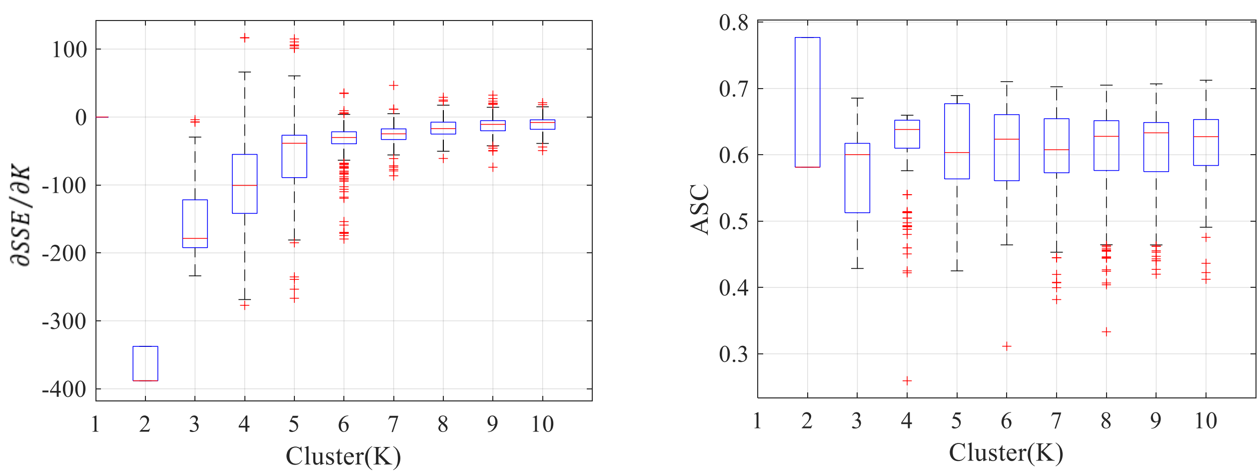
4.7.3. Optimal Clusters for Homes with Plug-in Electric Vehicles

A total of 44 annual charging profiles for the residential customers with PEV were observed between 2018 and 2019. Of these observations, 32 annual charging profiles were for Chevrolet Volt, 7 annual charging profiles for Tesla model S and 5 annual charging profiles for Nissan Leaf. In Figure 4.5 (a) – (c), it was observed that the explained variance in the first two principal components (PC1 and PC2) were 83%, 86% and 80% for Chevrolet Volt, Tesla Model S and Nissan Leaf, respectively.



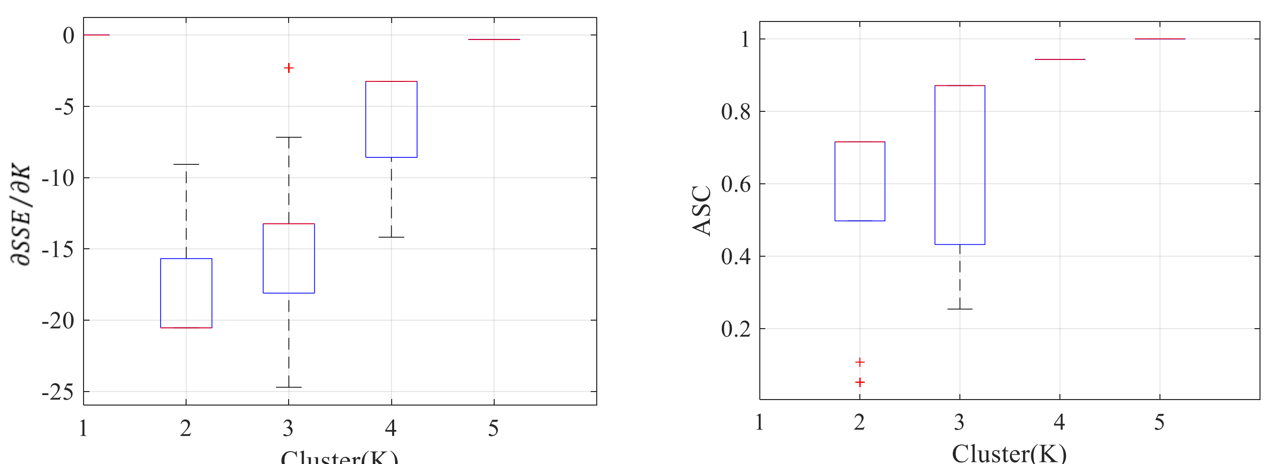
(a) (b)

Figure 4.2: Variance Percentage for each Principal Component: (a) PV Homes and (b) HBESS Homes



(a) (b)

Figure 4.3: Clustering Evaluation for PV Homes: (a) SSE gradient and (b) ASC



(a) (b)

Figure 4.4: Clustering Evaluation for HBESS Homes: (a) SSE gradient and (b) ASC

4.7.3.1. Optimal Clusters for Homes with Chevrolet Volt

From Figure 4.6 (a), it was observed that the median value of the SSE gradient decreases less significantly (less than -19.27 per cluster) for $K > 3$, implying that the "knee" point of the SSE plot occurs at $K = 3$. Visual inspection of Figure 4.6 (b) illustrates a parabolic trend in the median value of the ASC for K between 1 and 6, after which the value of the ASC decreases for $K > 7$. In the boundary of $2 < K < 7$, a local minimum ASC value occurs at $K = 4$ (0.63). This is because few clusters appear closer to one another and may seem not to be well-separated, which decreases the overall ASC value. After this turning point, for $K > 4$, the clusters start to become more cohesive and well-separated until $K = 7$ (0.74). The three highest values for the ASC from 1st to 3rd highest occur at $K = 2$, $K = 7$ and $K = 3$. Firstly, two clusters are not reasonable because they have a high SSE value. Secondly, seven clusters have a low SSE value, but this does not occur close to the "knee" of the SSE plot. This means that three clusters are the optimal number for the thirty-two observations of the Chevrolet Volt annual charging profiles.

4.7.3.2. Optimal Clusters for the Homes with Tesla Model S

From Figure 4.7 (a), it was observed that the median value of the SSE gradient decreases less significantly (less than -0.66 per cluster) for $K > 4$, implying that the "knee" point of the SSE plot occurs at $K = 4$. Visual inspection of Figure 4.7 (b) reveals that the median value of the ASC increases from 0.61 to 1 for $K = 1$ to $K = 7$. The highest value of the ASC is at $K = 7$, but this is not reasonable as it is produces clusters with single data observations. Therefore, a median ASC value at $K = 4$ (0.92), which coincides with the "knee" of the SSE gradient plot, was selected as the optimal number of clusters from 7 observations of Tesla Model S annual charging profiles.

4.7.3.3. Optimal Clusters for the Homes with Nissan Leaf

From Figure 4.8 (a), it was observed that the median value of the SSE gradient decreases less significantly (less than -4. 24 pre cluster) for $K > 3$, meaning that the “knee” point of the SSE plot occurs at $K = 3$. Visual inspection of Figure 4.8 (b) illustrates that an increasing trend in the ASC value from 0.51 to 1 for $K = 1$ to $K = 5$. The highest value of the ASC is at $K = 5$, but similar to the Tesla Model S, in subsection 4.7.3.2, this produces clusters with single data observations. Therefore, a median ASC value at $K = 3$ (i.e. 0.7), which coincides with the “knee” of the SSE gradient plot, was selected as the optimal number of clusters from 5 observations of Nissan Leaf annual charging profiles.

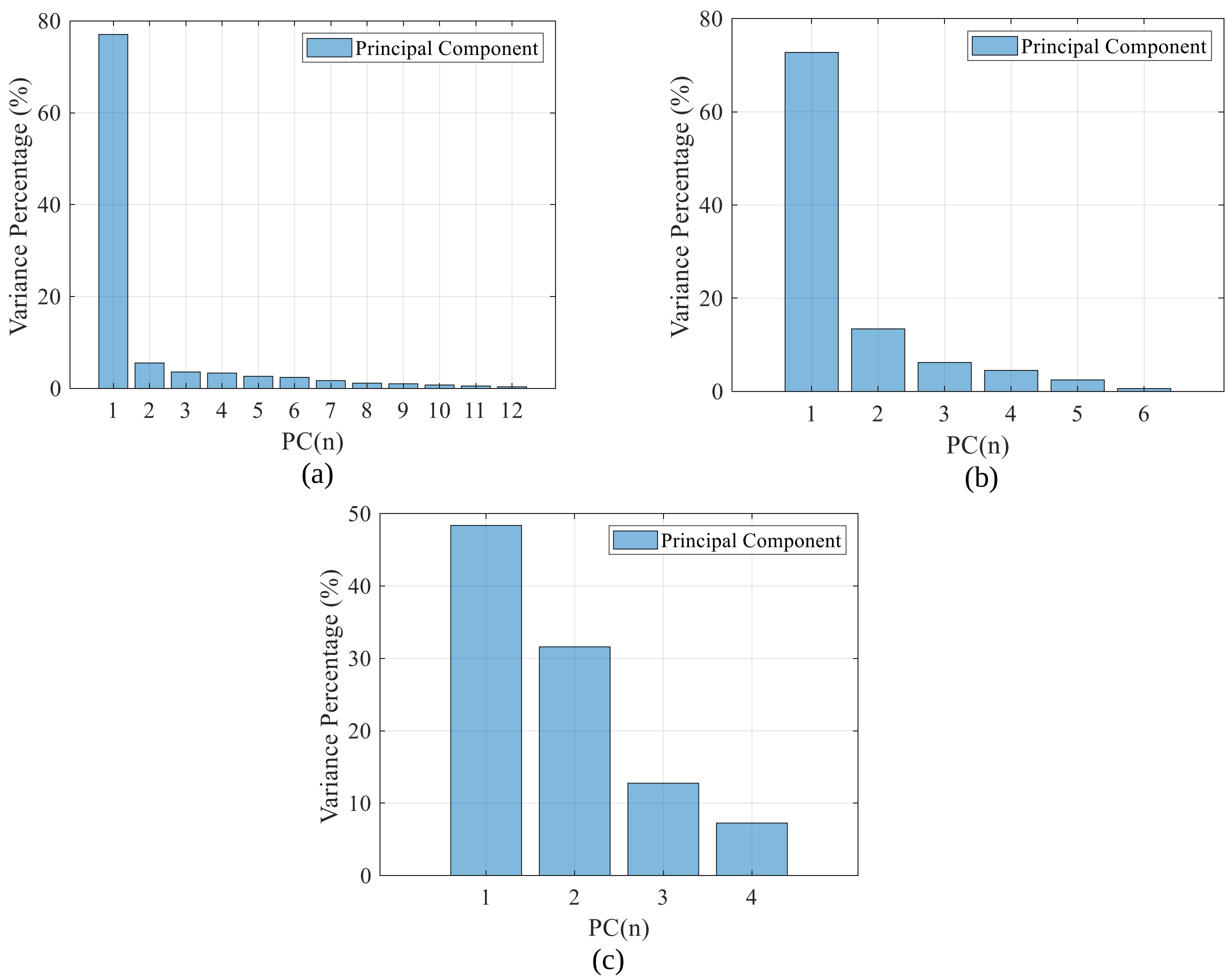
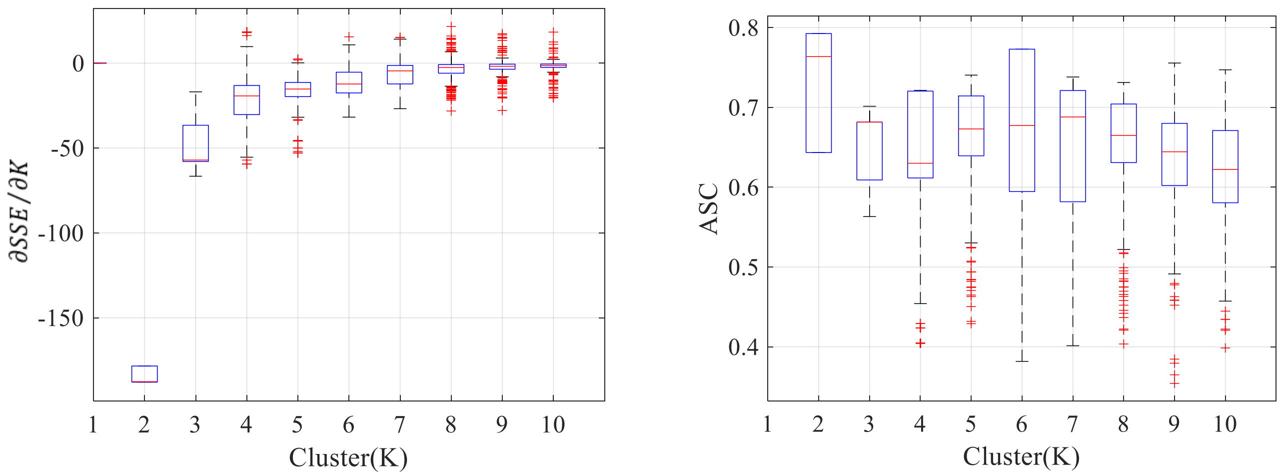
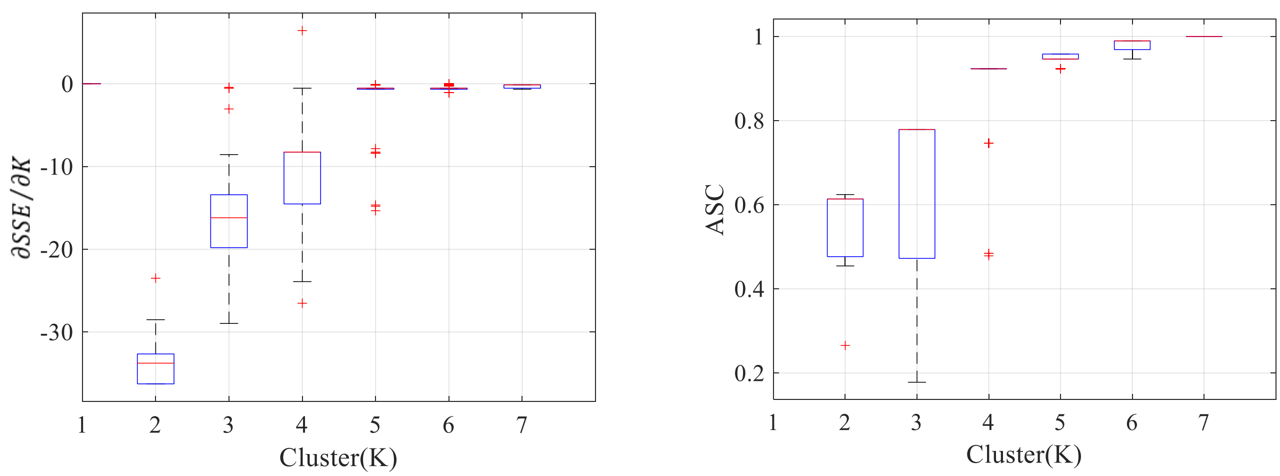


Figure 4.5: Variance Percentage for each Principal Component for PEV Homes: (a) Chevrolet Volt, (b) Tesla Model S and (c) Nissan Leaf



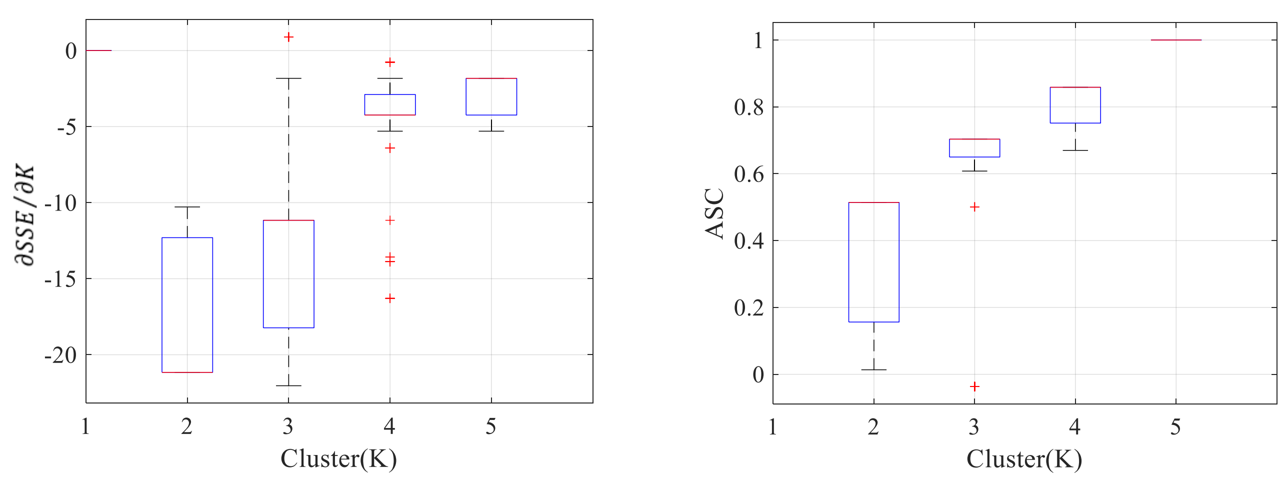
(a) (b)

Figure 4.6: Clustering Evaluation for Homes with Chevrolet Volt: (a) SSE gradient and (b) ASC



(a) (b)

Figure 4.7: Clustering Evaluation for Homes with Tesla Model S: (a) SSE gradient and (b) ASC



(a) (b)

Figure 4.8: Clustering Evaluation for Homes with Nissan Leaf: (a) SSE gradient and (b) ASC

4.8 Representative Profile Extraction and the Representative Profile List

In this process the representative profiles are extracted from the clusters identified in section 4.7. This is performed using K-nearest neighbor (K-NN) to find the closest data observation (K = 1) to each cluster centroid, as recommended in [41]. These observations are the representative profiles of a group of *N* annual home profiles (PV, HBESS or PEV). The expression for the K-NN representative profile extraction is shown in (4.9).

$$K - NN = min\big(d(c_i, x)\big)\,, where\ x\ \in\ c_i \tag{4.9}$$

Where, d is the Euclidean distance, x is the data observation within a cluster and c_i is the i^{th} cluster centroid. The annual capacity level of each representative profile is determined by referring to the original quantified 12-month features of generation/consumption. Additionally, the characteristic of each representative profile is described according to their annual capacity level from "Low" to "High". For example, three representative profiles are characterized as "Low", "Medium" and "High" capacity levels, respectively. Furthermore, four representative profiles are characterized as "Low", "Low-Medium", "High-Medium" and "High" capacity levels, respectively. In total, seventeen representative profiles were identified from 123 annual home profiles of PV, HBESS and PEV, as shown in Tables 4.1 – 4.3.

In Table 4.1, four PV representative profiles are shown, where the capacity levels are quantified as the average of monthly peak generation for the year (kW/month). In Table 4.2, three HBESS representative profiles are shown, where the capacity levels are quantified as the aggregated energy profile for the year (kWh/year). Lastly, in Table 4.3, three Chevrolet Volt representative profiles, four Tesla Model S representative profiles and three Nissan Leaf representative profiles are shown. For PEV, the capacity levels are quantified as the aggregated charging profile for the year (kWh/year).

Table 4.1: PV Home Representative Profile List

Home ID	Year	Profile Characteristics	Capacity Level (kW/month)
5035	2016	Low Generation	2.44
7017	2017	Low-Medium Generation	4.22
3009	2016	High-Medium Generation	5.48
5784	2017	High Generation	8.32

Table 4.2: HBESS Home Representative Profile List

Home ID	Year	Profile Characteristics	Capacity Level (kWh/year)
1185	2019	Low Capacity	1109
6836	2019	Medium Capacity	2221
2925	2019	High Capacity	3362

Table 4.3: PEV Home Representative Profile List

Home ID	Year	PEV Make	Profile Characteristics	Capacity Level (kWh/year)
1169	2019	Chevrolet Volt	Low Charging	1349
4998	2018	Chevrolet Volt	Medium Charging	3006
5109	2019	Chevrolet Volt	High Charging	4616
8857	2018	Tesla Model S	Low Charging	1838
8142	2018	Tesla Model S	Low-Medium Charging	3112
5749	2019	Tesla Model S	High-Medium Charging	4124
6691	2018	Tesla Model S	High Charging	5820
1202	2019	Nissan Leaf	Low Charging	1262
5357	2019	Nissan Leaf	Medium Charging	2430
7940	2019	Nissan Leaf	High Charging	2480

4.9 Estimated Cost of the Representative Profiles

The estimated costs (in US Dollars) of these representative profiles is required to relate the energy bill savings to the cost of purchasing L-DERs and/or PEVs. In Texas, where the Pecan Street homes are located, the estimated cost for a rooftop PV system is approximately $2.76/W [66]. According to the Pecan Street metadata [6], the homes with HBESS use the Tesla Powerwall 2, which has a power rating of 5 kW and a storage capacity of 13.5 kWh [54]. The estimated cost of a Tesla Powerwall 2 unit is $6,500 [67]. Finally, the manufacturer suggested retail price of a Chevrolet Volt, Tesla Model S and Nissan Leaf are $34,395 [68], $74.990 [69] and $31,600 [70], respectively. This is illustrated in Table 4.4.

Table 4.4: Estimated Cost of L-DERs and PEVs for Homes in Austin, Texas

L-DER or PEV	Estimated Cost ($)
Rooftop PV – 2.44 kW	$6,734
Rooftop PV – 4.22 kW	$11,647
Rooftop PV – 5.48 kW	$15,125
Rooftop PV – 8.32 kW	$22,963
Tesla Powerwall 2	Each $6,500
Chevrolet Volt	Each $34,395
Tesla Model S	Each $74,990
Nissan Leaf	Each $31,600

4.10 Summary

In this chapter, a systematic approach for L-DER and PEV representative profiling was presented that made use of five key processes. The unsupervised machine learning techniques that included the principal component analysis, K-means clustering and K-nearest neighbor were utilized to extract the monthly generation/consumption features from 1-minute data and identify the representative clusters for homes with PV, HBESS and PEV annual profiles. The outcome of this approach was a comprehensive list of 17 representative profiles of L-DERs and PEVs from 123 Pecan Street annual home profile observations. Additionally, the estimated cost of the representative profiles was determined to relate it to the energy bill savings in Chapter 6. In the following chapter the proposed methodology for retail electric provider (REP) plan selection will be presented, where the most suitable REP plan is selected for residential customers and those who intend to add these representative L-DER and/or PEV profiles.

Chapter 5: Retail Electric Provider Plan Selection

5.1 Introduction

This chapter presents a method to assist residential customers in selecting the retail electric provider (REP) plan. The method relies on the metered net energy usage and/or generation profiles of existing residential customers, representative profiles of local distributed energy resources (L-DERs) and/or plug-in electric vehicles (PEVs) as well as the pricing details of REP plans. The purpose of this method is to the extract energy (E), the variable cost (V) and the fixed cost (F) features from both the residential customers and the REP offering multiple service plans. These features will be used to develop the monthly energy bills for each REP plan, which is personalized to each customer's net energy usage and/or generation profile. Additionally, the residential customers who intend to add L-DERs and/or PEVs can anticipate their monthly energy bills for each REP plan. Based on these monthly energy bills, an ideal REP plan is selected that contributes to a minimum annual cost for the customer who are consumers and those with the intention to become prosumers. Furthermore, the energy bill savings can be computed for different combinations of L-DERs and/or PEVs that a customer may intend to add. This REP plan selection method forms the backbone of the personalized tool that will be designed in Chapter 7.

5.2 Overview of Proposed Methodology

The proposed method for REP plan selection consists of three fundamental processes for the residential customers that include: 1) data preprocessing, 2) monthly energy bill development and 3) REP selection, as illustrated in Figure 5.1.

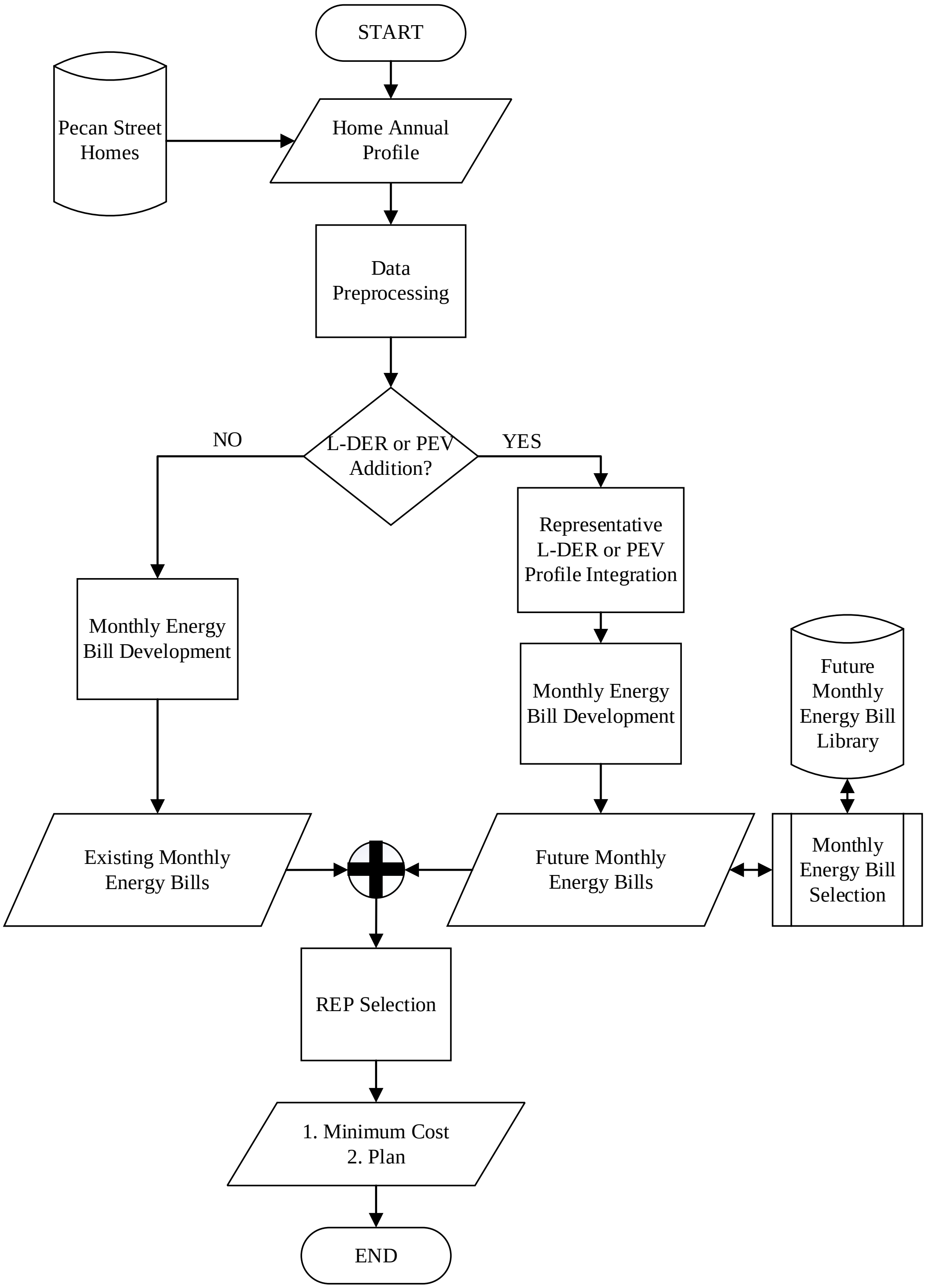


Figure 5.1: Flowchart of Proposed Methodology for REP Plan Selection

When a residential customer intends to add L-DERs and/or PEVs two more processes are included to: 1) superimpose the representative L-DER or PEV profiles (in Tables 4.1-4.3) and 2) store the annual energy bills for different combinations of L-DERs and/or PEVs. Each of these processes will be described in the following subsections.

5.3 Data Preprocessing

In this process, the annual net energy usage and/or generation profiles of 48 Pecan Street homes, sampled at 1-minute intervals, are preprocessed to address the issues of: 1) missing data entries and time stamps and 2) duplicate times stamps as discussed in section 4.3. In each home profile, the annual net energy usage in kWh from the main electric meter and the PV generation in kWh from rooftop solar panels (if they are present) are measured. In total, five subtypes of homes were used depending on the existing resources in the home, as illustrated in Table 5.1.

Table 5.1: Number of Pecan Street Home Subtypes

Home Subtypes	No. of Homes
No Resources	14
PV	19
PV and PEV	9
PV and HBESS	3
PV, HBESS and PEV	3

A detailed list of these Pecan Street homes can be found in Appendix B.1. Algorithm 5.1 describes the steps taken in preprocessing the 1-minute annual net energy usage and/or the generation profile of a home. The outcome of this algorithm is a preprocessed 15-minute annual net energy usage and/or generation profile for each home.

Algorithm 5.1: Data Preprocessing Algorithm

1 Input: Home Net Energy Usage and/or Generation Profile in 1-minute intervals
2 Replace missing data entries with a value of zero
3 Eliminate missing time stamps
4 Sort data in ascending time stamps
5 Replace data entries of duplicate time stamps by their mean value
6 Resample data to 15-minute intervals
7 Output: Preprocessed Home Net Energy Usage and/or Generation Profile

5.4 Representative L-DER or PEV Profile Integration

In this process, the existing residential customers who intend to add L-DERs and/or PEVs can superimpose the representative profiles to their existing annual home profile. The existing annual profile is the reference and the L-DER or PEV representative profile is added to each 15-minute time stamp. Firstly, since the L-DER and PEV representative profiles are from various years (2016 – 2019) the days of the week (Monday – Sunday) must be aligned to the existing annual home profile. This is performed by shifting the time series of the L-DER or PEV representative profile ahead or behind within a 7-day window. After shifting the representative profile, zero padding is needed to ensure that the length of the profile remains as 365 days × 96 minutes/day. Next, PV, HBESS or PEV profiles can be superimposed, one at a time, to the existing annual home profile where the net energy usage is updated during each addition. This is performed using the expression in (5.1), where the 15-minute net energy usage (kWh) is equivalent to the difference between the 15-minute energy demand (kWh) and generation (kWh).

$$Net\ Energy\ Usage = Demand - Generation \tag{5.1}$$

Based on the expression (5.1), the addition of a PV representative profile will change the 15-minute generation thus updating the 15-minute net energy usage. The addition of a HBESS representative profile will change the 15-minute energy demand or generation depending on if the battery is in charging or discharging mode, which updates the 15-minute net energy usage. Lastly, the addition of a PEV representative profile will change the 15-minute energy demand, which then updates the 15-minute net energy usage. In this thesis, the customers can only add PV, HBESS and PEV combinations that are not present in a home. For example, the customers with no resources can add PV, HBESS or PEV, but the customers with PV can only add HBESS or PEV. Algorithm 5.2 describes the steps for superimposing PV, HBESS and/or PEV representative profiles. The outcome of this is an updated 15-minute annual net energy usage and/or generation profile.

Algorithm 5.2: Superimposing L-DERs and/or PEVs Profiles Algorithm

```
Inputs:  1) Existing Annual Home Profile in 15-minute intervals
         2) PV, HBESS and/or PEV Representative Profiles in 15-minute intervals
Align the weeks of representative profiles to the existing annual home profile
Insert zero padding to the representative profiles to match lengths
Use expression (5.1) to superimpose each representative profile
Output: Updated Annual Home Profile in 15-minute intervals
```

5.5 Monthly Energy Billing Development

In this process, the monthly energy bills are developed using the preprocessed annual home profiles with 15-minute net energy usage and/or generation data, as well as the REP plans listed in Table 3.2. A monthly energy bill consists of a summary of the monthly energy usage and/or generation with the associated monthly cost. A feature-based approach is used, where the monthly energy features (E) are extracted from the annual home profiles and the monthly fixed (F) and variable (V) cost features are extracted from the REP plans. Based on the energy billing criteria of the 24 REP plans, six monthly energy features were identified that are represented in vector form in expression (5.2).

$$E = \{ N_U ; TOU_{WD}; TOU_{WE}; TOU_N; TOU_D; S_G \} \tag{5.2}$$

Where, N_U is the monthly net energy usage (kWh); TOU_{WD} is the monthly energy usage during weekdays (kWh); TOU_{WE} is the monthly energy usage during weekends (kWh); TOU_N is the monthly energy usage during night-time in kWh (9pm – 5:59am); TOU_D is the monthly energy usage during day-time in kWh (6am – 8:59pm); S_G is the monthly generation from PV (kWh). The monthly net energy usage (N_U) is typically associated with the time-invariant plans in Table 3.2. The time of use (TOU) monthly energy features – TOU_{WD}, TOU_{WE}, TOU_N and TOU_D – are typically associated with the time-variant plans (Free N and Free W) in Table 3.2. Lastly, the plans that offer compensation for PV generation (Standard AE and Green C) require the customer's monthly generation (S_G).

The second part of a monthly energy bill is the monthly cost. This is acquired by identifying the fixed (F) and the variable (V) cost features from the 24 REP plans in Table 3.2. These cost features are detailed in the electricity fact label (EFL) of each REP plan website, where the retail electricity rate, delivery costs, auxiliary costs, solar credit rates, promotional credit and contract lengths are specified [12]. The four fixed (F) and the three variable (V) cost features for all REP plans are expressed in (5.3).

$$F = \{ F_C; B_C; C_R; TDU_2 \} \ ; \quad V = \{ r; VOS; TDU_1 \} \tag{5.3}$$

Where, F_C is the monthly flat charge ($); B_C is the monthly base charge; C_R is the promotional credit offered by a plan ($); TDU_2 is the fixed transmission and distribution charge; r is the retail electricity rate ($/kWh); *VOS* is the value of solar credit rate ($/kWh) and TDU_1 is the transmission and distribution rate ($/kWh). The retail electricity rate (r) is applied to the monthly net energy usage, where as the value of solar credit rate (*VOS*) is applied to the monthly generation from PV. The list of these fixed and variable cost features is detailed in Appendix A.1 for all 24 REP plans.

Based on the units of each feature (E, F and V) the product of the monthly energy features (E) and the monthly variable cost features (V) creates part of the monthly energy bill. The other part of the monthly energy bill is created by the addition of the monthly fixed cost features (F). From this, three expressions of the monthly energy bills were developed according to the type of REP plan. The first monthly energy bill (B_1), expressed in (5.4), is for the time-invariant plans with no *VOS*. The main monthly energy feature (E) used is the monthly net energy usage (N_U).

$$B_1 = [(N_U \times r) + (N_U \times TDU_1) + F_C + B_C + TDU_2 - C_R] \tag{5.4}$$

The second monthly energy bill (B_2), expressed in (5.5), is for the time-invariant plans with *VOS*. Both the monthly net energy usage (N_U) and the monthly PV generation (S_G) are used as the monthly energy features (E). The retail electricity rate (r) is applied to the monthly energy demand ($N_U + S_G$) and the value of solar credit rate (*VOS*) is applied to the monthly PV generation (S_G).

$$B_2 = [(N_U + S_G) \times r + (N_U + S_G) \times TDU_1 - (S_G) \times VOS + F_C + B_C + TDU_2 - C_R] \tag{5.5}$$

The third monthly energy bill (B_3), expressed in (5.6), is for the time-variant plans with no *VOS*. Here, the monthly net energy usage (N_U) is replaced by the TOU monthly energy features (TOU_{WD}, TOU_{WE}, TOU_N or TOU_D). In this study, the time-variant plans with *VOS* were not considered but since the net metering is used in each home, the impact of PV generation still plays a role in reducing the monthly net energy usage.

$$B_3 = \ [(TOU \times r) + \ (TOU \times TDU_1) + F_C \ + B_C \ + \ TDU_2 - C_R] \tag{5.6}$$

Due to the seasonality of the monthly energy features (E), it is expected that the monthly energy bills (B_1, B_2 and B_3) will change. Therefore, the three types of monthly energy bills are calculated for 12 months and expressed in the form of a vector $\vec{B}$ in (5.7).

$$\begin{aligned} \overrightarrow{B_{1,m}} &= \ [B_{1,1}, B_{1,2}, B_{1,3}, B_{1,4}, B_{1,5}, B_{1,6}, B_{1,7} \ldots \ B_{1,12}] \\ \overrightarrow{B_{2,m}} &= \ [B_{2,1}, B_{2,2}, B_{2,3}, B_{2,4}, B_{2,5}, B_{2,6}, B_{2,7} \ldots \ B_{2,12}] \\ \overrightarrow{B_{3,m}} &= \ [B_{3,1}, B_{3,2}, B_{3,3}, B_{3,4}, B_{3,5}, B_{3,6}, B_{3,7} \ldots \ B_{3,12}] \end{aligned} \tag{5.7}$$

Where, the first index refers to the three types of the monthly energy bills in (5.4) – (5.6) and the second index (m) refers to the month of the year (January – December). Furthermore, the annual energy bill (A) was determined by summing the elements of the monthly energy bill vectors in (5.7). This is expressed in (5.8), where the first index (t) is the one of the three types of monthly energy bills in (5.4) – (5.6).

$$A_t = \ \sum_{m=1}^{12} B_{t,m} \ ; \ where \ \ t = 1,2,3 \tag{5.8}$$

Finally, an annual energy bill is assigned to each of the 24 REP plans, as expressed in the vector $\vec{A}$ in (5.9). This energy billing process, from (5.4) – (5.9), takes place for each residential customer or those customers who have superimposed L-DERs and/or PEVs profiles (in section 5.4)

$$\overrightarrow{A} = [A_1, A_2, A_3, A_4, \dots A_{24}] \tag{5.9}$$

Specifically, the customers who superimpose different combinations of L-DERs and/or PEVs can store their annual energy bills ($\overrightarrow{A}$) for each combination in a data library, as shown in Figure 5.1. This way the computational time in developing 24 annual energy bills for each L-DER and/or PEV combination is reduced, because the customer can easily access them from the library.

5.6 Ideal Retail Electric Provider Plan Selection

In this process a suitable REP plan is selected for a customer based on the annual energy bills of the 24 REP plans. Ideally, the REP plan with a minimum annual energy bill is considered as the most suitable REP plan for the customer. This is expressed as a minimum function in (5.10).

$$REP\ Plan\ Selection = min\ (\overrightarrow{A}) \tag{5.10}$$

5.7 Summary

In this chapter, the proposed methodology for the REP plan selection was described for the residential customers and the customers who intend to add L-DER and/or PEV representative profiles. The process of superimposing L-DER and PEV profiles was explained in order to create various combinations of PV, HBESS and PEV. Additionally, the development of the monthly energy bills was described, using a feature-based approach, with monthly energy features (*E*) from the customers and the fixed (*F*) and the variable (*V*) cost features from the REP plans. Furthermore, the final selection of a suitable REP plan was presented. In the following chapter, the results for the energy bill savings and the REP plan selection of different PV, HBESS and PEV combinations will be presented and analyzed to guide the "new" prosumers in choosing L-DERs and/or PEVs that will maximize their energy bill savings.

Chapter 6: Analysis and Results of the Energy Bill Savings and the Retail Electric Provider Plan Selection

6.1 Introduction

This chapter presents the analysis and the results for the energy bill savings and the retail electric provider (REP) plan selection for the residential customers that intend to add local distributed energy resources (L-DERs) and/or plug-in electric vehicles (PEVs) to their existing annual profiles. It presents different combinations of L-DERs and PEVs and evaluates the patterns in the energy bill savings and the REP plan selection for the customers in three net energy usage groupings (<600 kWh/month, 600 - 1,000 kWh/month and ≥1,000 kWh/month). This chapter starts by describing the total number of combinations and the three case studies. Thereafter, each of the case study is analyzed to determine the most suitable combinations of L-DERs and/or PEVs that will maximize the annual energy savings for a residential customer. Finally, the saving contribution of the suitable REP plan selection over a 10-year period is compared among the three case studies.

6.2 Combinations of L-DER and/or PEV and Case Studies

In this section, the total number of combinations of rooftop solar photovoltaics (PVs), home battery energy storage systems (HBESSs) and plug-in electric vehicles (PEVs) is determined based on the 17 representative profiles identified in Chapter 4 (Tables 4.1 – 4.3). Additionally, three case studies for annual energy bill savings and REP plan selection are developed for groups of residential customers based on their monthly net energy usage.

6.2.1. Combinations of PV, HBESS and/or PEV

The 17 L-DER and PEV representative profiles consist of four PV representative profiles; three HBESS representative profiles; four Tesla Model S representative profiles;

three Chevrolet Volt representative profiles and three Nissan Leaf representative profiles. A residential customer with no existing resources can choose to combine PV, HBESS and/or PEV at different capacity levels. Since there are three PEV makes (Tesla Model S, Nissan Leaf and Chevrolet Volt), the range of their charging capacities (kWh/year) in the representative profiles were evaluated to identify the overlaps, as illustrated in Figure 6.1.

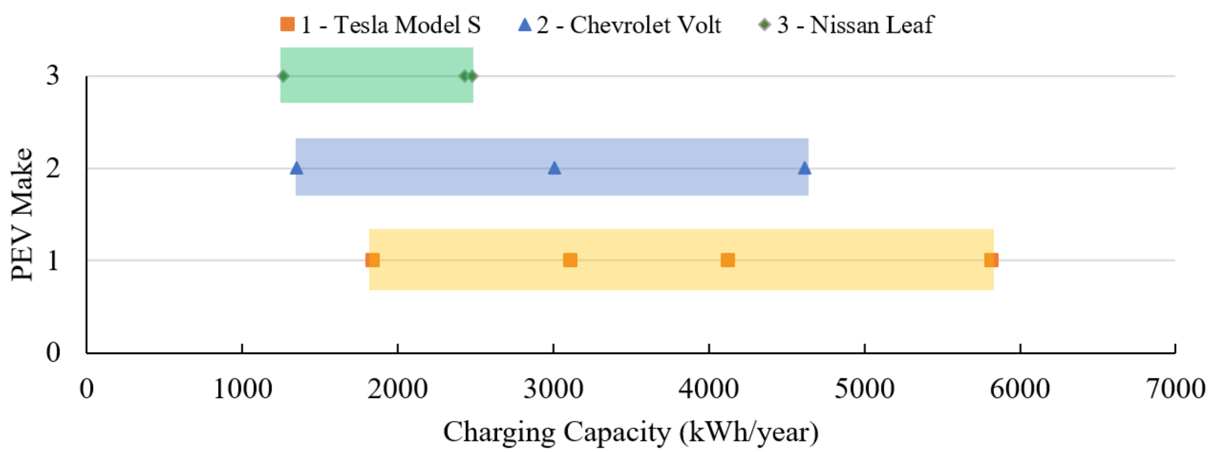


Figure 6.1: Overlap of Charging Capacities for: 1) Tesla Model S, 2) Chevrolet Volt and 3) Nissan Leaf

According to Figure 6.1, it was observed that the Chevrolet Volt representative profiles cover 93% of the charging capacity range of Nissan Leaf and 70% of the charging capacity range for Tesla Model S. On the other hand, the Tesla Model S representative profiles cover 85% of the charging capacity range of Chevrolet Volt, however only 53% of the lower charging capacities (Nissan Leaf) are considered. Lastly, the Nissan Leaf representative profiles only cover 35% and 16% of the charging capacity ranges of Chevrolet Volt and Tesla Model S, respectively. This implies that the three representative profiles from the Chevrolet Volt are sufficient for analyzing the combinations with PEV. More so, the majority of the PEV observations in the Pecan Street home data were from Chevrolet Volt, which justify the decision [6]. Therefore, the total number of combinations of PV, HBESS and/or PEV for a residential customer is 79 combinations, as shown in Table 6.1.

Table 6.1: Combinations of PV, HBESS and/or PEV

PV, HBESS and/or PEV	Combinations
PV	4
HBESS	3
PEV	3
PEV and HBESS	3 × 3
PV and HBESS	4 × 3
PV and PEV	4 × 3
PV, HBESS and PEV	4 × 3 × 3
Total	**79**

6.2.2. Case Studies for Residential Customers

The 79 combinations of PV, HBESS and/or PEV are applied to the residential customers who are divided into three groups based on their original monthly net energy usage. These groupings create three case studies for: 1) homes with a net energy usage less than 600 kWh/month, 2) homes with a net energy usage between 600 – 1,000 kWh/month and 3) homes with a net energy usage more than 1,000kWh/month. The analysis is performed this way to understand the impact of different PV, HBESS and/or PEV combinations on the annual energy bill savings and the REP plan selection of customers with low usage (< 600 kWh/month), medium usage (600 – 1,000 kWh/month) and high usage (≥1,000 kWh/month). The 48 Pecan Street homes in Appendix B.1 are tested, where the average of annual energy bill savings and the most common REP plan selection in each net usage group are presented in sections 6.3 – 6.5.

6.3 Case Study 1: Homes with Net Energy Usage Less than 600 kWh/Month

This case study presents the results of the annual energy bill savings (in U.S Dollars per year) and the REP plan selection for homes with a net energy usage less than 600 kWh/month. This is illustrated in Figure 6.2 (a) – (b).

(a)

		PV: No	PV: L	PV: LM	PV: HM	PV: H
	No		151	167	184	207
PEV	L	-81	15	68	93	132
PEV	M	-165	-85	-59	-37	-1
PEV	H	-214	-142	-124	-118	-112
HBESS	L	-60	63	86	108	140
HBESS	M	-101	-27	4	27	66
HBESS	H	-131	-78	-66	-56	-35
PEV & HBESS	L & L	-133	-50	-10	19	71
PEV & HBESS	L & M	-168	-94	-70	-54	-4
PEV & HBESS	L & H	-178	-119	-112	-104	-81
PEV & HBESS	M & L	-200	-132	-99	-81	-45
PEV & HBESS	M & M	-234	-156	-131	-120	-90
PEV & HBESS	M & H	-297	-172	-138	-128	-122
PEV & HBESS	H & L	-272	-167	-144	-139	-130
PEV & HBESS	H & M	-337	-195	-160	-149	-135
PEV & HBESS	H & H	-461	-268	-205	-174	-153

(b)

		PV: No	PV: L	PV: LM	PV: HM	PV: H
	No		1	2	2	2
PEV	L	3	1	5	5	5
PEV	M	3	3	3	5	5
PEV	H	3	3	3	3	3
HBESS	L	3	1	2	2	2
HBESS	M	3	1	2	2	2
HBESS	H	3	3	3	3	2
PEV & HBESS	L & L	3	3	5	5	5
PEV & HBESS	L & M	3	3	3	5	5
PEV & HBESS	L & H	3	3	3	3	3
PEV & HBESS	M & L	3	3	3	3	5
PEV & HBESS	M & M	3	3	3	3	3
PEV & HBESS	M & H	3	3	3	3	3
PEV & HBESS	H & L	3	3	3	3	3
PEV & HBESS	H & M	3	3	3	3	3
PEV & HBESS	H & H	3	3	3	3	3

Energy Bill Savings ($/yr): 800, 0, -800

REP Plans

1	Standard AE
2	Friends F24
3	Smart 48
4	Budget S
5	Free N
6	Classic 12

Figure 6.2: Case Study 1 - Homes with a net energy usage less than 600 kWh/month (a) Annual energy bill savings and (b) REP plan selection

6.3.1. Case Study 1: Energy Bill Savings Discussion

The results in Figure 6.2 (a) show that the customers in this group receive positive energy bill savings when PV at any capacity level is added. Conversely, when these customers add PEV or HBESS at any capacity level they are faced with negative energy bill savings. Essentially, PV must be present at a high capacity to make positive savings realizable for customers with PEV or HBESS. More so, the combination of PEV and HBESS is not advised for these customers, without PV, because no positive savings are possible. The role of PV is vital because during the day time, the irradiance from the sun is available for rooftop solar panels to generate electrical energy. Since a net metering scheme is used for the Pecan Street homes, their monthly net energy usage is reduced, which ultimately reduces the customer's energy bill. The maximum energy bill savings are achieved when PV is used at a high capacity, contributing up to $207/year in savings.

6.3.2. Case Study 1: Retail Electric Provider Selection Discussion

The results in Figure 6.2 (b) show that the selected REP plans that maximize the energy bill savings for this customer group are Friends F24 for PV only; Friends F24 for the combination of HBESS and PV and Free N for the combination of PEV and PV. Firstly, the Friends F24 plan is identified as a time-invariant plan specifically for low energy usage customers at a retail electricity rate of $0.06/kWh [59]. The presence of PV at a high capacity level also further reduces the net energy usage of these customers, who inherently have a low energy usage, which justifies the selection of this REP plan. Secondly, the Free N plan is identified as a time-variant plan with a retail electricity rate of $0.203/kWh during the day time and $0/kWh during the night time [58]. This REP plan was selected for the customers with PEV and PV because during the day time the net energy usage is reduced from the solar generation, which prevents the customer's energy bill from being heavily impacted by the day time rate. On the other hand, during the night time the customers arrive from work to charge their PEVs when the retail electricity rate is at its lowest rate. The combined effect of this REP plan is a low energy bill for the customers with PEV and PV. Furthermore, from Figure 6.2 (a), it was found that Smart 48 plan was selected for the customers who intend to add PEV and HBESS. The Smart 48 plan is a tiered time-invariant plan with a fixed charge of $58/month, specifically designed for the customers with a net energy usage less than 1,000 kWh/month [60].

6.4 Case Study 2: Homes with Net Energy Usage in Range 600 - 1000 kWh/Month

This case study presents the results of the annual energy bill savings (in U.S Dollars per year) and the REP plan selection for the homes with a net energy usage between 600 – 1,000 kWh/month. This is illustrated in Figure 6.3 (a) – (b).

		PV				
		No	**L**	**LM**	**HM**	**H**
	No		104	129	145	221
PEV	L	-97	81	98	102	150
	M	-252	2	76	88	95
	H	-422	-88	36	50	88
HBESS	L	-55	84	108	115	155
	M	-109	71	98	98	110
	H	-158	60	93	98	98
PEV & HBESS	L & L	-164	31	89	93	103
	L & M	-237	-13	74	82	98
	L & H	-322	-35	64	81	94
	M & L	-323	-72	22	40	82
	M & M	-427	-153	-28	-4	60
	M & H	-571	-225	-70	-26	37
	H & L	-517	-189	-52	-27	45
	H & M	-634	-303	-142	-111	1
	H & H	-760	-454	-253	-198	-75

(a)

		PV				
		No	**L**	**LM**	**HM**	**H**
	No		3	3	2	5
PEV	L	3	3	3	3	5
	M	3	3	3	3	3
	H	3	3	3	3	3
HBESS	L	3	3	3	3	5
	M	3	3	3	3	3
	H	3	3	3	3	3
PEV & HBESS	L & L	3	3	3	3	3
	L & M	3	3	3	3	3
	L & H	3	3	3	3	3
	M & L	3	3	3	3	3
	M & M	3	3	3	3	3
	M & H	3	3	3	3	3
	H & L	3	3	3	3	3
	H & M	4	3	3	3	3
	H & H	4	3	3	3	3

(b)

Energy Bill Savings ($/yr): 800, 0, -800

REP Plans

1	Standard AE
2	Friends F24
3	Smart 48
4	Budget S
5	Free N
6	Classic 12

Figure 6.3: Case Study 2 - Homes with a net energy usage between 600 – 1,000 kWh/month (a) Annual energy bill savings and (b) REP plan selection

6.4.1. Case Study 2: Energy Bill Savings Discussion

The results in Figure 6.3 (a) show that the customers in this group receive more energy bill savings than the low energy usage customers when they only add PV. The value of these savings can be up to $221/year. Additionally, it was observed that PEV or HBESS can be added at any capacity when PV is present, resulting in savings up to $150/year and

$155/year for PEV and HBESS, respectively. Furthermore, the combination of PEV and HBESS should be limited to a low capacity level while PV is at a medium to high capacity to ensure reasonable energy bill savings of up to $103/year.

6.4.2. Case Study 2: Retail Electric Provider Selection Discussion

The results in Figure 6.3 (b) show that the selected REP plans that maximize the energy bill savings for this customer group are Free N for PV coupled with PEV or HBESS and Smart 48 for PV coupled with PEV and HBESS. It was also observed that most combinations (92.4%) selected the Smart 48 plan, which was designed for the customers with a net energy usage less than 1,000 kWh/month that is the current case. The selection of the Free N plan was due to the presence of PV at a high capacity, which reduces the net energy usage during the day time and shifts the majority of the net energy usage to the night time. Furthermore, the customers with a high capacity of PEV and HBESS without PV were found to select the Budget S plan. The Budget S plan is identified as a tiered time-invariant plan that has a fixed charge of $71/month, specifically designed for the customers with a net energy usage more than 1,000 kWh/month [57]. Inherently, the customers in this group have a net energy usage in the range between 600 – 1,000 kWh/month but when a PEV and HBESS with a high charging capacity are added the customer transitions into a net energy usage of more than 1,000 kWh/month. Hence, this explains the selection of the Budget S plan with the absence of PV for such a group of customers.

6.5 Case Study 3: Homes with Net Energy Usage More than 1000 kWh/Month

This case study presents the results of the annual energy bill savings (in U.S Dollars per year) and the REP plan selection for homes with a net energy usage more than 1,000 kWh/month. This is illustrated in Figure 6.4 (a) – (b).

		No	PV L	PV LM	PV HM	PV H
	No		248	387	415	475
PEV	L	-133	131	282	317	400
PEV	M	-271	-72	109	162	265
PEV	H	-447	-201	-37	15	128
HBESS	L	-49	180	317	346	426
HBESS	M	-107	109	248	283	370
HBESS	H	-218	-3	183	235	333
PEV & HBESS	L & L	-170	73	199	241	337
PEV & HBESS	L & M	-233	-39	118	165	276
PEV & HBESS	L & H	-325	-165	26	86	211
PEV & HBESS	M & L	-381	-135	26	85	194
PEV & HBESS	M & M	-404	-190	-68	-2	123
PEV & HBESS	M & H	-401	-236	-181	-109	35
PEV & HBESS	H & L	-512	-311	-141	-85	40
PEV & HBESS	H & M	-526	-362	-251	-202	-54
PEV & HBESS	H & H	-497	-366	-329	-304	-178

(a)

		No	PV L	PV LM	PV HM	PV H
	No		3	3	3	3
PEV	L	4	3	3	3	3
PEV	M	4	3	3	3	3
PEV	H	4	4	3	3	3
HBESS	L	3	3	3	3	3
HBESS	M	4	3	3	3	3
HBESS	H	4	3	3	3	3
PEV & HBESS	L & L	4	3	3	3	3
PEV & HBESS	L & M	4	3	3	3	3
PEV & HBESS	L & H	4	4	3	3	3
PEV & HBESS	M & L	4	3	3	3	3
PEV & HBESS	M & M	4	4	3	3	5
PEV & HBESS	M & H	4	4	4	3	5
PEV & HBESS	H & L	4	6	3	3	3
PEV & HBESS	H & M	4	4	3	3	3
PEV & HBESS	H & H	4	4	4	4	3

(b)

Energy Bill Savings ($/yr): 800, 0, -800

REP Plans
1 Standard AE
2 Friends F24
3 Smart 48
4 Budget S
5 Free N
6 Classic 12

Figure 6.4: Case Study 3 - Homes with a net energy usage more than 1,000 kWh/month (a) Annual energy bill savings and (b) REP plan selection

6.5.1. Case Study 3: Energy Bill Savings Discussion

The results in Figure 6.4 (a) show that the customers in this group receive approximately double the energy bill savings, compared to the customers in case study 1 and 2, when only PV is added. The value of these savings can be up to $475/year. Additionally, it was observed that PEV or HBESS can be added at any capacity when PV is present, resulting in savings up to $400/year and $426 for PEV and HBESS, respectively. Furthermore, the combination of PEV and HBESS should be limited to a medium capacity level with PV at a medium to high capacity to ensure reasonable energy bill savings of up to $337/year.

6.5.2. Case Study 3: Retail Electric Provider Selection Discussion

The results in Figure 6.4 (b) show that the selected REP plan that maximizes the energy bill savings in this customer group is Smart 48. This was due to the presence of PV at high capacity levels that reduces the net energy usage of customers from the ≥ 1,000 kWh/month group to the 600 – 1,000 kWh/month group, where the Smart 48 plan is the most feasible. Furthermore, the customers with PEV and/or HBESS, without PV, selected Budget S as the most suitable plan. This is because the Budget S plan is design for high energy usage customers with more than 1,000 kWh/month. In Figure 6.4 (a), a few instances occurred were the Free N was selected for PEV and HBESS with a high capacity of PV. This was attributed to the shifting of the household load to the night time where the retail electricity rate is at its lowest ($0/kWh).

6.6 Saving Contribution of Suitable REP Plan Selection for Different Customer Groups

It was revealed in sections 6.3 – 6.5 that suitable REP plan selection and the presence of PV play a vital role in receiving significant annual energy savings for customers in the three net energy usage groups. These energy bill savings are compared to the estimated costs of investing in rooftop PV systems in Chapter 4 (Table 4.4) to evaluate the saving contribution of suitable REP plan selection. This thesis only focuses on the saving contribution of suitable REP plan selection for 10 years, without the inclusion of federal tax incentives and the excess generation credit from PV. The expression in (6.1) is used to calculate the contribution percentage.

$$\boldsymbol{Saving\ Contribution}\ (\%) = (1 - \left(\frac{I - (S \times 10)}{I}\right)) \times 100 \tag{6.1}$$

Where, I is the initial investment ($) of the rooftop PV system and S is the annual energy bill saving ($/year). The results for the saving contribution of suitable REP plan selection with respects to the initial investment of different PV capacities is shown in Table 6.2.

Table 6.2: Saving Contribution After 10 years of Suitable REP Plan Selection for 3 Case Studies.

PV Capacity Level	Saving Contribution (%)		
	Case Study 1	Case Study 2	Case Study 3
Low Generation – 2.44 kW	22%	15%	37%
Low-Medium Generation – 4.22 kW	14%	11%	33%
High-Medium – 5.48 kW	12%	10%	27%
High Generation – 8.32 kW	9%	10%	21%

In Table 6.2, it was observed that after 10 years of suitable REP selection between 9 – 22% of the initial rooftop PV system investment will be covered for customers in case study 1 and 2. On the other hand, after 10 years of suitable REP selection 21 – 37% of the initial rooftop PV system investment is covered for case study 3. This coincides with the results of the high energy usage customers receiving almost double the savings in comparison to the low and medium customer groups. Furthermore, since low capacity PVs have a low initial investment ($6,734), the saving contribution appears to be high. This is in comparison to the high capacity PVs that have a high initial investment ($22,963), which result in a lower saving contribution percentage. Despite this, the suitable REP plan selection still contributes significantly to the savings without the aid of federal tax incentives and excess generation credit from the electric utility.

6.7 Summary

In this chapter, the analysis and results of the energy bill savings and the REP plan selection were presented for three customer groups. A total of 48 Pecan Street homes were tested using 79 combinations of PV, HBESS and/or PEV. Also, the saving contribution of the suitable REP plans selection was evaluated for 10 years to determine how much of the initial rooftop PV system investment is covered from the proposed REP plan selection method. The results have shown that the presence of PV play a pivotal role in reducing the monthly net energy usage of the customers, which consequently leads to significant savings on the monthly energy bills. If HBESS and/or PEV is desired by a customer, a medium to high capacity of PV should be added to reduce the demand. Additionally, the savings that low (< 600 kWh/month) and medium (600 – 1,000 kWh/month) energy usage customer groups acquire with PV only is up to $221/year. More so, the high (≥ 1,000 kWh/month) energy usage customer group benefits significantly from PV, with almost double the energy bill savings ($475/year) compared to the low and medium energy usage groups. The ideal REP plan selection for the low and medium energy usage customer groups was revealed to be either time-invariant plans (Friends F24 and Smart 48) or time-variant plans (Free N). This was mainly due to the low rates and the fixed charges offered by these plans. Specifically, the combination of a high capacity PV and PEV commonly led to a shift in the demand to night time, where the retail electricity rate is zero. This justified the popularity of this time-invariant plan for such scenarios. On the other hand, the results revealed that ideal REP plan selection for high energy usage customers were time-invariant plans such as Smart 48 with PV, and Budget S without PV. The Budget S plan dominated for combinations without PV because of its fixed charge for high energy usage customers. Furthermore, the Smart 48 plan was the most ideal for the combinations with PV because the high energy usage customers transition into the medium energy usage group, due to a reduced monthly net energy usage from PV. Lastly, the results of the savings contribution from suitable REP plan selection revealed that even without the contribution from federal tax incentives and the credit from excess generation compensation, this approach of REP plan selection still covers between 9 – 37% of the initial PV investment after 10 years.

In the following chapter, the analysis and results from Chapter 6 will be used to design a knowledge base that will guide the residential customers to make a feasible decision on L-DER and/or PEV selection to maximize their energy bill savings. Furthermore, this will be incorporated into a personalized REP plan selection tool for the residential customers and those who intend to install L-DERs and/or PEVs.

Chapter 7: Design and Implementation of a Personalized Tool for Retail Electric Provider Plan Selection

7.1 Introduction

This chapter presents the design and implementation of the personalized tool for retail electric provider (REP) plan selection for the residential customers and those that intend to add local distributed energy resources (L-DERs) and/or plug-in electric vehicles (PEVs). The purpose of this personalized tool is to: 1) select a suitable REP plan for the residential customers, 2) provide decision support to the residential customers who intend to add combinations of L-DER and/or PEV, 3) select a suitable REP plan for the residential customers who intend to become prosumers and 4) calculate annual energy bill savings for the individual customers. This chapter starts with a design overview of the personalized REP plan selection tool. It then presents a knowledge base that consists of a set of rules for L-DER and/or PEV selection that maximizes the annual energy bill savings for customers in different net usage groups. Next, the calculation for personalized energy bill savings is presented. Finally, the implementation of the personalized tool on MATLAB App Designer, together with the graphic user interfaces, are presented.

7.2 Overview of Personalized REP Plan Selection Tool Design

This section provides an overview of the design of the personalized REP plan selection tool. In order to establish a personalized tool, the target of personalization, information being personalized, and the initiator of personalization need to be well defined [26]. This personalized tool has two targets, namely: 1) residential customers and 2) residential customers that intend to become prosumers. For residential customers, their ideal REP plan is personalized. On the other hand, the feasible L-DER and/or PEV combinations; the ideal

REP plan and the annual energy bill savings are personalized for residential customers who intend to become prosumers. Furthermore, these customers are the initiators of the personalization as they provide input monthly energy features (E) to the tool for the execution of personalization. This is summarized in Table 7.1 below.

Table 7.1: Target, Information and Initiator of Personalization for the REP Plan Selection Tool

Target Personalized	Information Personalized	Initiator of Personalization
Residential customer (Target 1)	Ideal REP plan	Customer
Residential customer intending to become a prosumer (Target 2)	1. Feasible L-DER and/or PEV combinations 2. Ideal REP plan 3. Annual energy bill savings	Customer

Based on Table 7.1, the tool processes can be developed to achieve the personalized outputs for each target. The REP plan selection approach was already defined in Chapter 5, but the L-DER and/or PEV decision support and personalized savings calculations will be explained in this chapter, as illustrated in Figure 7.1.

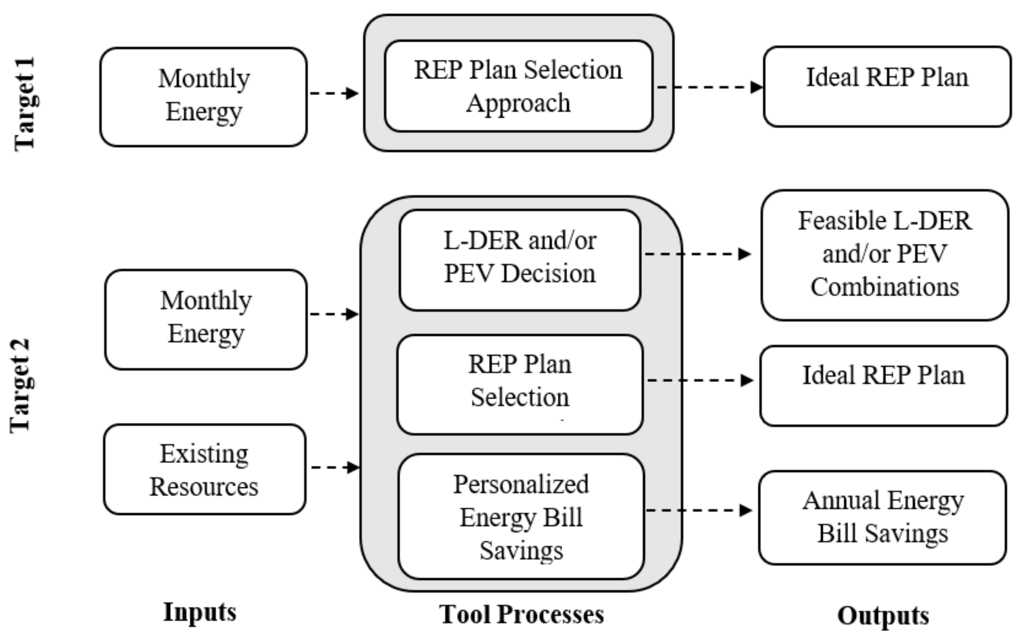


Figure 7.1: Inputs, Tool Processes and Outputs for the Personalization of each Target.

7.3 Knowledge Base for L-DER and/or PEV Decision Support

The residential customers who intend to add L-DERs and/or PEV (target 2) require decision support as to which combinations of L-DER and/or PEV are the most feasible for them. This was analyzed in Chapter 6 for the three groups of customers with a monthly net energy usage of: 1) less than 600 kWh/month, 2) between 600 – 1,000 kWh/month and 3) more than 1,000 kWh/month. From this analysis, a set of rules were developed based on the customer's existing monthly net usage and their existing resources in the home. There were five home subtypes, according to Chapter 5 (Table 5.1) and three net energy usage groups, which resulted in 15 rules being established. Furthermore, five combinations of L-DER and/or PEV were possible for each rule as illustrated in Table 7.2. The decisions are labelled as "PV, HBESS or PEV" _ "Capacity Level". Additionally, the non-recommended combinations have a decision of "Not Feasible".

Table 7.2: Rule Set of Feasible L-DER and/or PEV Combinations in Knowledge Base

	Rules	L-DER/PEV	Decision
r1	(Net Usage < 600) ∧ (Existing Resources = "No")	*No L-DER, 1 PEV*	Not Feasible
		1 L-DER, No PEV	PV_H
		1 L-DER, 1 PEV	PV_H ∧ PEV_L
		2 L-DERs, No PEV	PV_H ∧ HBESS_L
		2 L-DERs, 1 PEV	Not Feasible
r2	(600 ≤ Net Usage < 1000) ∧ (Existing Resources = "No")	*No L-DER, 1 PEV*	Not Feasible
		1 L-DER, No PEV	PV_H
		1 L-DER, 1 PEV	PV_H ∧ PEV_L
		2 L-DERs, No PEV	PV_H ∧ HBESS_L
		2 L-DERs, 1 PEV	PV_H ∧ HBESS_L ∧ PEV_L
r3	(Net Usage ≥ 1000) ∧ (Existing Resources = "No")	*No L-DER, 1 PEV*	Not Feasible
		1 L-DER, No PEV	PV_H
		1 L-DER, 1 PEV	PV_H ∧ PEV_L
		2 L-DERs, No PEV	PV_H ∧ HBESS_L
		2 L-DERs, 1 PEV	PV_H ∧ HBESS_L ∧ PEV_L
r4	(Net Usage < 600) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV")	*No L-DER, 1 PEV*	PEV_L
		1 L-DER, No PEV	HBESS_L
		1 L-DER, 1 PEV	Not Feasible
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible

Table 7.2: Rule Set of Feasible L-DER and/or PEV Combinations in Knowledge Base (Cont.)

	Rules	L-DER/PEV	Decision
r5	(600 ≤ Net Usage < 1000) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV")	*No L-DER, 1 PEV*	PEV_L
		1 L-DER, No PEV	HBESS_L
		1 L-DER, 1 PEV	HBESS_L ∧ PEV_L
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible
r6	(Net Usage ≥ 1000) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV")	*No L-DER, 1 PEV*	PEV_L
		1 L-DER, No PEV	HBESS_L
		1 L-DER, 1 PEV	HBESS_L ∧ PEV_L
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible
r7	(Net Usage < 600) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV ∧ HBESS")	*No L-DER, 1 PEV*	PEV_L
		1 L-DER, No PEV	Not Feasible
		1 L-DER, 1 PEV	Not Feasible
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible
r8	(600 ≤ Net Usage < 1000) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV ∧ HBESS")	*No L-DER, 1 PEV*	PEV_L
		1 L-DER, No PEV	Not Feasible
		1 L-DER, 1 PEV	Not Feasible
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible
r9	(Net Usage ≥ 1000) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV ∧ HBESS")	*No L-DER, 1 PEV*	PEV_L
		1 L-DER, No PEV	Not Feasible
		1 L-DER, 1 PEV	Not Feasible
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible
r10	(Net Usage < 600) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV ∧ PEV")	*No L-DER, 1 PEV*	Not Feasible
		1 L-DER, No PEV	HBESS_L
		1 L-DER, 1 PEV	Not Feasible
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible
r11	(600 ≤ Net Usage < 1000) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV ∧ PEV")	*No L-DER, 1 PEV*	Not Feasible
		1 L-DER, No PEV	HBESS_L
		1 L-DER, 1 PEV	Not Feasible
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible
r12	(Net Usage ≥ 1000) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV ∧ PEV")	*No L-DER, 1 PEV*	Not Feasible
		1 L-DER, No PEV	HBESS_L
		1 L-DER, 1 PEV	Not Feasible
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible

Table 7.2: Rule Set of Feasible L-DER and/or PEV Combinations in Knowledge Base (Cont.)

	Rules	L-DER/PEV	Decision
r13	(Net Usage < 600) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV ∧ HBESS ∧ PEV")	*No L-DER, 1 PEV*	Not Feasible
		1 L-DER, No PEV	Not Feasible
		1 L-DER, 1 PEV	Not Feasible
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible
r14	(600 ≤ Net Usage < 1000) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV ∧ HBESS ∧ PEV")	*No L-DER, 1 PEV*	Not Feasible
		1 L-DER, No PEV	Not Feasible
		1 L-DER, 1 PEV	Not Feasible
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible
r15	(Net Usage ≥ 1000) ∧ (Existing Resources = "Yes") ∧ (Resource Type = "PV ∧ HBESS ∧ PEV")	*No L-DER, 1 PEV*	Not Feasible
		1 L-DER, No PEV	Not Feasible
		1 L-DER, 1 PEV	Not Feasible
		2 L-DERs, No PEV	Not Feasible
		2 L-DERs, 1 PEV	Not Feasible

The outcome of the decision support rule set, in Table 7.2, are maximized energy bill savings for the residential customer as they transition to become prosumers.

7.4 Personalized Energy Bill Savings Calculation

In this section, the personalized energy bill savings are calculated for a customer (target 2) based on their feasible selection of L-DER and/or PEV combinations from Table 7.2. The REP selection approach in Chapter 5 is used to compute the difference in the minimum annual energy bill before and after a feasible L-DER and/or PEV combination has been added. The expressions in (5.2) – (5.10) are used to compute the minimum annual energy bill, where the monthly net energy usage (N_U) in expression (5.2) changes when a L-DER and/or PEV combination is added to the residential customer. Consequently, this updates the value of the other monthly energy features, in (5.2), that produces a new REP plan selection. This is shown in expression (7.1).

$$Annual\ Energy\ Bill\ Savings = \ min_1\left(\overrightarrow{A}\right) - \ min_2\left(\overrightarrow{A}\right) \tag{7.1}$$

Where $min_1\ (\vec{A})$ is the REP plan selection with a minimum annual energy bill for a customer without a feasible L-DER and/or PEV combination added and $min_2\ (\vec{A})$ is the REP plan selection with a minimum annual energy bill for a customer that has added a feasible L-DER and/or PEV combination.

7.5 Implementation of the Personalized REP Plan Selection Tool

In this section the implementation of the personalized REP plan selection tool for both targets are presented. The tool processes, namely: 1) REP plan selection approach in Chapter 5 expressions (5.2) – (5.10), 2) knowledge base for L-DER and/or PEV decision support in Table 7.2 and 3) personalized energy bill savings calculation in expression (7.1) are applied on the MATLAB App Designer platform [71] to display the personalized outputs shown in Figure 7.1 on an interactive graphical user interface (GUI). In the following subsection the GUI's will be explained through an example of a residential customer with a monthly net energy usage of 1,115 kWh/month and no L-DER or PEV. The home page of the tool is shown in Figure 7.2 below.

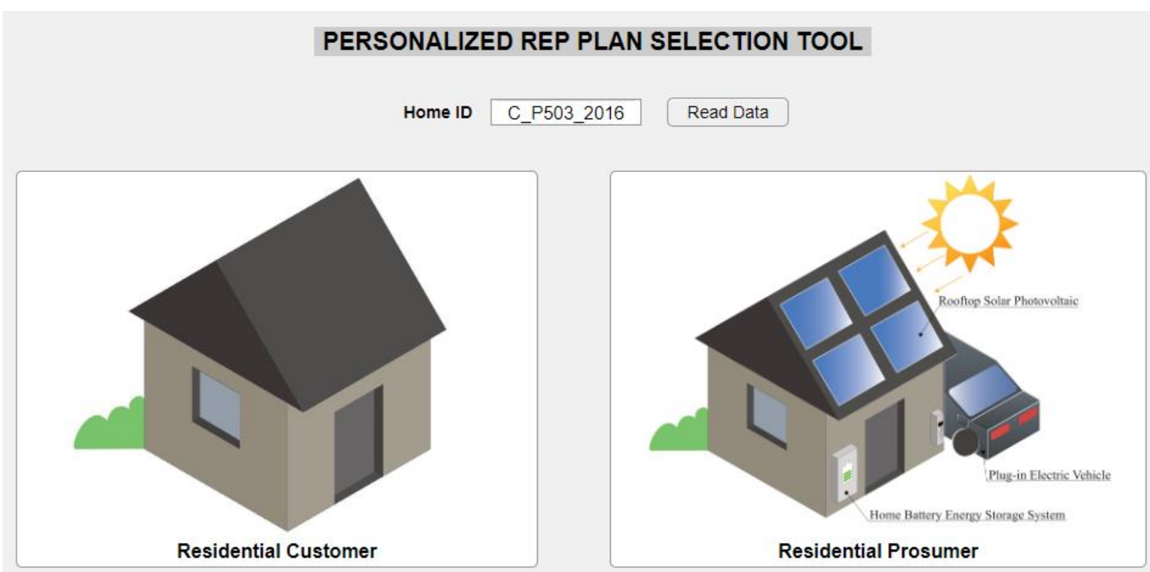


Figure 7.2: Graphical User Interface Home Page with Two Target Options: 1) Residential Customers and 2) Residential Customers Intending to Become Prosumers

On the home page, in Figure 7.2, the monthly energy features (E) are gathered from the residential customer before they select a target i.e. a residential customer or a residential customer that intends to become a prosumer. Firstly, the residential customer GUI will be considered, followed by the L-DER and/or PEV decision support GUI, then the residential prosumer GUI.

7.5.1. Graphical User Interface for Residential Customers

In this GUI, the monthly energy features (E) for 12-months is displayed for the residential customer, where the monthly net usage is 1,115 kWh/month as shown in Figure 7.3. Once the REP plan selection approach is applied to this customer, the tool identifies an ideal REP plan with a minimum energy cost of $1,224.05/year on the Budget S plan. Additionally, the annual costs of the other REP plans are displayed on a bar chart, as shown on the right-hand side of Figure 7.3.

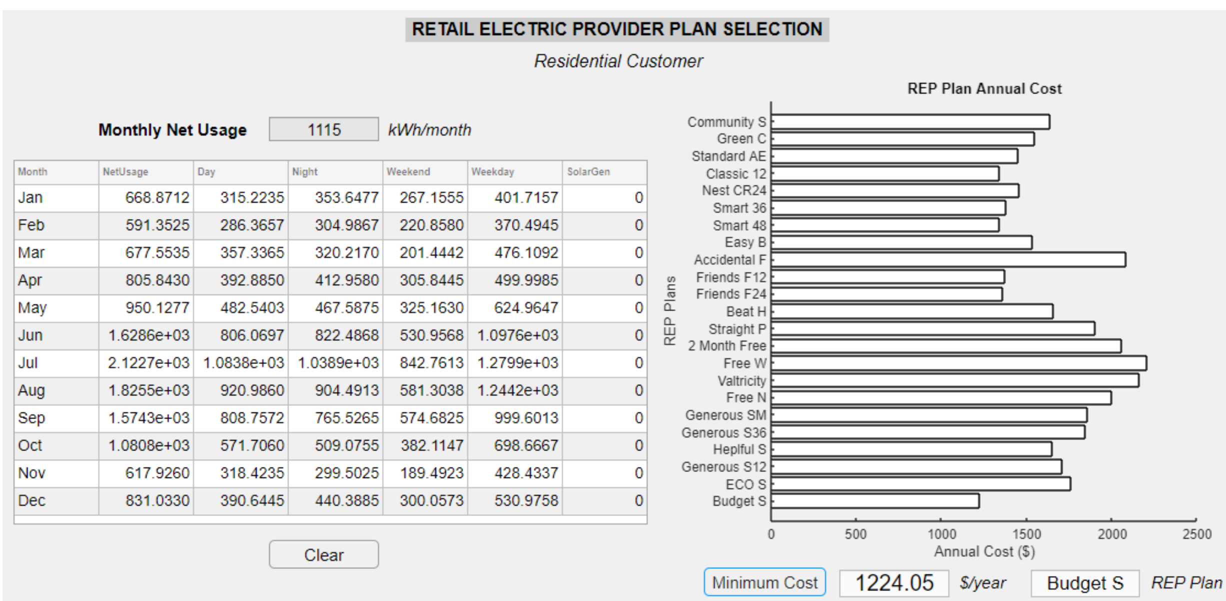


Figure 7.3: Graphical User Interface of Residential Customer with no L-DER or PEV

7.5.2. Graphical User Interface for L-DER and/or PEV Decision Support

In this GUI, the customer has decided to add a feasible combination of L-DER and/or PEV. Therefore, the customer inputs their existing monthly net energy usage (1,115 kWh/month) and select the option of "No Resources" existing in the home, as illustrated in Figure 7.4. The tool then applies decision support to find the most feasible combinations of L-DER and/or PEV. These are shown to the customer with corresponding capacity levels for PV, HBESS and PEV. For this case, it was assumed that the customer selected "1 L-DER & No PEV", which suggests a high capacity PV, to realize the absolute maximum energy bill savings.

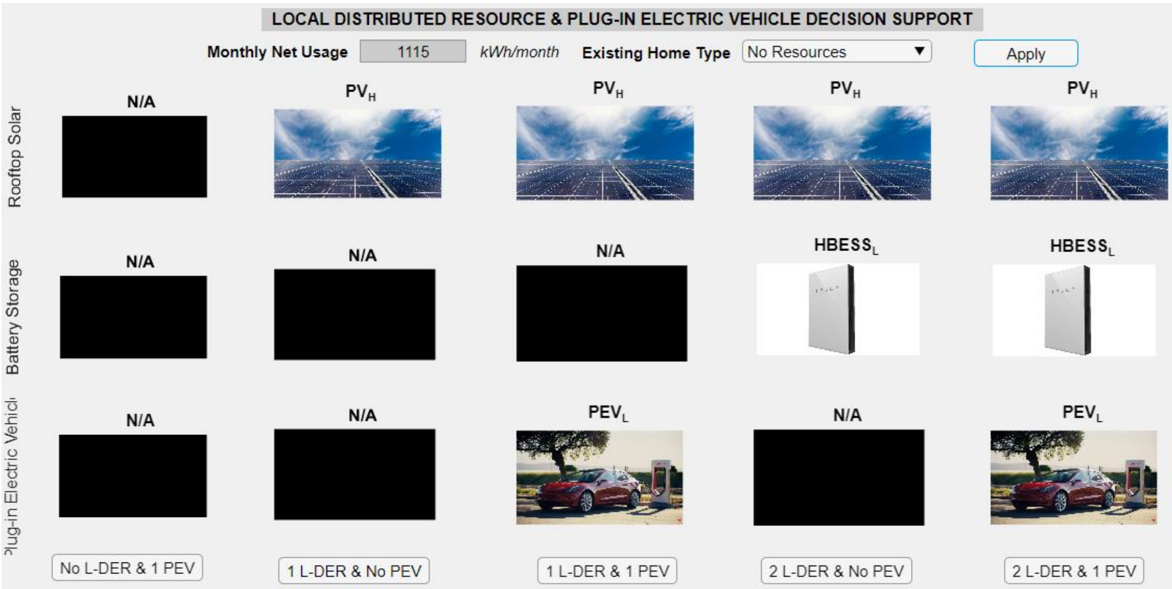


Figure 7.4: Graphical User Interface for L-DER and/or PEV Decision Support

7.5.3. Graphical User Interface for Residential Prosumers

In this GUI the feasible combination of L-DER and/or PEV is applied to the residential customer, essentially making them a prosumer with a high capacity PV. This is shown on the left-hand side of Figure 7.5. The REP plan selection approach is applied to this prosumer, who has updated the monthly energy features, resulting in the tool identifying a new ideal REP plan. The selected REP plan has a minimum cost of $763.59/year on the Smart 48 plan, as shown in Figure 7.5. Previously, the tool selected a minimum cost of $1,224.05 on the Budget S plan in Figure 7.3. This results in a personalized annual energy bill saving of $460.46/year after the addition of an L-DER, also shown in Figure 7.5.

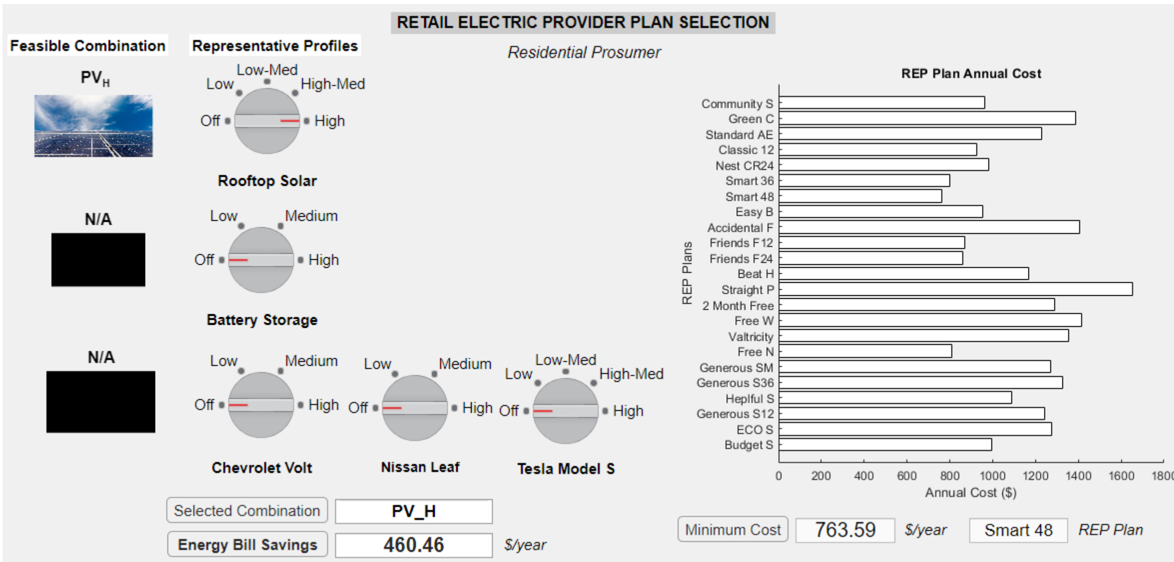


Figure 7.5: Graphical User Interface of a New Residential Prosumer with a High Capacity Rooftop Solar Photovoltaic

7.6 Summary

In this chapter, the design and implementation of the personalized REP plan selection tool was presented. The target, information and initiator of personalization were defined to establish a basis for the design of the personalized tool. Additionally, the tool processes of L-DER and/or PEV decision support and the personalized energy bill saving calculations were developed in this chapter. Furthermore, the implementation of the tool was illustrated for the two targets on MATLAB App Designer platform. The graphical user interfaces on this platform were used to explain the operation and capabilities of this personalized tool.

Chapter 8: Conclusion and Recommendations

8.1 Conclusion

The work in this thesis presented a solution for retail electric provider (REP) plan selection targeted towards the residential customers and those that intend to add local distributed energy resources (L-DERs) and/or plug-in electric vehicles (prosumers) through the design and implementation of a personalized tool. A testbed of 48 annual home profiles from the Pecan Street dataset and 24 REP plans in the jurisdiction of Austin, Texas were evaluated in this study. A feature-based approach was used to extract the monthly energy features (E) from the residential customers metered data and the fixed (F) and the variable (V) cost features from the REP plans to create the monthly energy bills. A minimization function was then used to select the REP plan with the lowest cumulative monthly energy bill for 12-months i.e. the annual energy bill. This was considered to be the most suitable/ideal REP plan for the residential customer. Additionally, the residential customers who intended to install rooftop solar photovoltaics (PVs), home battery energy storage systems (HBESSs) and/or plug-in electric vehicles (PEVs) were evaluated by superimposing the generation/consumption representative profiles. A systematic approach using K-means clustering, principal component analysis and K-nearest neighbor was used to extract 17 representative profiles of PV, HBESS and PEV of different capacity levels from a separate set of 123 Pecan Street generation/consumption profiles. A total of 79 combinations of these PV, HBESS and/or PEV representative profiles were analyzed to determine a suitable REP plan and the most feasible combination of resources that maximize the energy bill savings of the "new" prosumer. Furthermore, a knowledge base was developed that consists of a rule-set that guides residential customers in selecting the feasible L-DER and/or PEV combinations with calculated energy bill savings. Lastly, the work in this thesis implemented the proposed approach for the REP plan selection as a personalized tool on MATLAB App Designer for both residential customers and “new” prosumers.

In the case of residential customers who intend to install PV, HBESS and/or PEV, customers were organized into three net energy usage groups with a low energy usage (< 600 kWh/month), medium energy usage (600 – 1,000 kWh/month) and high energy usage (≥1,000 kWh/month). The results revealed that the presence of PV plays a vital role in contributing to annual energy bill savings for all customer groups. The low and medium energy usage customer groups acquire annual energy bill savings up to $207/year and $221/year, respectively, with PV only. On the other hand, the high energy usage customers acquire almost twice the annual energy bill savings with PV (up to $475/year). Additionally, if a customer intends to add HBESS and/or PEV it was found that a high capacity of PV should be used to maintain significant savings. More so, low and medium energy usage customer groups are advised to maintain a low capacity of HBESS or PEV where as high energy usage customers have more liberty to select any capacity of HBESS or PEV with PV at a medium to high capacity.

The results for REP plan selection revealed that time-invariant plans (Friends F24 and Smart 48) or time-variant plans (Free N) are ideal for low and medium energy usage customer groups. The time-invariant plans were selected due to their low retail electricity rate and fixed charge. The time-variant plan was popular in cases where a high capacity PV and PEV was installed. This selection is justified by the shifting of demand to the night time where the retail electricity rate is at its lowest. On the other hand, the high energy usage customers maximize the savings with tiered time-invariant plans (Smart 48). This is because when a medium to high capacity of PV is added to a high energy usage customer their net usage is reduced to the medium energy usage group, where the Smart 48 plan (time-invariant) is a popular choice. Also, the Budget S plan (time-invariant) was found to be the most ideal option for high energy usage customers without rooftop solar PV.

Finally, the results of the saving contribution of this REP plan selection approach suggest that over a 10-year period between 9 – 37% of the initial PV investment can be covered by identifying a suitable plan. Without the assistance of federal incentives and excess generation compensation credit, this is significant for residential prosumers.

8.2 Recommendations

It is important to note that the personalized tool designed in this thesis is specific to the group of residential customers and REP plans in Austin, Texas. Therefore, it is recommended to use the systematic approach for the representative profiling in Chapter 4 to find PV, HBESS and PEV representatives specific to the residential community under study. It is also recommended that a feature-based approach of the monthly energy billing, as conducted in Chapter 5, be used to extract the monthly energy features from a group of residential customers, but more especially a sufficient number of fixed and variable cost features from REP plans. Additionally, the formulation of a rule-set for decision support, in Chapter 7, is recommended to build a knowledge base of valuable results. This way the selection process of feasible L-DERs and/or PEVs combinations can be automated. Furthermore, for a simple implementation of a personalized interactive tool with graphical user interfaces, the MATLAB App Designer platform in Chapter 7 is convenient for smart grid researchers who are looking to prototype customer-based applications.

8.3 Future Work

The next step for this personalized REP plan selection tool is test it in regions where the retail electricity market is developing, to understand the feasibility of “retail choice” in comparison to the incumbent rate from the electrical municipal. This way utilities at distribution level can evaluate if it is more profitable to join the retail electricity market and begin deregulating electricity rates. Additionally, the personalized REP plan selection tool can be further improved to a web-based tool that is more dynamic and can be updated with the real-time features from both the residential customer and the REP plans.

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Appendix A Retail Electric Provider Plans

Table A.1: Monthly Fixed and Variable Cost Features of Retail Electric Provider Plans

No.	REP Plans	Retail Rate ($/kWh)	Fixed Charge ($)	Credit ($)	VOS Rate ($/kWh)	Base Charge ($)	TDU1 ($/kWh)	TDU2 ($)
1	Budget Saver 12_1	0	71	0	0	0	0	0
2	Budget Saver 12_2	0	0	0	0	0	0	0
3	Budget Saver 12_3	0	71	0	0	0	0	0
4	Budget Saver 12_4	0	0	0	0	0	0	0
5	Budget Saver 12_5	0.139	0	0	0	0	0	0
6	Budget Saver 12_6	0.139	0	0	0	0	0	0
7	ECO Saver Plus 12_1	0.103	0	0	0	9.95	0.038447	3.42
8	ECO Saver Plus 12_2	0.103	0	0	0	9.95	0.038447	3.42
9	ECO Saver Plus 12_3	0.058	0	25	0	9.95	0.038447	3.42
10	ECO Saver Plus 12_4	0.058	0	25	0	9.95	0.038447	3.42
11	ECO Saver Plus 12_5	0.103	0	50	0	9.95	0.038447	3.42
12	ECO Saver Plus 12_6	0.103	0	50	0	9.95	0.038447	3.42
13	Generous Saver Plus 12_1	0.0989	0	0	0	9.95	0.038447	3.42
14	Generous Saver Plus 12_2	0.0989	0	0	0	9.95	0.038447	3.42
15	Generous Saver Plus 12_3	0.0539	0	25	0	9.95	0.038447	3.42
16	Generous Saver Plus 12_4	0.0539	0	25	0	9.95	0.038447	3.42
17	Generous Saver Plus 12_5	0.0989	0	50	0	9.95	0.038447	3.42
18	Generous Saver Plus 12_6	0.0989	0	50	0	9.95	0.038447	3.42
19	Heplful Saver 24_1	0.139	0	0	0	0	0	0
20	Heplful Saver 24_2	0.139	0	0	0	0	0	0
21	Heplful Saver 24_3	0.139	0	35	0	0	0	0
22	Heplful Saver 24_4	0.139	0	35	0	0	0	0
23	Heplful Saver 24_5	0.139	0	70	0	0	0	0
24	Heplful Saver 24_6	0.139	0	70	0	0	0	0
25	Generous Saver Plus 36_1	0.1089	0	0	0	9.95	0.038447	3.42
26	Generous Saver Plus 36_2	0.1089	0	0	0	9.95	0.038447	3.42
27	Generous Saver Plus 36_3	0.0639	0	25	0	9.95	0.038447	3.42
28	Generous Saver Plus 36_4	0.0639	0	25	0	9.95	0.038447	3.42
29	Generous Saver Plus 36_5	0.1089	0	50	0	9.95	0.038447	3.42
30	Generous Saver Plus 36_6	0.1089	0	50	0	9.95	0.038447	3.42
31	Generous Saver Monthly_1	0.117	0	0	0	0	0.038447	3.42
32	Generous Saver Monthly_2	0.117	0	0	0	0	0.038447	3.42
33	Generous Saver Monthly_3	0.072	0	25	0	0	0.038447	3.42
34	Generous Saver Monthly_4	0.072	0	25	0	0	0.038447	3.42
35	Generous Saver Monthly_5	0.117	0	25	0	0	0.038447	3.42
36	Generous Saver Monthly_6	0.117	0	25	0	0	0.038447	3.42

Table A.1: Monthly Fixed and Variable Cost Features of Retail Electric Provider Plans (Cont.)

No.	REP Plans	Retail Rate ($/kWh)	Fixed Charge ($)	Credit ($)	VOS Rate ($/kWh)	Base Charge ($)	TDU1 ($/kWh)	TDU2 ($)
37	Free Nights Plan_1	0	0	0	0	6.25	0.038447	3.42
38	Free Nights Plan_2	0	0	0	0	6.25	0.038447	3.42
39	Free Nights Plan_3	0	0	0	0	6.25	0.038447	3.42
40	Free Nights Plan_4	0	0	0	0	6.25	0.038447	3.42
41	Free Nights Plan_5	0	0	0	0	6.25	0.038447	3.42
42	Free Nights Plan_6	0	0	0	0	6.25	0.038447	3.42
43	Free Nights Plan_7	0.203	0	0	0	0	0.038447	0
44	Free Nights Plan_8	0.203	0	0	0	0	0.038447	0
45	Free Nights Plan_9	0.203	0	0	0	0	0.038447	0
46	Free Nights Plan_10	0.203	0	0	0	0	0.038447	0
47	Free Nights Plan_11	0.203	0	0	0	0	0.038447	0
48	Free Nights Plan_12	0.203	0	0	0	0	0.038447	0
49	Valtricity Plan_1	0.122	0	8.219178	0	6.25	0.038447	3.42
50	Valtricity Plan_2	0.122	0	8.219178	0	6.25	0.038447	3.42
51	Valtricity Plan_3	0.122	0	8.219178	0	6.25	0.038447	3.42
52	Valtricity Plan_4	0.122	0	8.219178	0	6.25	0.038447	3.42
53	Valtricity Plan_5	0.122	0	8.219178	0	6.25	0.038447	3.42
54	Valtricity Plan_6	0.122	0	8.219178	0	6.25	0.038447	3.42
55	Free Weekends_1	0	0	0	0	6.25	0.038447	3.42
56	Free Weekends_2	0	0	0	0	6.25	0.038447	3.42
57	Free Weekends_3	0	0	0	0	6.25	0.038447	3.42
58	Free Weekends_4	0	0	0	0	6.25	0.038447	3.42
59	Free Weekends_5	0	0	0	0	6.25	0.038447	3.42
60	Free Weekends_6	0	0	0	0	6.25	0.038447	3.42
61	Free Weekends_7	0.182	0	0	0	0	0.038447	0
62	Free Weekends_8	0.182	0	0	0	0	0.038447	0
63	Free Weekends_9	0.182	0	0	0	0	0.038447	0
64	Free Weekends_10	0.182	0	0	0	0	0.038447	0
65	Free Weekends_11	0.182	0	0	0	0	0.038447	0
66	Free Weekends_12	0.182	0	0	0	0	0.038447	0
67	2 Month Free_1	0.114	0	8.219178	0	6.25	0.038447	3.42
68	2 Month Free_2	0.114	0	8.219178	0	6.25	0.038447	3.42
69	2 Month Free_3	0.114	0	8.219178	0	6.25	0.038447	3.42
70	2 Month Free_4	0.114	0	8.219178	0	6.25	0.038447	3.42
71	2 Month Free_5	0.114	0	8.219178	0	6.25	0.038447	3.42
72	2 Month Free_6	0.114	0	8.219178	0	6.25	0.038447	3.42

Table A.1: Monthly Fixed and Variable Cost Features of Retail Electric Provider Plans (Cont.)

No.	REP Plans	Retail Rate ($/kWh)	Fixed Charge ($)	Credit ($)	VOS Rate ($/kWh)	Base Charge ($)	TDU1 ($/kWh)	TDU2 ($)
73	Straight Power 12 ONC_1	0	0	58	0	157	0	0
74	Straight Power 12 ONC_2	0	0	0	0	157	0	0
75	Straight Power 12 ONC_3	0	0	0	0	157	0	0
76	Straight Power 12 ONC_4	0	0	0	0	157	0	0
77	Straight Power 12 ONC_5	0.176	0	0	0	157	0	0
78	Straight Power 12 ONC_6	0.176	0	0	0	157	0	0
79	Beat the Heat 12_1	0.1033	0	0	0	7.95	0.038447	3.42
80	Beat the Heat 12_2	0.1033	0	0	0	7.95	0.038447	3.42
81	Beat the Heat 12_3	0.1033	0	75	0	7.95	0.038447	3.42
82	Beat the Heat 12_4	0.1033	0	75	0	7.95	0.038447	3.42
83	Beat the Heat 12_5	0.1033	0	75	0	7.95	0.038447	3.42
84	Beat the Heat 12_6	0.1033	0	75	0	7.95	0.038447	3.42
85	Friends & Family 24+_1	0.06	0	0	0	0	0.038447	3.42
86	Friends & Family 24+_2	0.06	0	0	0	0	0.038447	3.42
87	Friends & Family 24+_3	0.06	0	0	0	0	0.038447	3.42
88	Friends & Family 24+_4	0.06	0	0	0	0	0.038447	3.42
89	Friends & Family 24+_5	0.06	0	0	0	0	0.038447	3.42
90	Friends & Family 24+_6	0.06	0	0	0	0	0.038447	3.42
91	Friends & Family 12+_1	0.061	0	0	0	0	0.038447	3.42
92	Friends & Family 12+_2	0.061	0	0	0	0	0.038447	3.42
93	Friends & Family 12+_3	0.061	0	0	0	0	0.038447	3.42
94	Friends & Family 12+_4	0.061	0	0	0	0	0.038447	3.42
95	Friends & Family 12+_5	0.061	0	0	0	0	0.038447	3.42
96	Friends & Family 12+_6	0.061	0	0	0	0	0.038447	3.42
97	Accident Forgiveness_1	0.134	0	0	0	24.095	0	0
98	Accident Forgiveness_2	0.134	0	0	0	24.095	0	0
99	Accident Forgiveness_3	0.134	0	0	0	24.095	0	0
100	Accident Forgiveness_4	0.134	0	0	0	24.095	0	0
101	Accident Forgiveness_5	0.134	0	0	0	24.095	0	0
102	Accident Forgiveness_6	0.134	0	0	0	24.095	0	0
103	Easy Bill OA_1	0	0	0	0	74	0	0
104	Easy Bill OA_2	0	0	0	0	74	0	0
105	Easy Bill OA_3	0.199	0	0	0	74	0	0
106	Easy Bill OA_4	0.199	0	0	0	74	0	0
107	Easy Bill OA_5	0.199	0	0	0	74	0	0
108	Easy Bill OA_6	0.199	0	0	0	74	0	0

Table A.1: Monthly Fixed and Variable Cost Features of Retail Electric Provider Plans (Cont.)

No.	REP Plans	Retail Rate ($/kWh)	Fixed Charge ($)	Credit ($)	VOS Rate ($/kWh)	Base Charge ($)	TDU1 ($/kWh)	TDU2 ($)
109	48-month Smart_1	0	0	0	0	58	0	0
110	48-month Smart_2	0	0	0	0	58	0	0
111	48-month Smart_3	0.2	0	0	0	58	0	0
112	48-month Smart_4	0.2	0	0	0	58	0	0
113	48-month Smart_5	0.2	0	0	0	58	0	0
114	48-month Smart_6	0.2	0	0	0	58	0	0
115	36-month Smart_1	0	0	0	0	61	0	0
116	36-month Smart_2	0	0	0	0	61	0	0
117	36-month Smart_3	0.2	0	0	0	61	0	0
118	36-month Smart_4	0.2	0	0	0	61	0	0
119	36-month Smart_5	0.2	0	0	0	61	0	0
120	36-month Smart_6	0.2	0	0	0	61	0	0
121	24 mo Nest Cam Rate_1	0.062396	0	0	0	9.95	0.038447	3.42
122	24 mo Nest Cam Rate_2	0.062396	0	0	0	9.95	0.038447	3.42
123	24 mo Nest Cam Rate_3	0.062396	0	0	0	0	0.038447	3.42
124	24 mo Nest Cam Rate_4	0.062396	0	0	0	0	0.038447	3.42
125	24 mo Nest Cam Rate_5	0.062396	0	0	0	0	0.038447	3.42
126	24 mo Nest Cam Rate_6	0.062396	0	0	0	0	0.038447	3.42
133	Classic 12-month_1	0.061369	0	0	0	5	0.038447	3.42
134	Classic 12-month_2	0.061369	0	0	0	5	0.038447	3.42
135	Classic 12-month_3	0.032162	0	0	0	5	0.038447	3.42
136	Classic 12-month_4	0.032162	0	0	0	5	0.038447	3.42
137	Classic 12-month_5	0.032162	0	0	0	5	0.038447	3.42
138	Classic 12-month_6	0.032162	0	0	0	5	0.038447	3.42
139	Standard (Austin Energy)_1	0.02801	0	0	0.097	10	0.0485	0
140	Standard (Austin Energy)_2	0.05832	0	0	0.097	10	0.0485	0
141	Standard (Austin Energy)_3	0.07814	0	0	0.097	10	0.0485	0
142	Standard (Austin Energy)_4	0.09314	0	0	0.097	10	0.0485	0
143	Standard (Austin Energy)_5	0.09314	0	0	0.097	10	0.0485	0
144	Standard (Austin Energy)_6	0.10814	0	0	0.097	10	0.0485	0
145	Green Choice 100% Wind_1	0.02801	0	0	0.097	10	0.056	0
146	Green Choice 100% Wind_2	0.05832	0	0	0.097	10	0.056	0
147	Green Choice 100% Wind_3	0.07814	0	0	0.097	10	0.056	0
148	Green Choice 100% Wind_4	0.09314	0	0	0.097	10	0.056	0
149	Green Choice 100% Wind_5	0.09314	0	0	0.097	10	0.056	0
150	Green Choice 100% Wind_6	0.10814	0	0	0.097	10	0.056	0

Table A.1: Monthly Fixed and Variable Cost Features of Retail Electric Provider Plans (Cont.)

No.	REP Plans	Retail Rate ($/kWh)	Fixed Charge ($)	Credit ($)	VOS Rate ($/kWh)	Base Charge ($)	TDU1 ($/kWh)	TDU2 ($)
151	Community Solar 100% locally generated_1	0.02801	0	0	0	10	0.06245	0
152	Community Solar 100% locally generated_2	0.05832	0	0	0	10	0.06245	0
153	Community Solar 100% locally generated_3	0.07814	0	0	0	10	0.06245	0
154	Community Solar 100% locally generated_4	0.09314	0	0	0	10	0.06245	0
155	Community Solar 100% locally generated_5	0.09314	0	0	0	10	0.06245	0
156	Community Solar 100% locally generated_6	0.10814	0	0	0	10	0.06245	0

Where REP Plan_1 is for customers with a net energy usage less than 500 kWh/month, REP Plan_2 is for customers with a net usage between 500 – 1,000 kWh/month, REP Plan_3 is for customers with a net energy usage between 1,000 – 1,500 kWh/month. REP Plan_4 is for customers with a net energy usage between 1,500 – 2,000 kWh/month, REP Plan_5 is for customers with a net energy usage between 2,000 – 2,500 kWh/month and REP Plan_6 is for customers with a net energy usage more than 2,500 kWh/month.

Appendix B Pecan Street Existing Homes

Table B.1: Pecan Street Existing Homes with their Average Monthly Net Energy Usage and Monthly PV Generation

L-DER/ PEV	Home (ID_Year)	Average Monthly Net Energy Usage (kWh/month)	Average Monthly PV Generation (kWh/month)
No Resources	946_2016	563	0
	994_2016	572	0
	1796_2016	338	0
	2859_2016	302	0
	3413_2016	873	0
	3831_2016	403	0
	4213_2016	786	0
	4633_2016	545	0
	5317_2016	824	0
	7787_2016	546	0
	8386_2016	724	0
	503_2016	1,115	0
	2472_2016	1,151	0
	9333_2016	1,174	0
PV	668_2016	565	684
	781_2016	598	706
	2461_2016	523	873
	3009_2016	401	720
	3506_2016	544	736
	3538_2016	360	532
	3849_2016	676	651
	5035_2016	918	303
	5658_2016	773	843
	5921_2016	408	563
	6063_2016	428	572
	8086_2016	562	585
	8243_2016	441	735
	8767_2016	541	458
	8995_2016	382	701
	9134_2016	758	590
	9971_2016	504	692
	5784_2016	1,112	1,123
	7017_2016	1,130	578

Table B.1: Pecan Street Existing Homes with their Average Monthly Net Usage and Monthly PV Generation (Cont.)

L-DER/ PEV	Home (ID_Year)	Average Monthly Net Usage (kWh/month)	Average Monthly PV Generation (kWh/month)
PV & PEV	379_2016	934	697
	5450_2016	555	690
	6248_2016	815	927
	7024_2016	407	645
	8156_2016	900	755
	9932_2016	328	528
	5749_2016	1,042	300
	6691_2016	1,406	610
	7719_2016	1,197	767
PV & HBESS	974_2019	972	562
	9982_2019	391	145
	2925_2019	1,500	349
PV & PEV & HBESS	5403_2019	573	415
	6836_2019	553	298
	1185_2019	1,014	381

Appendix C Correlation Matrices for Monthly Features

Table C.1: Correlation Matrix for Rooftop Solar Photovoltaic Monthly Generation Features

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	1.00	0.92	0.91	0.87	0.86	0.83	0.84	0.86	0.86	0.85	0.67	0.60
Feb	0.92	1.00	0.98	0.95	0.95	0.94	0.95	0.93	0.92	0.84	0.65	0.53
Mar	0.91	0.98	1.00	0.97	0.96	0.95	0.96	0.93	0.92	0.84	0.65	0.55
Apr	0.87	0.95	0.97	1.00	0.98	0.97	0.96	0.95	0.92	0.82	0.62	0.51
May	0.86	0.95	0.96	0.98	1.00	0.98	0.98	0.95	0.92	0.82	0.59	0.49
Jun	0.83	0.94	0.95	0.97	0.98	1.00	0.98	0.95	0.92	0.81	0.57	0.47
Jul	0.84	0.95	0.96	0.96	0.98	0.98	1.00	0.94	0.91	0.80	0.59	0.49
Aug	0.86	0.93	0.93	0.95	0.95	0.95	0.94	1.00	0.96	0.86	0.64	0.52
Sep	0.86	0.92	0.92	0.92	0.92	0.92	0.91	0.96	1.00	0.91	0.72	0.63
Oct	0.85	0.84	0.84	0.82	0.82	0.81	0.80	0.86	0.91	1.00	0.84	0.78
Nov	0.67	0.65	0.65	0.62	0.59	0.57	0.59	0.64	0.72	0.84	1.00	0.93
Dec	0.60	0.53	0.55	0.51	0.49	0.47	0.49	0.52	0.63	0.78	0.93	1.00

Pearson's Correlation Coefficient

1.0

0.5

0.0

Table C.2: Correlation Matrix for Chevrolet Volt Monthly Charging Features

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	1.00	0.76	0.72	0.80	0.74	0.70	0.69	0.67	0.81	0.74	0.73	0.68
Feb	0.76	1.00	0.79	0.80	0.78	0.72	0.66	0.77	0.75	0.73	0.72	0.68
Mar	0.72	0.79	1.00	0.78	0.73	0.63	0.76	0.67	0.81	0.79	0.84	0.69
Apr	0.80	0.80	0.78	1.00	0.85	0.78	0.84	0.68	0.80	0.71	0.72	0.68
May	0.74	0.78	0.73	0.85	1.00	0.85	0.74	0.79	0.81	0.81	0.72	0.66
Jun	0.70	0.72	0.63	0.78	0.85	1.00	0.74	0.83	0.74	0.70	0.66	0.57
Jul	0.69	0.66	0.76	0.84	0.74	0.74	1.00	0.66	0.86	0.74	0.84	0.72
Aug	0.67	0.77	0.67	0.68	0.79	0.83	0.66	1.00	0.77	0.78	0.69	0.66
Sep	0.81	0.75	0.81	0.80	0.81	0.74	0.86	0.77	1.00	0.88	0.86	0.74
Oct	0.74	0.73	0.79	0.71	0.81	0.70	0.74	0.78	0.88	1.00	0.83	0.73
Nov	0.73	0.72	0.84	0.72	0.72	0.66	0.84	0.69	0.86	0.83	1.00	0.81
Dec	0.68	0.68	0.69	0.68	0.66	0.57	0.72	0.66	0.74	0.73	0.81	1.00

Pearson's Correlation Coefficient

1.0

0.5

0.0

Table C.3: Correlation Matrix for Tesla Model S Monthly Charging Features

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	1.00	0.95	0.84	0.39	0.88	0.74	0.91	0.60	0.99	0.35	0.80	0.79
Feb	0.95	1.00	0.82	0.34	0.87	0.80	0.98	0.59	0.97	0.18	0.62	0.82
Mar	0.84	0.82	1.00	0.71	0.93	0.88	0.81	0.66	0.83	0.67	0.74	0.92
Apr	0.39	0.34	0.71	1.00	0.68	0.38	0.35	0.38	0.36	0.79	0.39	0.48
May	0.88	0.87	0.93	0.68	1.00	0.81	0.83	0.76	0.88	0.55	0.74	0.87
Jun	0.74	0.80	0.88	0.38	0.81	1.00	0.81	0.77	0.75	0.39	0.65	0.98
Jul	0.91	0.98	0.81	0.35	0.83	0.81	1.00	0.57	0.93	0.13	0.57	0.83
Aug	0.60	0.59	0.66	0.38	0.76	0.77	0.57	1.00	0.60	0.34	0.76	0.82
Sep	0.99	0.97	0.83	0.36	0.88	0.75	0.93	0.60	1.00	0.29	0.75	0.79
Oct	0.35	0.18	0.67	0.79	0.55	0.39	0.13	0.34	0.29	1.00	0.56	0.44
Nov	0.80	0.62	0.74	0.39	0.74	0.65	0.57	0.76	0.75	0.56	1.00	0.72
Dec	0.79	0.82	0.92	0.48	0.87	0.98	0.83	0.82	0.79	0.44	0.72	1.00

Pearson's Correlation Coefficient

1.0
0.5
0.0

Table C.4: Correlation Matrix for Nissan Leaf Monthly Charging Features

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	1.00	0.60	0.60	0.92	0.82	0.52	0.62	0.14	0.62	0.00	0.60	-0.08
Feb	0.60	1.00	0.92	0.67	0.86	0.34	-0.12	-0.28	-0.13	-0.43	-0.15	-0.23
Mar	0.60	0.92	1.00	0.63	0.85	0.62	-0.10	0.10	-0.06	-0.52	-0.03	-0.10
Apr	0.92	0.67	0.63	1.00	0.93	0.57	0.65	0.05	0.65	0.21	0.61	0.19
May	0.82	0.86	0.85	0.93	1.00	0.65	0.37	0.04	0.38	-0.03	0.37	0.16
Jun	0.52	0.34	0.62	0.57	0.65	1.00	0.43	0.77	0.51	0.02	0.59	0.54
Jul	0.62	-0.12	-0.10	0.65	0.37	0.43	1.00	0.36	1.00	0.72	0.97	0.50
Aug	0.14	-0.28	0.10	0.05	0.04	0.77	0.36	1.00	0.44	0.03	0.56	0.46
Sep	0.62	-0.13	-0.06	0.65	0.38	0.51	1.00	0.44	1.00	0.69	0.99	0.53
Oct	0.00	-0.43	-0.52	0.21	-0.03	0.02	0.72	0.03	0.69	1.00	0.64	0.72
Nov	0.60	-0.15	-0.03	0.61	0.37	0.59	0.97	0.56	0.99	0.64	1.00	0.56
Dec	-0.08	-0.23	-0.10	0.19	0.16	0.54	0.50	0.46	0.53	0.72	0.56	1.00

Pearson's Correlation Coefficient

1.0
0.0
-1.0

Table C.5: Correlation Matrix for Home Battery Energy Storage Monthly Energy Features

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	1.00	0.67	0.76	-0.32	-0.19	-0.46	-0.72	0.34	-0.20	-0.46	-0.39	-0.41
Feb	0.67	1.00	0.97	0.17	0.26	-0.82	-0.97	0.61	0.26	0.35	0.39	0.36
Mar	0.76	0.97	1.00	0.20	0.32	-0.69	-0.93	0.72	0.31	0.20	0.20	0.17
Apr	-0.32	0.17	0.20	1.00	0.98	0.14	0.01	0.70	0.99	0.57	0.43	0.43
May	-0.19	0.26	0.32	0.98	1.00	0.13	-0.06	0.81	1.00	0.51	0.34	0.34
Jun	-0.46	-0.82	-0.69	0.14	0.13	1.00	0.91	-0.08	0.11	-0.42	-0.60	-0.58
Jul	-0.72	-0.97	-0.93	0.01	-0.06	0.91	1.00	-0.43	-0.07	-0.25	-0.36	-0.33
Aug	0.34	0.61	0.72	0.70	0.81	-0.08	-0.43	1.00	0.79	0.27	0.08	0.06
Sep	-0.20	0.26	0.31	0.99	1.00	0.11	-0.07	0.79	1.00	0.53	0.37	0.37
Oct	-0.46	0.35	0.20	0.57	0.51	-0.42	-0.25	0.27	0.53	1.00	0.94	0.94
Nov	-0.39	0.39	0.20	0.43	0.34	-0.60	-0.36	0.08	0.37	0.94	1.00	1.00
Dec	-0.41	0.36	0.17	0.43	0.34	-0.58	-0.33	0.06	0.37	0.94	1.00	1.00

Pearson's Correlation Coefficient

1.0

0.0

-1.0

The Pearson's correlation coefficient [44] for two data objects *x* and *y* is described by the expression (C.1):

$$corr(\boldsymbol{x},\boldsymbol{y}) = \frac{covariance(\boldsymbol{x},\boldsymbol{y})}{\sigma_x \times \sigma_y} \tag{C.1}$$

Where, the covariance for a total of *n* data observations is shown by expression (C.2):

$$covariance(\boldsymbol{x},\boldsymbol{y}) = \frac{1}{n-1}\sum_{k=1}^{n}(x_k - \bar{x})\,(y_k - \bar{y}), where\ k \le n \tag{C.2}$$

And the standard deviations for *x* and *y* are described for *n* data observations by expression (C.3) and (C.4), respectively. It should be noted that $\bar{x}$ and $\bar{y}$ symbolize the mean value of *x* and *y*, individually.

$$\sigma_x = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(x_k - \bar{x})^2}\ , where\ k \le n \tag{C.3}$$

$$\sigma_y = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(y_k - \bar{y})^2} \; , where\ k \leq n \tag{C.4}$$