Agent-Based Modeling Framework for Energy Policies

by

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

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Abstract

Energy infrastructure systems – including energy generation, transmission, and distribution systems – provide consumers with access to energy. Energy systems have been relatively static for several decades but due to recent technological changes such as development of new renewable energy sources, improved sensing and control, and increasingly effective storage technologies, energy systems and the corresponding socio-technical interactions are quickly changing and transitioning into new configurations. In addition, some of these technologies result in changes in consumer behaviour, causing a second-order effect, in turn, on energy systems themselves.

The role of policymakers is to guide energy system transitions so as to achieve a certain desired goal. However, implementing an effective energy policy requires a detailed understanding of energy systems as complex socio-technical systems involving human behaviour and human-system interactions. A common approach to evaluate a policy is the use of a pilot study where a group of people in a certain representative geography are selected and the policy is tested in real-world circumstances. The downside of pilot studies is that they can be expensive, with costs up to millions of dollars, and it is impossible to evaluate more than a small handful of policy alternatives.

The goal of this thesis is to provide energy system stakeholders with a tool to estimate and evaluate the potential impacts of new policies and technologies, guiding the transition of energy systems. To do so, we design and propose an alternative approach for evaluating energy policies: a data-driven agent-based modeling framework. While other system modeling techniques are known in the literature, Agent-Based Models (ABMs) have long been used to study socio-technical systems and they capture the emergent system properties resulting from the actions of adaptive and autonomous agents. In addition, we propose the concept of an *energy agent* suited for modeling energy systems with ABMs. Using this framework, we have studied the impact of different policies on the adoption of solar panels and batteries in Ontario, Canada, as well as the adoption of electric cars in San Francisco and Los Angeles, California. We also study the response of Ontario residents to Time-of-Use (ToU) electricity pricing, comparing different pricing policies. For each study, we make policy recommendations based on our results.

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List of Acronyms

ABM	agent-based model
MAS	multi-agent system
EV	electric vehicle
BEV	battery electric vehicle
HEV	hybrid electric vehicle
PHEV	plug-in hybrid electric vehicle
PEV	plug-in electric vehicle
ToU	time-of-use
FiT	feed-in tariff
AMI	advanced metering infrastructure
DR	demand response
DOD	depth of discharge
DG	distributed generation
PV	photovoltaic
ST	socio-technical
ACT	affect control theory
EPA	evaluation, potency, activity
SOC	battery state of charge
EVSE	electric vehicle supply equipment
ICEV	internal combustion engine vehicle
SD	system dynamics
IESO	independent electricity system operator
DES	discrete event simulation
CGE	computable general equilibrium
TCO	total cost of ownership
NPV	net present value
PAR	peak-to-average ratio
TPB	theory of planned behaviour
RoI	return on investment
LARS	least angle regression
NMNL	nested multinomial logit
LoI	location of interest
NREL	national renewable energy laboratory
WTP	willingness to pay

CPP	critical peak pricing

Chapter 1

Introduction

Energy infrastructure systems[1] are critical systems that provide the energy required for people's everyday activities [5, 141]. They harness natural resources for energy generation, generate energy, distribute energy, and distribute fuels for energy generation. Examples are natural gas distribution networks, power plants, and electricity distribution systems. One critical property of such systems is their capability to change over time; these changes are termed *transitions*. Transitions in energy systems occur due to factors such as new or improved technologies, changes in energy consumer behaviour, and policies. This is currently the case in the transportation industry with an increasing number of Electric Vehicles (EVs) on the road [130], and in the electricity supply sector with scalable Distributed Generation (DG) technologies such as solar PhotoVoltaic (PV) systems [19].

In the transportation industry, EVs are gradually becoming more appealing to car buyers given their improvements in vehicle driving range and reductions in price; the growing EV industry has also impacted battery technologies as batteries are becoming cheaper due to the EV industry *learning* process [97], i.e., the improvement in battery technology and the reduction of battery prices as battery supply increases. Similarly, PV systems are currently disrupting the electricity supply industry, making microgrids more viable and providing an alternative energy source for electricity consumers. In addition, as people acquire new technologies, energy consumption patterns are changing. For example, the increasing number of EVs on the road will also change electricity consumption patterns with an increase in charging load when most people arrive at their homes, assuming that no form of EV charging control policy is in place. These are examples of transitions in energy systems resulting from technological advancements and changes in consumption patterns.

[1]henceforth referred to as energy systems

The goal of policymakers is to influence system transitions in order to achieve a desired outcome. For example, to reduce the daily consumption of electricity, since Light Emitting Diode (LED) bulbs consume much less electricity than incandescent bulbs, a policy that provides households and offices with the option to swap incandescent bulbs for LED bulbs could be implemented. Policies can also be implemented to maintain balance in energy systems. For example, to avoid peak charging loads in a community with a high penetration of EVs, a policy of centralized control combined with the the deployment of coordinated charging may be required.

Given that energy systems are complex socio-technical systems, with somewhat unpredictable human elements, it is important to test that a policy attains its desired outcome before it is widely deployed. One way of evaluating the impact of a potential energy policy is by carrying out a pilot study. In a pilot study, a group or population of people are selected and the policy is carried out in real-world circumstances. For example, households in a small town could be subjected to Time-of-Use (ToU) electricity pricing[2] in order to reduce consumption during certain periods of day. However, these pilot studies can be very expensive, with costs in the range of hundreds of thousands to millions of dollars. In addition, pilot studies can only be used to explore a small handful of policy choices.

An attractive alternative to pilot studies is the use of simulation models that attempt to simulate relevant aspects of a socio-technical system. Examples include System Dynamics (SD) [47], Discrete Event Simulation (DES) [52], agent-based modeling [86], Computable General Equilibrium (CGE) [72], and econometrics and scenario analysis [50, 41]. In this chapter, we first compare and contrast several competing system modeling approaches, based on features such as the capacity to model system components and interactions at high and low levels, having explanatory power, software execution, data incorporation, and provision of policy insights (Section 1.1). We then elaborate on using Agent-Based Models (ABMs) for modeling energy systems (Section 1.3). We believe that the ABM approach is best suited to capturing the dynamics of energy systems and policies. Therefore, in this thesis we use agent-based modeling.

Our agent-based framework for energy policies improves on prior work in this area by incorporating energy cultures, utilizing surveys, being data-driven, and introducing the concept of an energy agent useful in modeling energy systems. We have used this framework to study the adoption of electric cars in San Francisco [3] and Los Angeles [2], the adoption of solar panel and battery systems in Ontario, and the effectiveness of ToU electricity pricing in Ontario.

[2]This is a pricing scheme where the per-kWh price of electricity is dependent on the time of the day and the day of the week.

1.1 Modeling Energy Systems

In this section, we discuss the desired qualities of an ideal energy systems modeling approach and the degree to which different modeling approaches meet these requirements. After comparing system modeling approaches, we show why we selected ABMs for our work.

1.1.1 Characteristics of an Ideal Modeling Approach

We first discuss prior work that compares different aproaches to modeling energy/socio-technical (ST) systems. Behdani [16] studies and compares the System Dynamics (SD), Discrete Event Simulation (DES), and ABM methods, highlighting the effectiveness of each approach in modeling complex systems. Chappin [26] also compares different modeling paradigms and rates them on certain modeling requirements. Building on these existing studies, we believe that the following desirable characteristics describe an ideal system model.

1. **Permits modeling of physical components[3]:** These are the physical (technological) entities in the ST system. Within a typical energy system, examples of physical components could include PV systems, batteries, electric cars, electric car charging stations, and household appliances.

2. **Permits modeling of social components:** The social components are the actors within a system, e.g., consumers of electricity, an electric utility, etc. By modeling different classes of social components, the heterogeneity found in the ST system can be incorporated.

3. **Models socio-technical interactions:** Socio-technical interactions are the interactions between actors in the system, interactions between technical components, and interactions between actors and technical components. For example, in a PV adoption model, such interactions would include agents buying PV systems and generating electricity that goes into the grid.

4. **Implementable in software:** The model should be expressible using software-based simulations.

[3] Also known as technical components.

5. **Provides actionable insight:** The modeling approach should provide actionable insight on the policies being studied. That is, the lessons learnt from simulating the model should be applicable in the real-world.

6. **Has explanatory power:** The modeling approach should be capable of providing an understanding of how changes and transitions occur within the system of interest. That is, the causes of system transition should be traceable from the results. With this quality, policy interventions can be more refined and directed at the right actors within the ST system. For example, if increasing the grid electricity price results in increased PV adoption, it should be possible to explain why the change in electricity price drives more people towards purchasing PV systems.

7. **Able to incorporate data:** The modeling approach should be able to take advantage of available data in order to develop a data-driven and comprehensive model.

8. **Models emergence in systems:** System transitions are based on the actions of individual system components and interactions amongst them. The model should exhibit emergence, that is, aggregating these micro-level interactions should lead to macro-level system patterns.

9. **Can express dynamic evolution:** The model should express the process of change that occurs in the components of a system over time.

10. **Scales up:** The model should be scalable for use with respect to number and dynamics of system components and interactions.

1.1.2 System Modeling Paradigms

Several approaches for modeling complex systems, such as an energy system, are well studied in the literature. These include system dynamics, discrete-event simulations, econometrics and scenario analysis, computational general equilibrium, and agent-based modeling [137, 86, 145, 26]. It is important to note that there is no 'best' way to model ST systems, the approach used depends on the reason for modeling the systems in the first place. We now discuss these standard approaches and then determine the degree to which they meet the criteria identified in Section 1.1.1.

System Dynamics (SD)

System Dynamics is "the study of information-feedback characteristics of industrial activity to show how organizational structure, amplification (in policies), and time delays (in decisions and actions) interact to influence the success of the enterprise" [47]. The system dynamics approach involves the decomposition of a system into different system components, i.e., subsystems, and finding dependencies between these components. These dependencies are represented by functional links (differential equations) that define the behaviour of the system. Identifying feedback loops in SD modeling is crucial [145]. SD models can focus at the macro-level or the micro-level. However, oversimplification of a SD model can result in the omission of crucial system dynamics. As in other modeling approaches, a balance of simplicity and comprehensiveness has to be achieved. An example of application of SD is Struben and Sterman's model for forecasting alternative fuel vehicle adoption [124].

Discrete Event Simulation (DES)

DES involves the modeling of change within a system via a discrete set of events. In its basic form, a DES cyclically passes a set of events through a queue of processes, that in turn, determine the state of the system as whole. The primary advantage of DES is its ability to represent entities – events, activities, and processes – with distinct attributes, therefore capturing micro-level dynamics. However, these entities are passive as there is no active decision making involved and as a result, the social interactions and emergent behaviours in a system cannot be easily observed [137, 16].

Computable General Equilibrium (CGE)

CGE, also known as applied general equilibrium, models systems from a macroeconomic perspective, focusing on supply, demand, market prices, etc. CGE models provide some explanatory power as long as the model is properly structured [33]. As a result, the causality between policies and simulation outcomes can be empirically verified. In the CGE approach, the system is modeled to reach an equilibrium in each time step. It uses macroeconomic equations, therefore employing a top-down approach with aggregate variables and averaging out the heterogeneity in a ST system. In addition, CGE requires strong assumptions about utility functions of participants [26, 72, 34].

Econometrics and Scenario Analysis

These models study correlations in a dynamic system via statistical analysis. Different scenarios of policy interventions are considered, and a 'what-if' analysis of each intervention is conducted, leading to different future system states. This approach, however, does not directly model the dynamics of the system being studied, i.e., the underlying processes that lead to system evolution [26].

Agent-Based Modeling

Agent-based modeling is the abstraction of a system into agents that have specific characteristics and behaviours, interactions between agents that affect agent behaviour, and an environment that interfaces with the agents [86]. An agent in an ABM can represent an individual, a group of people, or an organization, depending on the perspective of the modeler. ABMs employ a bottom-up perspective, where there is a focus on the micro-level system dynamics that are aggregated to obtain macro-level system dynamics. Agent-based modeling is similar to DES in the incorporation of heterogeneity via micro-level dynamics. However, the micro-level entities in ABMs are active agents while those in Discrete Event Simulations (DES) are passive entities [16]. For example, in an ABM that simulates PV system adoption, an agent can decide to make an autonomous decision any point during the simulation to purchase a PV system based on its preferences, influence from other agents, and the environment variables. On the other hand, with a DES, modeling the social aspect of PV system purchase is challenging since system progression in a DES is based on a predetermined and ordered set of events and actions can only be executed in the DES when events are triggered.

The bottom-up perspective of an ABM allows it to model the emergent properties of a system. Emergence results from the collective impact of agent actions, and their interactions with one another and the environment. However, ABMs are challenging to design because of factors such as the high level of complexity required to represent agents within a system, and the difficulty of validating the models. The former is solved by making a model simple and minimal, while adequately representing system processes of interest [145, 12, 40].

1.1.3 Comparing System Modeling Paradigms

Based on the characteristics of an ideal approach for modeling ST systems, Table 1.1 shows compares the capabilities of different system modeling paradigms. It is immediately obvious

Table 1.1: Comparing System Modeling Paradigms

Characteristic	**CGE**	**Econometrics**	**SD**	**DES**	**ABM**
Social components					X
Physical components	X		X	X	X
Socio-technical interactions					X
Implementable in software	X	X	X	X	X
Actionable insight	X	X	X	X	X
Explanatory power	X		X	X	X
Able to incorporate data	X	X	X	X	X
Emergence					X
Dynamic evolution					X
Scalability				X	X

that modeling socio-technical interactions requires the inclusion of the social and physical components of a system. Only ABMs meet this requirement since social components are simply not incorporated in other modeling approaches. Thus, in the remainder of this thesis, we use ABMs as our tool to evaluate policy alternatives in socio-technical systems. We next describe the ABM modeling process in more detail.

1.2 Agent-Based Modeling

We begin by noting that ABMs have already been used to solve real-world problems. For example, TRANSIMS [92] has been used to model transportation traffic at a large scale in Switzerland [107]. Similarly, Lammel et al. [80] present a decision support system based on an ABM, used to study the evacuation of people from a city in response to different emergencies: this system has been used in emergency situations [60]. We now review past work in the general area of ABM frameworks, followed by a review of ABMs used specifically for modeling energy systems. This is a very large area of work, and thus, we focus on only a few representative examples.

1.2.1 ABM Frameworks

Macal and North [86, 28] detail the agent-based modeling approach, highlighting the importance of a comprehensive representation of agent behaviour and agent interactions; these are the model aspects that result in emergent system behaviours. Furthermore, the authors mention that uncertainty in a model can be represented using stochastic components in the system model. Factors that justify the use of agent-based modeling include the need to model spatial elements, availability of clear agent behaviours and decisions, the need to represent agent interactions, etc. Their procedure for agent-based modeling is summarized as follows [28]:

1. Agent identification: The agents are typically the actors within the system of interest and their characteristics are determined by the factors that motivate their actions.
2. Environment identification: The environment variables determine the conditions within which the agents exist and carry out actions. These variables are defined after agent identification. These are also the variables that are crucial to the model but are not agent properties.
3. Agent behaviours: The actions executed by each agent type are defined based on frequency of actions and conditions attached to the actions. Agent behaviours are also influenced by the agent-environment interactions.
4. Agent-Agent interactions: The relationship between agents, regardless of agent type, are defined and the social interactions of agents are identified.
5. Model implementation: The ABM is transferred from a concept into software.

Nikolic and Ghorbani [96] present a structured approach for developing ABMs focused on socio-technical systems. This approach, which considers Multi-Agent System (MAS) and ABMs, comprises different stages: system analysis, model design, model specification, software development, and model evaluation. This work provides a detailed structure for designing a comprehensive and effective ST system ABM. This approach is broadly similar to the agent-based modeling approach discussed by Macal and North [28].

Tang et al. [128] present an ACP (Artificial system, Computation, Parallel implementation) approach for modeling a population of agents. They divide an artificial society into agents, the environment, and events. Events trigger agent behaviour which affect, and are affected by, the environment. In addition, formal and non-formal agent organizations are identified within the agent population, resulting in dynamics of social interaction. Here, a formal organization indicates a social network that has a clear and ordered structure.

Houwing et al. [61] focus on the representation of energy infrastructures as a system of systems. This work identifies the interdependency of the technological, institutional, and economic subsystems within the complex energy infrastructure system. The authors also discuss the viability of ABMs in identifying possible emergent high-level system behaviours, based on low-level agent behaviours and interactions.

Keirstead and van Dam [76] compare two ontologies for modeling energy systems as ABMs: van Dam [138] focuses on ST system while Keirstead et al. [75] focus on urban energy systems. van Dam decomposes the system into physical nodes, social nodes, physical nodes and physical edges. This enables the abstraction of the ST system as a socio-technical network. Keirstead et al. decompose the energy system into resources, infrastructures, and processes. The significant difference between these approaches is the addition of social nodes in [138].

Snape et al. study the potential of ABMs in elucidating energy behaviours. The electrical grid as an ST system is affected by individual behaviours and social interactions of these individuals that affect their energy behaviours [122]. This work focuses on three possible changes in energy behaviours: adopting smart control appliances, generating electricity, and changing electricity usage patterns. It is important to understand the reason for energy behaviours, in order to change them. Also, the authors emphasize the importance of appropriate learning models, whereby agents can learn from their experiences and other agents they interact with. As a result, each agent has a potential to influence other agents, and is also susceptible to influence. The learning models include reinforcement, Bayesian, and least-squares models. This work uses the energy cultures model in [123] to classify energy behaviours. We also use a similar model in our work.

Wilson and Dowlatabadi [142] discuss different behavioural model approaches for reducing residential energy consumption. These approaches include technology adoption, social and environmental psychology, and behavioural economics, to mention a few. The authors focus on interventions, i.e., actions that are used to influence behaviour. In particular, technology adoption models incorporate social network externalities and technological details. Diffusion models are related to the Theory of Planned Behaviour, with respect to a person's mindset being dependent on the perspective and appraisal of a certain behaviour [6]. They conclude that five attributes of innovations that engender adoption are basic advantages (e.g., cost and quality), ease of adaptation, ease of use, possibility of trial use, and observability of the innovation [112].

Chappin and Dijkema [27, 26] created a specialized framework for simulating energy policies and their impacts. They used this framework to evaluate CO_2 emission trading policies [25] and policies influencing high-efficiency light bulbs such as the Light Emitting Diode (LED) bulb [82]. While this framework is useful for energy policies, it excludes a significant aspect of creating ABMs for energy policies: eliciting and identifying the specific energy culture of the agents and geography being studied.

Stephenson et al. [123] study the fundamental behaviours that result in energy cultures, and present a framework for eliciting and structuring energy cultures into three integrated aspects: energy practices, cognitive norms, and material culture. This work, which uses a multi-disciplinary approach in defining energy cultures, is aimed at influencing behaviours within a ST system by identifying existing behaviours and determining which factors successfully influence these behaviours, which provides a foundation for the ABM approach. The authors also emphasize the need to change a cluster of behaviours rather than typical individual behaviours; for example, knowing the energy culture of a cluster of customers would enable a utility operator to define tariff plans for those customers, and modify energy consumption profiles accordingly. This energy culture can be identified via tailored questionnaires and existing energy consumption profiles. The energy culture approach has been applied in Waitati, New Zealand, in order to increase the number of insulated homes by providing government subsidies.

1.2.2 Modeling Human Behaviour in ABMs

In creating an ABM with human agents, a theory for representing agent behaviour has to be established. When using ABMs to research energy systems, it is important to consider modeling non-rational aspects in human behaviour. Kennedy [77] provides an overview of how human behaviour can be abstracted into agent behaviour in ABMs. The three broad approaches for representing human behaviour (not specific to ABMs) are simple mathematical models, conceptual frameworks, and cognitive models:

- Simple mathematical models simplify agent behaviours in terms of utility functions. They use threshold values for some variables in order to model agent decision making. For example [56].
- Conceptual frameworks model agent decision making by using concepts such as beliefs, emotions, and desires. Examples of conceptual frameworks include BDI (Beliefs, Desires, and Intentions) [108], Theory of Planned Behaviour (TPB) [6], and PECS (Physis, Emotion, Cognition, Social Status) [134].

- Cognitive models originally designed for generally modeling human behaviour, can also be used for agent-based modeling. Examples include Soar [81] and ACT-R [10]. One theory that is well suited to model energy agents is Affect Control Theory (ACT) [59]. According to ACT, people have affective identities, as well as affective (emotional) representations of actions and events, and they take actions in order to minimize the deflection from their identities caused by these actions and events. ACT models culturally shared affective sentiments along three dimensions – Evaluation, Potency, and Activity (EPA) – and deflections are measured as distances within this space. Evaluation ranges from good to bad, potency ranges from strong to weak, and activity ranges from active to passive. According to Shank [120], ACT can be used for human-technology interactions. We discuss ACT more in Section 2.2.2.

1.3 An Approach to Designing ABMs for Energy Policies

We now discuss our proposal for developing ABMs for energy systems. We build on the Chappin ABM framework [26] by adding energy cultures and the concept of a data-driven energy agent. To incorporate energy cultures, we first carry out a survey, that is informed by an *agent set*, a *policy set*, and available energy system data (Figure 1.1). The agent set comprises the different agent types, with certain characteristics and behaviours. The policy set comprises the policies already being implemented in the energy ecosystem of interest and policies that could influence energy system transitions.

Using this approach, we can learn about the energy culture of the survey respondents within the geography being studied without having to make assumptions about them. For example, the motivations for purchasing PV panels could include solar panel price, influence of the environment, system payback period, etc. With a survey, we can determine the specific impact of each component. Furthermore, this survey is used in determining agent properties, and is used to interpolate the response of agents to different policies within the feature space. In addition, we emphasize the secondary impacts of policies on the ecosystem. For example, we simulate the impact of solar panel and battery adoption on the electric load profile; accompanying policies that manage the load profile can be implemented if necessary.

The work closest to ours is by Rai and Robinson [106] who study energy technology adoption, using solar panel adoption in Austin, Texas as a case study. However, this study does not propose any framework. Furthermore, our ABM framework goes beyond

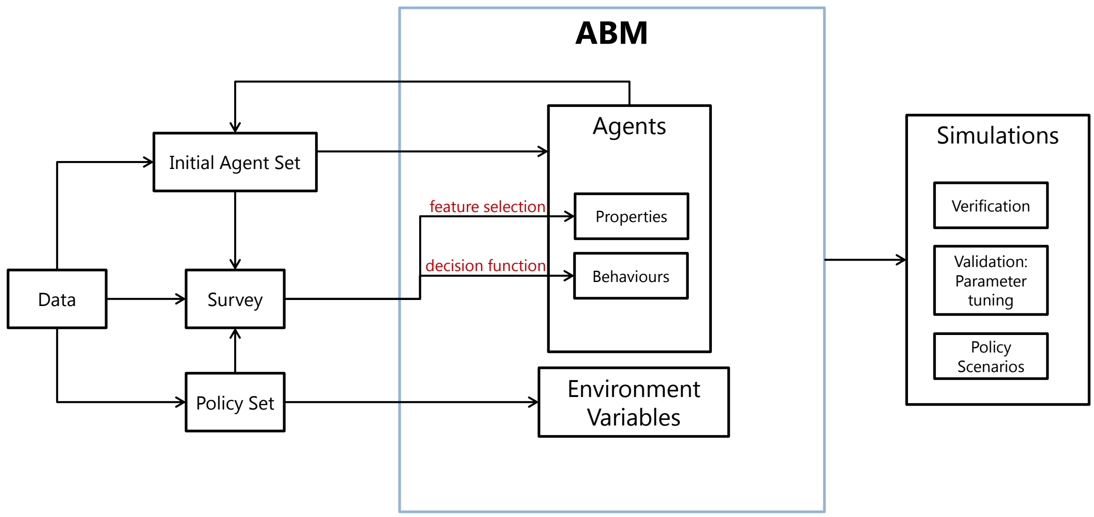


Figure 1.1: Overview of ABM Framework for Energy Policies

modeling only energy technology adoption and has been used for other energy policies such as Time-of-Use (ToU) electricity pricing.

The main idea of our framework is to develop an ABM based on the initialization of data-driven agents via a survey. Before discussing the process in greater detail, we first summarize it as follows:

1. Collect data on energy ecosystem of interest.
2. Identify and define the agent set, policy set, and environment variables.
3. Design and publish survey.
4. Identify the non-trivial factors that influence agent behaviour using feature selection and develop an agent decision function based on the relative impact of the selected features.
5. Create ABM based on responses from the survey. Here, the agent set is redefined based on the feature selection and agent decision functions. The survey provides the ground truth for policy outcomes with certain parameter settings. Also, the agent set, policy set, survey, and environment variables form the core of the ABM (Figure 1.1).

6. Verify and validate ABM.

7. Simulate policy scenarios and compare the impacts of different policies.

The function of each component and the existing relationships between them are now discussed in detail.

1.3.1 Collect Contextual Data

The results from an ABM are only as good as the contextual data used to create the model. In studying energy policies, typical data sources include official reports from public institutions and utilities, private industry reports, and vendor quotes – surveys also constitute data but are separated out in this framework due to the interactions between the agent set, policy set, and the survey as seen in Figure 1.1.

The energy ecosystem data inform the agent set, the policy set, survey design, environment variables, and consequently, the scenario simulations. For example, when modeling the adoption of PV panels and batteries, it is important to collect data that define how PV panels and batteries are acquired and used. This includes system prices, generation capacity, solar irradiation, maximum installation capacity, modes of system operation, etc. This is important in creating environment parameters that affect the purchase decision of agents and system usage pattern. As a result, the ABM for energy policies has to be data-driven.

1.3.2 Agent Set

We define an energy agent as an agent that

- makes decisions to acquire energy appliances/technologies;
- generates, consumes, and/or stores energy;
- is social (modeled in ABMs as agent-agent interactions); and
- is data-driven.

The agent set comprises the energy agents that model the energy ecosystem. Typically, these are the targets of energy policies. For example, when considering the adoption of PV panels in Ontario under the microFiT program[4], agents include homeowners and small business owners. Once the potential agents are identified, their characteristics and behaviours need to be defined. For example, with solar panel and battery adoption, the agent behaviours include purchasing PV panels and batteries, consuming electricity from the grid and PV panels, and storing electricity in the batteries. The agent behaviours further determine what characteristics are required for the agent, e.g., an hourly electrical load profile. Also, in defining the agent, it is imperative to consider how the agent generates, consumes, or stores energy.

Furthermore, in modeling agent behaviour, both rational and irrational determinants of behaviour must be considered. With respect to the adoption of PV panels, rational factors include price of PV panels, payback period, return on investment, and income, while irrational factors include the influence of the social network, environmental concerns, and sentimental impressions of PV panels. These variables are obtained from the survey and the importance of each factor is identified through feature selection and logistic regression.

1.3.3 Policy Set and Environment Variables

The policy set includes both the current policies being used in the ecosystem of interest as well as potential policies that could be introduced into the system to obtain a favourable system transition. Policies can be incorporated into an ABM by modifying one or more environment variables accordingly. In our framework and ABMs in general, policies can be expressed as certain settings of the environment variables that affect agent behaviour. Continuing with our PV adoption example, policies determine the price of PV panels, the price of batteries, the FiT, and the price of electricity. These variables influence the decision of each agent to purchase PV panels and batteries. As a result, the effectiveness of each policy can be compared based on the response of agents to the parameters corresponding to each policy.

Note that certain policy parameters can change over time. For example, the decay in FiT prices over a period of time, which is determined by policymakers, would influence the rate of PV adoption. This dynamic modeling of policy parameters should be based on data where possible. This is likely to be more realistic than policies determined using the

[4]This is a program where homeowners and small business owners in Ontario can purchase solar panels with a maximum capacity of 10 kW, and are paid a certain amount for each kWh of electricity generated from the solar panels over a period of 20 years.

alternative approach of studying the response of agents to a certain policy at a single point in time. An example of this is seen in a study by Pat [104] where the model focuses on the response of people to different policies that affect their energy consumption. In contrast, we model time evolution in order to evaluate policy performance over a period of time, typically, years.

It is important to determine the limits that constrain policymaker choices. For example, to study a policy that enforces PV system price reduction, we need to consider a *realistic* range of PV system prices based on industry forecasts and domain knowledge. In our work, with this range of prices, we found that the PV system payback period in Ontario would be, at least, 6 years. Also, the maximum reasonable payback period is 20 years, given this is the duration of Ontario microFiT contracts. Having thus established the upper and lower limits of the payback period, the survey asks respondents to consider purchasing PV systems with payback periods in this range. This approach can be applied to other decision variables as well, such as the return on investment.

The environment parameters and agent decision parameters constitute an n-dimensional variable space. We choose different policy scenarios, with each policy scenario corresponding to one point in this variable space. Using ABM simulations, we study these policy scenarios and then in some cases, can interpolate agent decisions in-between the chosen points (more on this below in Section 1.3.4). With this approach, we can estimate the impact of policies whose specific environment parameters were not tested in the survey, reducing the number of questions we need to ask in a survey.

We use survey responses to create data-driven agents and agent decision functions (Section 1.3.5), that are used in simulations (Section 1.3.6). In simulations, we map policies to environment variables, e.g., reduction of the PV system price, increasing the electricity price, increasing the FiT, etc. These variable changes are then mapped to each agent's purchase decision outcomes.

1.3.4 Survey

One important aspect of this approach is using the survey to elicit the parameters and behaviour of an energy agent. The energy agent characteristics and behaviours are based on the energy culture [123] – energy practices, cognitive norms, and material culture – identified within the ecosystem being studied. Here we discuss how the survey is designed, and how it influences the ABM parameters and agent decision functions.

As mentioned earlier, the survey is designed based on the agent and policy sets. The survey design should be influenced by the initial definition of the agent set. That is, the agent characteristics and behaviours should determine the questions that are asked since the survey should aim to identify the factors that influence agent behaviour, the energy culture of the jurisdiction being studied, and the demographics that are important in the study. Subsequently, by using feature selection (Section 1.3.5), the important and trivial agent characteristics can be separated based on the survey results. In some cases, a mathematical function of how an agent makes decisions can be defined (see in Section 1.3.5). As mentioned in Section 1.2, one property of ABMs is the agent-agent interaction modeled as social networks. The decisions taken by an agent could be influenced by its social network. For example, in solar panel adoption, an agent would not purchase PV panels unless a certain fraction of its social network own PV panels.

Survey questions should be selected such that they can be used to determine which features are important in the model, and how agents make decisions. For example, factors that affect solar panel adoption could include system price, payback period, care for the environment, etc. An example of a question that could be used to measure the validity of the concern for the environment could be *"By how much does your concern for the environment influence your decision to purchase PV panels?"*. As a result, the impact of the concern for the environment on solar panel adoption could be measured using feature selection.

The survey respondents should be representative of the population being studied. While this may be difficult with online surveys, measures could be taken to verify the demographics of the population being studied. For example, while studying PV adoption in Ontario, survey responses from other provinces in Canada were not included in the study. While there might be a bias with the initial set of variables selected as being potentially relevant, this selection should be based on domain knowledge, industry trends, and prior studies. We note in passing that this initial bias problem plagues any domain study that involves data analysis.

It is also important to ensure that each question in the survey translates to additional information in the ABM, i.e., no question should be redundant. For example, while it might be interesting to know how much respondents spend on electricity, a question that asks for the monthly electricity bill should not be included in a survey if it does not inform the solar panel purchase decision. Furthermore, test questions should be included in order to eliminate respondents that may not be answering questions attentively, particularly in online surveys. An example of such a question is *"Do you agree that three dollars plus 6 dollars is 4 dollars?"*.

1.3.5 Feature Selection

Feature selection is the process of identifying variables that are essential for estimating a certain target variable. Feature selection improves a model by excluding irrelevant features, making the model simpler while improving its effectiveness. In feature selection, each feature is correlated with the target variable – survey respondent purchase decisions – and the features that influence the target variable are selected. Furthermore, we use cross validation to ensure the validity of the features selected. By selecting features, we can obtain a better understanding of energy cultures and have more focused energy policies. For example, we found that in Ontario, the factors that mostly affect purchase of solar panel and battery systems include system cost, payback period, the inclusion of a battery in the system, and the maximum budget each person would spend on the system. In other regions and countries, the important features could be different; with a similar study in Germany, the concern for the environment turned out to be also important.

Different feature selection methods exist and they are broadly classified as filter, wrapper, and embedded methods [24]. While each class has its benefits, embedded methods in particular, train the model and select features simultaneously – regression algorithms fall within this class. In our work, we use the Lasso Least Angle Regression (LARS Lasso) [116, 36] for feature selection; LARS Lasso combines the benefits of the Lasso and the LARS models. LARS provides a stable variable coefficients, that is, independent variables that similarly influence the target variable have coefficients that increase at similar rates. Lasso is suitable for feature selection because a significant number of the calculated coefficients are zero, therefore reducing the data dimensionality [116, 36].

Agent Decision Function

The agent decision function is a mathematical function that determines what action an agent would take in any given situation. For example, the decision to adopt PV panels could be a function of payback period, system cost, return on investment, etc., where each variable is assigned a level of importance via a coefficient. Therefore, such a function estimates the utility of the purchase decision.

Different methods of modeling human behaviour in ABMs have been highlighted in Section 1.2.2. In our approach, we use a logistic regression (logit) model, where the probability of a decision is the output of the function based on a logit transformation of previously selected features. This regression method is a common approach for modeling functions with a binary output [49], hence, its suitability for our ABM. For example, the choices made by agents could be purchasing a PV-battery system or not – this corresponds to a binary output. In our work, when carrying out the regression, any feature that does not meet the 95% confidence interval is excluded from the model. The logit model is trained on survey responses to the policy set and used to model agent decisions in different policy scenarios. With this logit model, we can interpolate within the environment parameter space and determine the probability that each agent makes a given decision based on the input features.

In some cases, the logistic regression on survey responses does not result in a statistically significant model. In such a situation, the agent decisions cannot be interpolated within the policy parameter space, limiting the policy scenarios that can be tested to only the ones included in the survey. In this case, the agent decisions must be encoded directly from the corresponding survey responses to different policy scenarios.

In our work, we carry out case studies on adoption of technologies. It is well known that a purchase decision for any technology can be influenced by level of adoption of the technology in the agent's social network [79]. According to Bass [15], adopters of products or services can be categorized as follows: innovators, early adopters, early majority, late majority, and laggards. Innovators are those who adopt new products regardless of social influence while laggards adopt a product after it is commonplace. In our adoption case studies, we represent this level of adoption with the social threshold T where $0 \leq T \leq 1$ [53]. An agent will not adopt a product if the fraction of its social network that has adopted that product is less than the agent's T_i. We should point out that T_i is unique to each agent i and is randomly drawn from a Gaussian distribution with a certain mean μ and standard deviation σ. This distribution is also used in ABM validation (discussed in Section 1.3.6).

1.3.6 Simulations

In simulations, the system model is executed with an abstraction of system processes over a period of time. This is accompanied by the generation of system model outputs. According the ABM approach [28], a model should be verified and validated before executing scenario simulations. Heath et al. survey different ABM models published over a period of 10 years (1998 - 2008) [58] and emphasize need for proper verification and validation in ABMs. Verification and validation in ABMs has been discussed by Galán et al. [48]. In agent-based modeling, *errors* result from mistakes in simulating the model while *artefacts* result from assumptions made during modeling. In other words, an artefact occurs when significant aspects of a system are assumed to be inconsequential, while an error occurs when the model does not match the developer's concept of the model. The authors present a general approach for ABM development, and discuss where errors and artefacts may occur, and how to correct them. Verification is used to identify errors while validation is used to identify artefacts within the model. In this thesis, both verification and validation were carried out on the ABM models[5].

Verification

Verification checks the model for errors in code and model simulations. We conduct test-case simulations to ensure that the model simulations follow the conceptual model. For example, in the Ontario solar panel adoption model, we ensure that the model calculates the payback period correctly, and that payback periods considered fall below the maximum limit of 20 years listed in Ontario FiT contracts. This is done by creating test cases, where the payback period is known, and testing the payback period estimation function to ensure that the right value is produced by the simulation. In doing this, different common cases and parameter edge cases are tested.

Validation

Validation identifies artefacts in the model and ensures that the ABM correctly models agent behaviour and system processes. That is, the conceptual system model should adequately and correctly represent the real-world system. Validation differs from verification; validation checks for discrepancies in the conceptual model while verification checks for errors in code and conceptual model execution. Validation is done by comparing simulation results with known outcomes from the past. For example, given the adoption of PV panels in Ontario under the FiT program, we validate the model by simulating the adoption of PV panels under the same price conditions as in the past. We model the social threshold distribution in the agent population as a truncated normal distribution with a certain mean μ and standard deviation σ, where each agent is randomly assigned a particular T_i within this distribution.

To validate the ABM, we select a range of μ and σ for T and find the pair with the closest fit to historical adoption. This parameter tuning acts as a form of validation and provides a reference point for future scenario simulations. This tuning approach could be applied to any hidden variables within the system of interest.

[5] In the ToU electricity pricing study, we did not carry out validation. This is discussed further in Chapter 4

1.4 Limitations

While the modeling framework detailed in this chapter is viable for evaluating energy policies, there are several limitations to this approach:

- Validation: As stated earlier, validating an ABM is often difficult.
- Availability of data: Data is often scarce and expensive to obtain, sometimes unavailable. In cases where the required data for designing the model is not available, reasonable assumptions have to be made.
- Validity of survey responses: Survey respondents might not always be truthful in answering questions. We attempt to solve this problem by including test questions and excluding survey responses with incorrectly answered test questions..

1.5 Summary

We have discussed an ABM framework for energy policies, highlighting the importance of each underlying component. The framework builds on the agent-based modeling paradigm, taking advantage of the emergent property of ABMs in modeling energy systems and adding features suitable for evaluating energy policies. In addition, we show how this framework improves on other similar approaches by integrating energy cultures and defining the concept of a data-driven energy agent, therefore providing a data-driven ABM framework.

We have used this framework to define and evaluate energy policies with case studies on different problems and regions. In summary, the contributions of this thesis are as follows:

1. An ABM framework for energy policies, based on the concept of a data-driven energy agent. This is not a contribution to agent-based modeling as a practice but a contribution to the evaluation of energy policies using ABMs. We have used this framework to carry out three case studies.
2. An ABM focused on solar PV and battery adoption, with a case study on Ontario. The price of solar panels and batteries continue to reduce, and this could disrupt the energy industry. Furthermore, there is a need for more sustainable and efficient energy systems given the current climate challenges. As a result, we study the adoption of PV and batteries in Ontario, considering different policies that could drive

PV adoption. The results show that it is unlikely that the rate of adoption would grow in Ontario unless there is a policy intervention. The most effective policy would be one focused on PV and battery system price reduction.

3. An agent-based EV ecosystem model, comprising EV purchase and use. Here, agents can purchase, drive, and charge EVs. We use this model to EV adoption in San Francisco and Los Angeles. We found that the EV selling price is the most significant barrier to EV adoption, and policies that would effectively reduce the price of EVs should be maintained. Furthermore, with improved battery technology, the need for public charging stations is likely to reduce but there does not appear to be any need for additional driving range since most trips are short. The two case studies have been published [3, 2].

4. An ABM to study the impact of ToU electricity pricing. ToU pricing was implemented in Ontario in 2006. We conducted a study [4] and found that the ToU pricing peak, mid-peak, and off-peak periods do not match the Ontario load data. As a result, we conduct a study to analyze how residents of Ontario use their most flexible loads – washing machine, clothes dryer, dishwasher – and how they would respond to different ToU pricing schemes.

Chapter 2

Solar PV and Battery Adoption

Publication Reference:

A. Adepetu, S. Keshav. Understanding Solar PV and Battery Adoption in Ontario: An Agent-Based Approach. *ACM e-Energy 2016.*[1]

The adoption of solar photovoltaic panels and batteries greatly reduces a grid customer's carbon footprint, while simultaneously reducing their dependency on conventional electricity supply. Given the significance of both outcomes, it is important to understand the potential effect of energy policies on the adoption of these 'PV-battery systems' before they are actually implemented. We therefore design and implement an Agent-Based Model (ABM) that captures the purchase and usage of PV-battery systems. Focusing on Ontario, we use a survey to elicit the responsiveness of residents to potential energy policies. We parameterize the ABM based on survey results to forecast the relative performance of different energy policies[2].

2.1 Introduction

Solar Photovoltaic (PV) systems are perhaps the single best technology to reduce mankind's carbon footprint. A major challenge to widespread adoption of solar PV systems, particularly in a domestic setting, is their intermittency. Storage solutions, such as the Tesla

[1]The research work from this paper that is included in the thesis was carried out and documented by the author of this thesis.

[2]The ABM simulation code can be found at `bitbucket.org/adeda/pv-battery-adoption`

Powerwall [119], can mitigate this intermittency, storing excess generation and releasing it when needed. This suggests that future homeowners could adopt a PV-battery system to generate their own electricity and thus greatly reduce both their carbon footprint and their electricity costs [119, 133]. Customer-owned batteries can also provide secondary services such as time-of-use price bill management, backup power, and reduction of peak power charges [46], further lowering their effective cost. Yet, there has been only a low level of PV system adoption over the past 5 years in Ontario, our jurisdiction of interest[67]. Thus, we seek to study the reasons for this situation, whether we can expect it to change in the near future, as well as policy decisions that could improve PV-battery adoption. A secondary focus of our work is to estimate the grid impact due to the adoption of PV-battery systems, so that their increased adoption does not impact grid stability.

Estimating the effect of policies on PV-battery system adoption requires a careful modeling of the system purchase decision by individual homeowners, who are, in the end, the true agents of change. Instead of using regression to extrapolate growth based on past trends which is the typical approach used by policy makers, we use an ABM to study the impact of individual decision-makers on the adoption and usage of PV-battery systems. An ABM comprises agents with certain properties and behaviours, that interact with one another and with their environment. These behaviours and interactions model real-world processes and hence the impact of different environment conditions. This simple yet powerful method can be used as an effective tool to forecast changes in socio-technical systems [138, 137, 96, 71]. In our work, agents are homeowners who decide to purchase (or not) a PV-battery system in each simulated time period. These agents are defined by properties such as budget for PV-battery system, hourly electric load, and social network, and they respond to policy decisions such as the designated Feed-in Tariff (FiT) rate. We also consider both rational and irrational components of the purchase decision process.

While most related ABM-based studies focus on PV adoption and a few study the impact of PV adoption on the electric grid [111, 102, 91, 62, 147, 148] we go further by modeling *both* PV and battery adoption as well as their resulting effect on the electric grid. This is important because battery storage fundamentally changes the interaction of PV systems with the electric grid. Moreover, we employ a data-oriented approach to calibrate agent and environment properties by conducting a survey and collecting data from utilities, official reports, and vendors.

Using this approach, we find that the price, payback period[3], purchase budget, and inclusion of a battery (or not) are the factors that influence the decision to purchase a system. Also, our results show that there is unlikely to be a sudden increase in PV adoption

[3]The payback period is the time it takes for an investment to pay for itself.

in the next 10 years in Ontario. To address this, reducing the price of PV-battery systems is the most effective approach; increasing the price of electricity could also force some people to consider the PV-battery option.

2.2 PV-Battery System ABM

In this section, we discuss the adoption and usage of PV-battery systems in Ontario. In addition, we detail the ABM parameters used in our work.

2.2.1 ABM Design

In this study, we focus on an ABM for PV-battery system and usage, where agents are homeowners that can buy PV-battery systems, use these systems to generate and store electricity, and consume electricity based on certain load patterns. In addition, the interaction between agents is modeled as a form of social influence where one agent can be influenced by its social network to purchase a PV-battery system. Our goal is to use our model to compare different policies, with a methodology that allows us to study purchase decisions in response to policies other than those presented in our survey.

2.2.2 Agent Decision Making

To define agent behaviour, we create a mathematical model of agent decision making. In our work, we model both the rational and irrational components of decision making. Specifically, in purchasing PV-battery systems, we consider the following rational factors: budget, payback period, system cost, annual Return on Investment (RoI), prior knowledge of PV systems, perceived impact on the environment, and whether the system includes a battery or not. We also consider the following irrational factors: susceptibility to social influence and emotional impressions of PV systems.

We model the irrational components of decision making using Affect Control Theory (ACT), which we outline in Section 2.2.2. Social influence determines how knowledge of other agents' actions influences when an agent enters the market to purchase a PV-battery system (Section 2.2.2) while other variables are fitted to a logistic regression equation that determines whether an agent purchases a particular system or not.

Modeling Irrationality using Affect Control Theory (ACT)

ACT is a theory to model the sentimental (or *affective*) aspects of actors, objects, and their behaviours [59], including human-technology interactions [120]. This theory is quite rich and we can only sketch it in what follows.

ACT models shared cultural affective sentiments of agents, objects, and behaviours in a space with three dimensions – Evaluation, Potency, and Activity (EPA). Evaluation ranges from good to bad, potency ranges from strong to weak, and activity ranges from active to passive. Thus agents, objects, and behaviours can be thought to be tagged with a three-tuple from this EPA space. Moreover, the space allows us to compute the distance (or *deflection*) between any two entities.

Actors have *affective self-identities*, as well as *affective representations* of behaviours. Agents always act in order to minimize the deflection of actions from their self-identity. Specifically, the deflection measures how an actor feels about taking a particular action on another object. The higher the deflection, the less comfortable the actor is with that action. For instance, if a homeowner has a self-identity that he or she is 'green,' then they would act in ways that reinforce this identity, that is, to minimize the deflection between their self-identity and action. This deflection is computed from the actor's EPA ratings of himself/herself, the behaviour, and the actor/object that the behaviour is directed to.

In making a purchase decision, agents are influenced by both context-independent (*fundamental*) and context-sensitive (*transient*) sentiments [114]. Transient impressions are the EPA ratings of the actor, object, and behaviour within a particular situation whereas fundamental impressions are situation-independent. For example, in the case where a homeowner buys solar panels, the Actor A is the homeowner, the Object O is the solar panel, and the Behaviour B is buying. These elements have EPA tags that are situation-independent and can be found using a questionnaire. The deflection D created by a particular situation is obtained from both the fundamental impressions of an Agent A, Behaviour B, and Object O, as well as the transient impressions represented by A', B', and O' when A carries out B on O using a technique developed by Schröder [114]. In this work, we use this deflection as a variable in the agent's PV-battery purchase decision function.

Social Influence

As discussed in Section 1.3.6, adopters of products or services can be categorized as follows: innovators, early adopters, early majority, late majority, and laggards [15]. Innovators are those who adopt new products regardless of social influence while laggards adopt a product after it is commonplace. While we do not assign agent to the listed adoption categories, we model agents with the social threshold T where $0 \leq T \leq 1$ [53]; an innovator would have a low T while a laggard would have a high T.

An agent will not adopt a product if the fraction of its social network that has adopted that product is less than the agent's T_i. We should point out that T_i is unique to each agent i. Unlike other consumer goods, PV systems are easy to spot on rooftops. Thus, the critical parameter in terms of social influence is not the degree of adoption in the agent's social network but rather the degree of adoption in the *entire* visible population. We should note that the sensitivity of PV-battery system adoption to social influence is not considered in our work; Graziano and Gillingham [54] provide insight on the importance of social influence in PV adoption.

We model the social threshold distribution in the agent population as a truncated normal distribution with a certain mean μ and standard deviation σ, where each agent is randomly assigned a particular T_i within this distribution. To validate the ABM, we select a range of μ and σ for T and find the pair with the closest fit to historical adoption. We now discuss ABM validation.

2.2.3 Data Description

Typical data sources include surveys, official reports from public institutions and utilities, private industry reports, and vendor quotes. Official utility reports and documents provide information on system constraints, prices, and current trends within the socio-technical system of interest. For example, in Ontario, FiT contracts (except waterpower contracts) run for only 20 years [66] even though PV systems are generally expected to function for 30 years. This is important in creating environment parameters that affect the purchase decision of agents and system usage pattern. In addition, industry reports and vendor quotes also provide information on past prices and predicted future price trends; these are useful in model validation and simulations of future scenarios.

For our analysis and simulations, we use actual hourly load data from anonymized smart meter readings in 100 residences in Ontario, Canada. This data has been provided by a local utility company. These hourly load values are used in our economic analysis in the survey design process. In addition to the load data, we use solar PV generation data available from simulations in System Advisor Model (SAM) [93] with solar radiation data from a solar station in Toronto, Ontario.

The main environment variables that are used to model changes in simulation scenarios are as follows: ToU pricing scheme, FiT value, PV prices, and battery prices. Other environment variables include discount rates, battery life, hourly PV generation per kW, and simulation date and time (these are explained in Table 2.1[4]). The actions executed by agents are the purchase of PV-battery systems and the consumption of electricity, and these are determined by the agent and environment variables. Agent variables are discussed in Section 2.2.6. Other data such as electricity prices and PV-battery system prices are obtained from online sources [100, 126] and vendor quotes[5].

[4]All prices listed in this study are in Canadian Dollars, unless stated otherwise

[5]We cannot provide the vendor names since they requested not to be cited.

Table 2.1: Environment Parameters

Variable	**Definition**	**Source**
FiT ($/kWh)	This is the amount paid to a PV owner for each kWh generated from solar PV.	Ontario's microFiT program pays $0.384/kWh for rooftop PV installations not more than 10 kW [64]. In our model, we assume solar PV systems are installed on the rooftop.
ToU Electricity Price	In the ToU pricing scheme, electricity consumers are charged at a rate based on the season and the time of day.	Figure 2.1 shows the ToU pricing scheme in Ontario (at the time of writing).
Installed Solar PV price ($/kW)	This is the cost of purchasing and installing a solar PV system of a certain capacity.	The rate per kW is dependent on the capacity. Figure 2.2 [126] shows the rate for each PV capacity range used in our work.
Installed Battery Price ($/kWh)	This is the cost of purchasing and installing a battery of a certain capacity.	With current market conditions [118], we set this at $1500/kWh.
Battery Depth of Discharge (DoD)	This is the maximum percentage of the listed battery capacity that can be used.	The current lithium ion (Li-ion) battery technologies have a DoD of about 80% [51, 140].
Battery Life (years)	This is the amount of time a battery can be used.	With Li-ion current technology, there is no particular fixed time as it depends on usage. For usage with solar PV in a home, one vendor provides a 10-year warranty for their batteries where the battery is replaced if its state of health falls below 80% [44]. As a result, we set the battery life at 10 years.
Battery Charge Efficiency (years)	This is the ratio of the amount of energy stored on a battery while charging to the total energy dissipated in the charging process.	Li-ion batteries have a charge efficiency of 85% [140].
Battery Discharge Efficiency (years)	This is the ratio of the amount of energy obtained from a battery while discharging to the total energy dissipated in the discharging process.	Li-ion batteries have a discharge efficiency of nearly 100% [140].

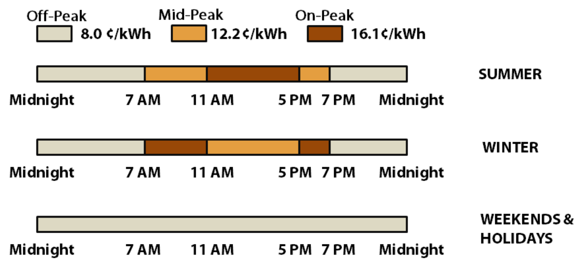


Figure 2.1: Ontario ToU Pricing Scheme [4, 99]

2.2.4 Survey

We conducted a survey targeted at Ontario's residents. The aim of the survey was to evaluate the rational and irrational (affective) responses of people to PV-battery systems. Specifically, we focused on the following:

i. The decision of respondents to purchase PV systems, or not, with and without batteries under several distinct price conditions.

ii. The concern of respondents about the environment and how this may have affected their purchase choices.

iii. An EPA rating, based on ACT, for concepts such as PV panels, batteries, buying, homeowner, and business owner.

We needed to present survey respondents with different options for PV-battery systems, where a homeowner can choose to use electricity from the battery rather than the grid during peak hours and see their corresponding costs. Thus, prior to doing the survey, we first evaluated the costs and net returns of different solar PV capacities ranging from 2 to 10 kW, with and without corresponding battery sizes between 2 and 7 kWh (Figure 2.3)[6]. We assumed that the battery is charged during the Ontario ToU pricing mid-peak and off-peak hours (Figure 2.1), and the battery is discharged to (partly or wholly) serve the load during the peak hours.

These preliminary calculations let us estimate the payback, Return on Investment (RoI), and system costs associated with purchasing different capacities of PV-battery systems. Here, we take into consideration the cost savings from the battery operation scheme

[6] We limit the PV component to 10 kW since this is the Ontario microFiT limit.

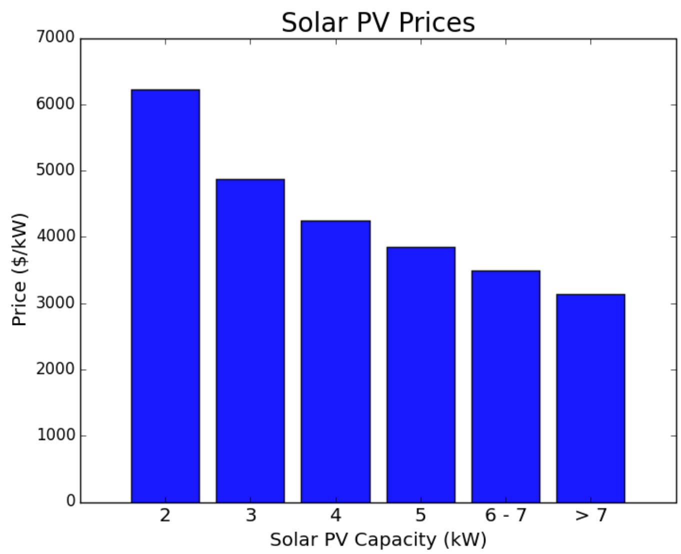


Figure 2.2: Solar PV Prices in 2015

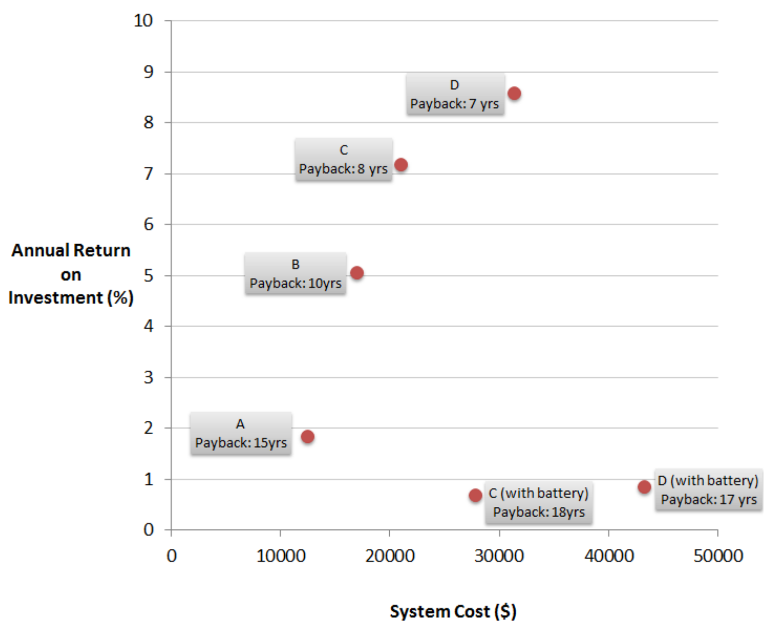


Figure 2.3: Sample Survey Question (1): Which system(s) would you buy?

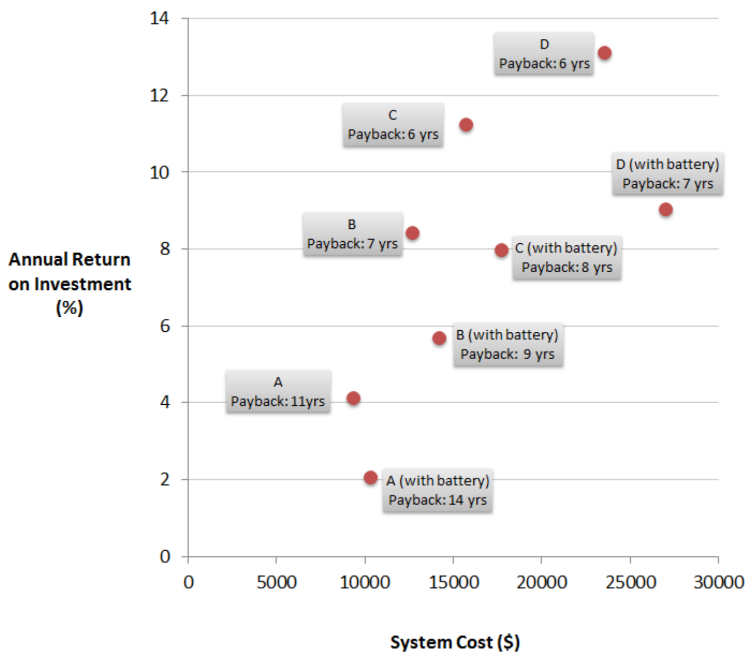


Figure 2.4: Sample Survey Question (2): Consider a different cost and price scenario; which system(s) would you buy?

and the profit from selling electricity to the grid through the Ontario microFiT program. The payback period (years), based on a discounted payback calculation given by [45]:

$$Discounted\ Payback = \frac{\ln(\frac{AI}{AI - Capex \times d})}{\ln(1+d)} \tag{2.1}$$

where d is the discount rate, $Capex$ is the capital expenditure, and AI is the annual cash inflow, which is assumed to be the same every year. In addition, the RoI is given by:

$$RoI = \frac{Total\ Lifetime\ Inflow - System\ Cost}{System\ Cost} - 100\% \tag{2.2}$$

If a system has a $RoI \leq 0$, it is considered to be a bad investment. As a result, systems A and B with batteries are not shown in Figure 2.3. We should note that the cost of replacing batteries at the end of the battery life is included in the analysis. Our analysis therefore provides the economic analysis from a few examples of PV-battery systems for our survey, for which we can directly estimate the degree of adoption. However, with the ABM, we can additionally interpolate within these example systems based on factors such as payback, system costs, RoI, etc. Furthermore, to represent future scenarios, we change variables such as PV-battery system prices, resulting in a different payback and RoI for each system option. An example is shown in Figure 2.4. As a result, we can interpolate and model agent decisions in scenarios with different electricity and system prices than those in our survey.

In addition to selecting PV-battery systems, respondents were also asked to rate different concepts on each EPA dimension; the terms rated were 'homeowner', 'buying', 'solar panel', and 'battery'. A transformation matrix obtained from prior ACT surveys [114] was used to estimate the deflection associated with each respondent purchasing solar panels and batteries. We should note that responses that involved the selection of one rank on all EPA scales were excluded from the estimation since this suggests that little or no thought was put into answering the question.

The survey was distributed using Crowdflower [29], with a restriction for only respondents in Ontario. We also added test questions to check if respondents were paying attention to the questions and used only those surveys that answered the test questions correctly. Figures 2.3 and 2.4 are examples of options in the survey questions, where respondents are asked to choose to buy or decline each system. We had 648 survey respondents from Ontario, out of which 381 were valid since they answered our attention test question correctly.

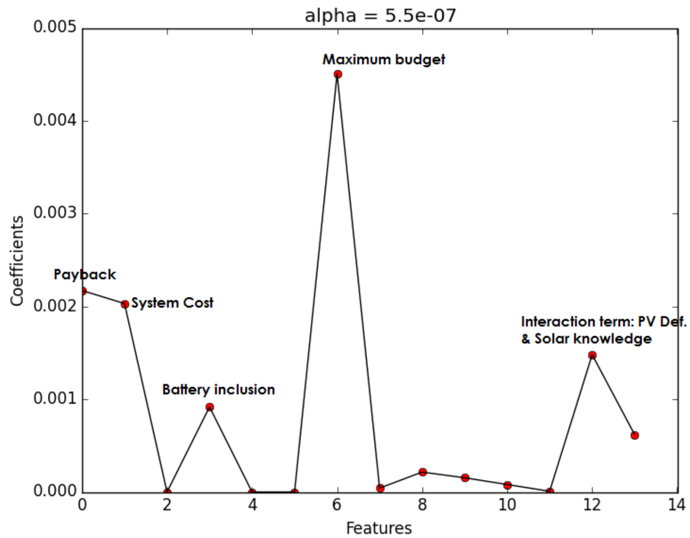


Figure 2.5: Magnitude of Coefficients for Feature Selection using Lasso LARS

2.2.5 Feature Selection and Logistic Regression

To understand purchase decisions better, we identified factors influencing a purchase decision such as payback, annual savings, RoI, and capital cost. In addition, we considered people's budgets, attitudes towards the environment, ACT-based deflection associated with purchasing PV-battery systems, and knowledge of solar systems. These variables are described as follows:

- Payback period: For each PV-battery system option, there is an associated payback period (Figure 2.3).
- System cost: This is the cost listed for each PV-battery system in the survey.
- RoI: This is the return on investment listed for each PV-battery system in the survey.
- Budget: This is the maximum amount each respondent would spend on a PV-battery system.
- Deflection: This is the deflection estimated from each respondents ranking of actors, behaviours, and objects on the EPA scale (See Section 2.2.4).

- Environmental impact of PV: Respondents were asked if they agreed using PV systems has a positive environmental impact. This was done on a *Likert* scale ranging from strongly disagree to strongly agree.

- Influence of environmental impact on decision: Respondents were asked how much the significance of the environmental impact of PVs would affect their decision to purchase a PV-battery system. This was also done on a Likert scale ranging from nothing to very significant.

- Expected social influence: This is level of influence each respondent expected that their friends and relatives purchasing PV systems would have on their PV-battery system purchase decision.

- Knowledge of PV systems: Each respondent was asked to select a particular level of PV system knowledge. The level of knowledge ranges from knowing nothing to having expert knowledge.

Using Lasso Least Angle Regression (Lasso LARS) [36], we identified the features that had the most impact on purchase decisions. To do so, all valid survey responses were divided into 10 randomized folds, and the variable coefficients were recorded. In addition, we set the regularization parameter at 5.5×10^{-7} in order to get a clear distinction of significant variables. Figure 2.5 shows the average Lasso LARS coefficients for each variable.

From the feature selection process, we found that the payback, system cost, presence of a battery in the system, maximum budget stated by the respondent, and one interaction variable – a combination of solar PV knowledge and deflection – were the dominant parameters. Interestingly, the non-monetary parameters from ACT did not appear to have any influence on the purchase decision! This could indicate that when the capital outlay is high, homeowners are driven to be rational rather than sentimental in their actions.

The logistic regression showed that the interaction variable does not fall within the desired 95% confidence interval. Table 2.2 shows the logistic regression variables and coefficients. Here, we set a decision to purchase the system as 0 and a decision to not purchase the system is 1. From the coefficients, we see that the higher the stated budgets, the more likely an agent is to purchase the system. In addition, the longer the payback period, the lesser the likelihood of a system purchase. This result is as expected, considering the desirable features of PV-battery systems.

Table 2.2: Logistic Regression Result

Variable	**Coefficient**	**Standard Error**	z	$P > \|z\|$
Intercept	-1.0535	0.159	-6.641	0.000
Payback	0.0945	0.009	10.265	0.000
Battery	0.3810	0.065	5.843	0.000
PV Budget	-0.2142	0.020	-10.774	0.000
System Cost	2.89e-05	4.41e-06	6.554	0.000

2.2.6 Agent Parameters and Behaviours

After executing feature selection and fitting the logistic regression model, the only agent parameter that directly influences the decision to purchase PV-battery systems is the maximum PV budget. As a result, we select the agent parameters shown in Table 2.3 for the ABM. This table also defines the agent parameters that determine the following agent behaviours: electricity generation and consumption, and PV-battery system purchase, as discussed next.

Electricity Generation and Consumption

We estimate electricity generation and consumption for each hour of each year. The electricity generated hourly is a function of the PV capacity installed in each agent's household, as well as the irradiance, for which we obtain data traces from SAM [93]. In terms of revenue from generation in Ontario, customers can sell their generation either under a FiT contract or under a net metering contract. In the former, the agent must sell all its generation to the grid, for an attractive rate. In the latter, the agent reduces its electricity bill by its level of generation, and carries over generation credits for up to 12 months. The former is attractive when the FiT rate is higher than the cost of electricity, and the latter when the conditions are reversed.

An agent's consumption pattern is also dependent on whether or not they purchase a battery. If they have a battery, the rules of operation are as described earlier, that is the battery is only charged during the mid-peak and off-peak hours of the Ontario ToU pricing. During each on-peak period, the battery is used to serve the load until there is no charge left.

Table 2.3: Agent Parameters

Agent Parameters	**Definition**	**Source**
Electric Load (kWh)	This is the amount of electricity consumed by the agent during each hour in a year.	Electrical load data from some households in Ontario.
Maximum Solar PV Budget ($)	This is the highest amount of money that each survey respondent says they will pay on a PV-battery system. This does not place a limit on the cost of a system that an agent will buy but we found from our survey that this value correlates with agent's decisions to purchase systems.	Ontario survey.
PV-Battery System Ownership	At the start of each simulation, each agent is assigned a 3 kW PV system based on the corresponding survey response. This system is represented by the capacities of solar PV and battery. In addition, an agent is assigned a system after purchase.	Ontario survey and simulation purchase decisions.
Social Network (S)	Each agent is assigned a social network from other agents. The size of each agent's social network is obtained from a beta distribution, such that few agents have a large social network and many agents have a small social network.	To build an agent's social network, agents are randomly selected from the pool of all other agents, using a uniform distribution until the agent's assigned social network size is reached.
Adoption Threshold (T)	This value is used to place each agent on the spectrum of adoption, i.e., from being an innovator, early adopter, up to being a laggard [15]. An agent cannot purchase a PV-battery system if the fraction of its social network that own solar PV systems is less than its social threshold.	Randomly assigned from a truncated normal distribution that has been validated using historical adoption of solar PV.

PV-Battery Purchase

The algorithm for the PV-battery system purchase decision process, which is executed every simulation epoch – set at 6-months – is shown in Algorithm 1. During each simulation epoch, any agent who does not own a PV-battery system considers buying a PV-battery system. Each agent considers PV sizes of 3, 6, and 9 kW, without and with batteries of 4 and 8 kWh capacity. A list of potential purchases are obtained based on the different combinations of PV and battery capacities, and the choice of the agent to purchase each system configuration. A final system choice is selected randomly from the viable alternatives (that is, ones with a positive RoI); we take this approach since it is difficult to specify which system a person would choose in reality given the system alternatives.

Algorithm 1 The PV-Battery System Purchase Process

```
function PurchasePVBattery(Agents, Systems)
    for all agent ∈ Agents do
        SocialPV ← (number of friends with PV) / (total number of friends)

        if agent.PVBatt is ∅ and agent.T ≤ SocialPV then
            ViableSys ← {}
            for sys ∈ Systems do
                if agent.WillBuy(sys) then    ▷ Result of decision function in Table 2.2
                    ViableSys ← ViableSys ∪ sys
                end if
            end for
            agent.PVBatt ← Random(ViableSys)
        end if
    end for
end function
```

2.2.7 Verification

To verify our model, we conduct the following verification tests[7]

[7] In this thesis, we only highlight the verification simulation results but do not include charts or specific test results.

- A single-agent simulation to ensure that agents are initialized with all the appropriate and required parameters.
- A test simulation to ensure that the environment variables are initialized and updated correctly.
- A simulation to test adoption in edge cases; one scenario with exorbitantly high PV-battery system price and another with a PV-battery system price of $1. The adoption is expected to vary significantly with the system price.
- A test simulation to verify the operation of electricity generation, storage, and consumption.
- A debug test of the survey importation to ensure that data from the survey are interpreted appropriately.
- A debug simulation to ensure that results are presented correctly.

2.2.8 Validation

To validate our model, we fit parameters for the five categories of adopters discussed in Section 2.2.2. We represent these categories using a truncated normal distribution of T from which we assign T_i to each agent. The Ontario microFiT program started at the beginning of 2010, and the number of PV microFiT contracts signed each month up to the end of 2014 has been published by the Independent System Operator, IESO [67].

We assume that all PV microFiT contracts were by households, and we scale down this number of contracts to the agent population in the ABM (i.e., 2,616 agents). Also, we set the environment variables such as PV and battery prices, ToU pricing, and FiT to vary in our simulation as they did in reality during this period of time (Figure 2.6). Figure 2.6 shows the PV price and ToU price multipliers; for example, we see that the PV price in January 2010 is about twice the PV price in January 2015. In addition, Figure 2.6 shows the actual FiT during the 2010 - 2015 period. The ToU and PV price multipliers are applied to the prices as of January 2015, which is when the survey was conducted and are justified as follows:

- We obtain the FiT change over time from the official IESO report [67].
- We apply a linear transition of ToU price, from January 2010 to January 2015 [100].

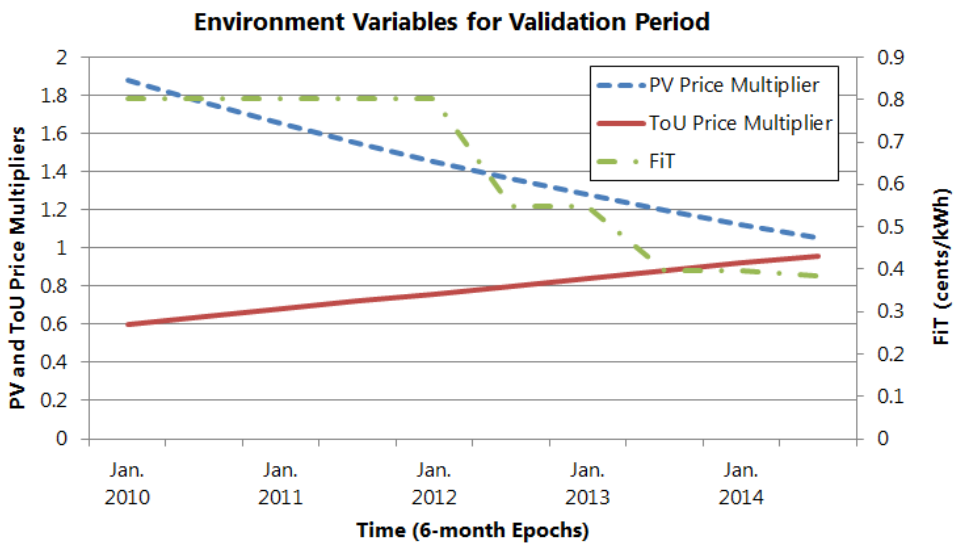


Figure 2.6: Environment Variable Changes during the Validation Period

- According to NREL [43], the median price drop for PV systems from 2010 to 2013 is from US$7/W to US$5/W. When extrapolated to 2015, this is equivalent to a 50% reduction. We apply a similar price decay to the PV price from 2010 to the PV price in 2015.

Populating the ABM with survey responses, we simulate results with 2,616 agents replicated from the survey – each valid response from the survey is reproduced as an agent eight times, with each reproduced agent having different T values. In addition, we ran simulations with different means μ and standard deviations σ for T in order to find the best match for historical adoption. For each μ and σ of T, we executed 20 simulations and report the average adoption results. Figure 2.7 shows the root-mean-square errors associated with each T distribution; the error for each distribution is included in the corresponding square. These are the errors between the historical PV adoption in Ontario and the simulated PV adoption between 2010 and 2015; the historical PV adoption is scaled-down based on the ratio of the Ontario household population to the simulated agent population. The T distribution with the lowest error and closest fit is that with μ = 0.42 and σ = 0.14 (box with green outline in Figure 2.7). As a result, we use this T distribution for ABM simulations of future policy scenarios. Figure 2.8 shows the scaled historical adoption compared to the simulated adoption.

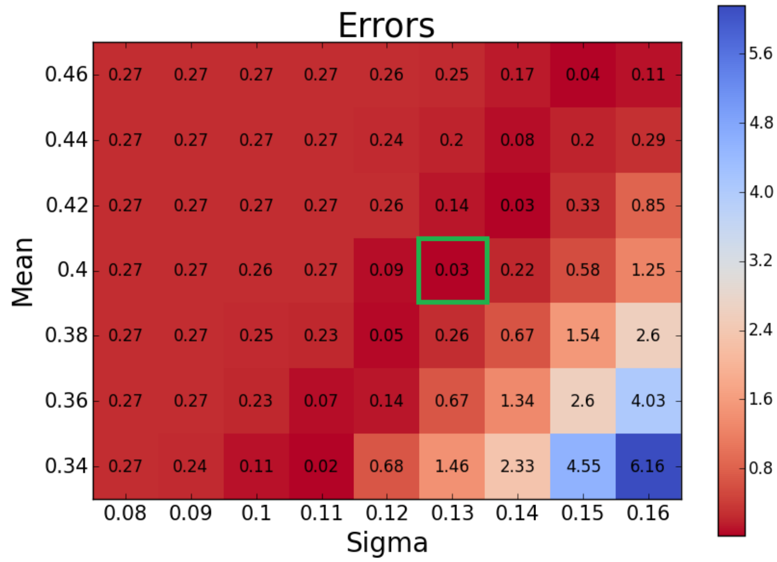


Figure 2.7: PV Adoption Validation RMSE; the Green Box shows the T Distribution with the Lowest Error

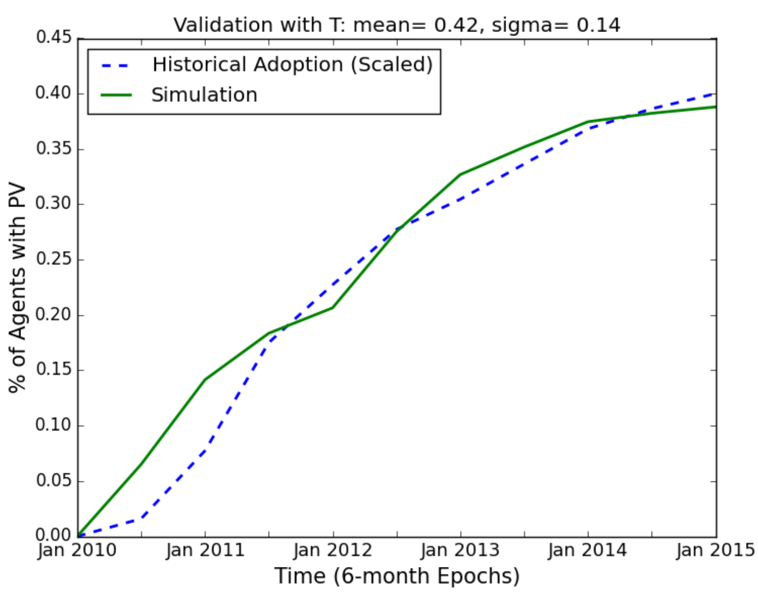


Figure 2.8: PV Adoption Validation and Scaled Historical Adoption

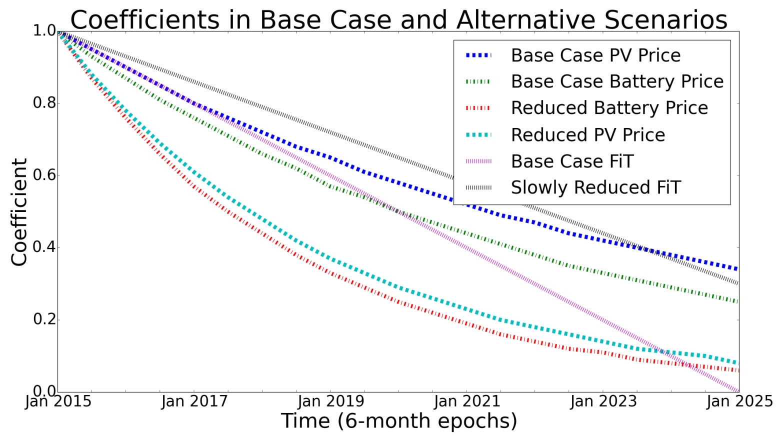


Figure 2.9: Coefficients for PV Price, Battery Price, and FiT in Base Case and Alternative Scenarios

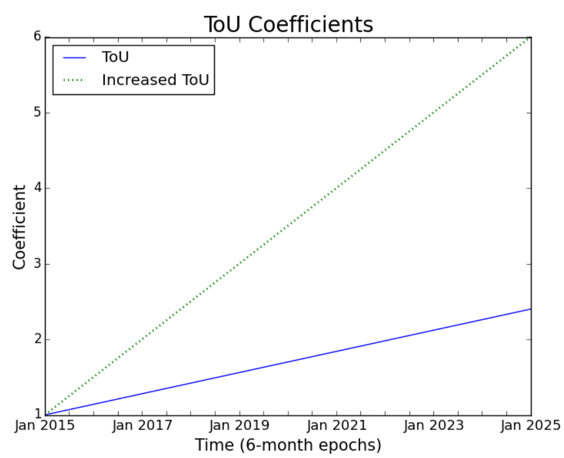


Figure 2.10: Coefficients for ToU Price in Base Case and Increased ToU Scenario

2.3 Results

We consider several scenarios to determine the sensitivity of system adoption to system prices, ToU pricing, and FiT. Since these are the environment variables that can be affected directly or indirectly by policies, we control these variables differently to visualize the impacts of different policies. We vary the listed environment variables over the course of the simulation by coefficients shown in Figures 2.9 and 2.10 – these coefficients are used to model changes in the ecosystem resulting from policies over time. For example, in the base case, the January 2017 PV price is set at 80% of its January 2015 value, while in a scenario with reduced PV price[8], the PV price is set at about 60%. Similarly, the ToU price in each period (as seen in Figure 2.1) is proportionally increased using the coefficients in Figure 2.10. Each simulation is executed over a 10-year period.

The base case is the scenario where prices change at their current rate and there is no intervention. The justifications for the base case values are as follows:

- By 2018, PV prices are expected to be 75% of the price in 2015 [103]. We extrapolate this decay in price to 2025. We use the following exponential decay function to model the PV and battery prices:

$$P(t) = P_0 e^{-\lambda t} \tag{2.3}$$

  where $P(t)$ is the price at year t, P_0 is the initial price (that is, in 2015), and λ is the decay factor.

- We use the same ToU price trend from the past 5 years [100], using a linear function.

- Due to lack of information on how the FiT is changed over time, we assume that the scenario in Ontario will mimic that of Germany. In Germany today, the FiT is lower than the price of grid electricity [143]. To model this, in our simulations, FiT reduces linearly to 0 cents/kWh in 2025.

- Batteries are expected to reduce to about 40% - 60% of today's price by 2020 [110, 139]. Assuming a price of 50% in 2020, we extrapolate this decay in price to 2025 using Equation 2.3.

We make the following changes in alternate scenarios (Figures 2.9 and 2.10): reduced battery price, slowed FiT reduction, increased ToU Price, reduced PV Price, reduced PV

[8]While reducing the PV price is not a policy by itself, it can be modeled as the result of policies that effectively reduce the price of PV systems such as rebates and tax breaks.

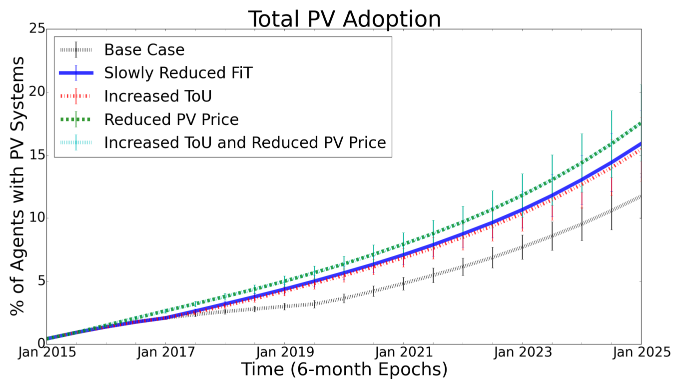


Figure 2.11: Total PV Adoption in Different Scenarios

and battery prices, increased ToU and reduced PV prices, and finally, increased ToU and reduced battery prices. We now compare the adoption in different scenarios and the impact of changes in environment variables.

2.3.1 PV Adoption

Figure 2.11 shows the adoption of solar PV in different scenarios – for clarity, scenarios not shown here are those that did not materially affect PV adoption. Also, the PV adoption here comprises both FiT and net metering contracts, shown in Figures 2.12 and 2.13 respectively. In the base case, we can see that solar PV adoption growth is relatively slow for the first 4 years but increases at a faster rate after 6 years. These trends are due to the simultaneous reduction in FiT and increase in ToU prices, which result in improving the attractiveness of net metering contracts to agents since the cost of electricity from PV systems is cheaper than the effective price of electricity from the grid. This is confirmed in Figure 2.13 where, in the base case, adoption due to net metering alone starts only after about 5 years.

Another insight from Figure 2.11 is that increasing electricity (ToU) prices at a rate higher than that in the past 10 years would drive customers towards PV adoption, with most customers opting for net metering. To see this, note that in Figure 2.12 that the FiT program PV adoption in the increased ToU price scenario is slightly less than that in the base case while net metering adoption burgeons (Figure 2.13). Furthermore, slowing down the decrease in FiT might aid PV adoption for some years but as net metering becomes more profitable for consumers, there would be more adoption as seen in the base case. As

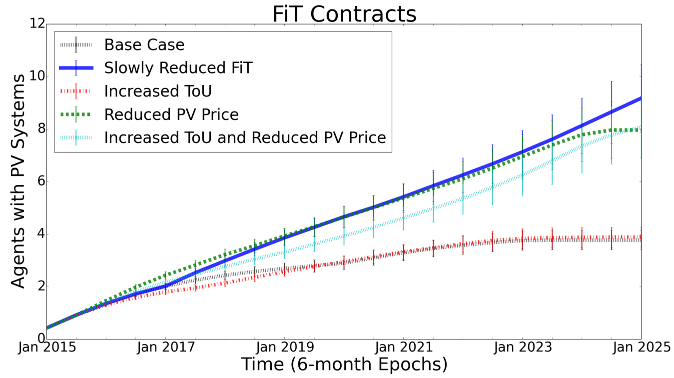


Figure 2.12: PV Adoption: FiT Contracts in Different Scenarios

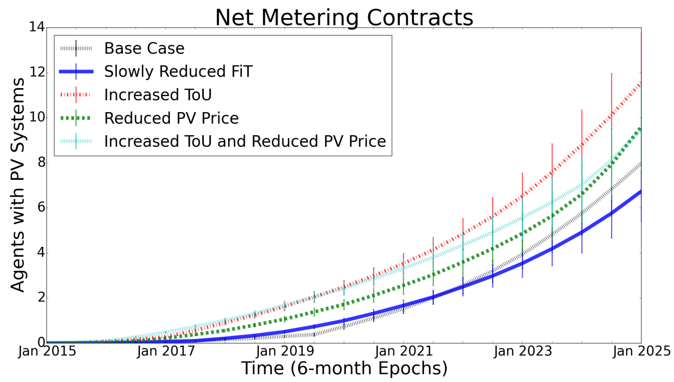


Figure 2.13: PV Adoption: Net Metering Contracts in Different Scenarios

a result, while the FiT should be decreased with care, the FiT program can be canceled as soon as net metering is profitable for most consumers.

We should note that the large error bars, showing the 95% confidence interval, indicate that it is difficult to forecast specific adoption levels due to noise in the survey data and not being sure which agents are early adopters or late adopters. However, we believe that the relative adoption trends in different scenarios are still valid and this informs policy evaluation and comparison. Furthermore, the low level of PV adoption in 2015 (0.4%) points to the need for a publicity campaign to inform more Ontario homeowners about the benefits of PV-battery systems. This would increase the overall level of innovation towards PV-battery systems in the population. Such a campaign would aid other energy policies such as PV price reduction.

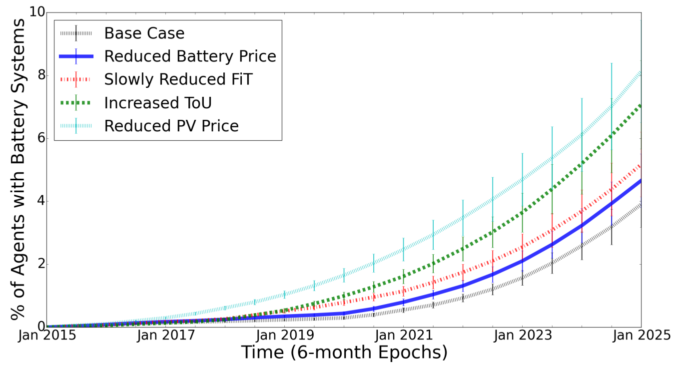


Figure 2.14: Battery Adoption in Different Scenarios with Single Variables Changed from Base Case

2.3.2 Battery Adoption

Figure 2.14 shows the adoption of battery systems in scenarios where only one environment variable is changed from the base case while Figure 2.15 pertains to scenarios with multiple variable changes. In Figure 2.14 we see that battery adoption is lowest in the base case, where it takes about 5 years for battery adoption to increase significantly. Keeping in mind that agents would not purchase batteries without solar PV already installed, PV prices also affect battery adoption. We choose this approach in our model design because of our focus on the benefit of coupling battery storage with solar PV. We should also note that we observe the highest adoption over the 10-year simulation period in two of the scenarios with reduced PV prices.

Also, in Figure 2.15, we find that reducing the price of PV-battery systems results in the most battery adoption. Increasing the ToU price and reducing the PV price has a similar effect. These are thus the two best options available for improving battery adoption in Ontario.

2.3.3 Impact on Electric Grid

Due to the low level of PV adoption forecast by our model – only about 11% even after 10 years in scenarios with the highest levels of adoption – and the low levels of battery adoption, the net domestic load remains largely unchanged. To get a better view of the generation and consumption, Figures 2.16 shows the total weekly PV electricity generation

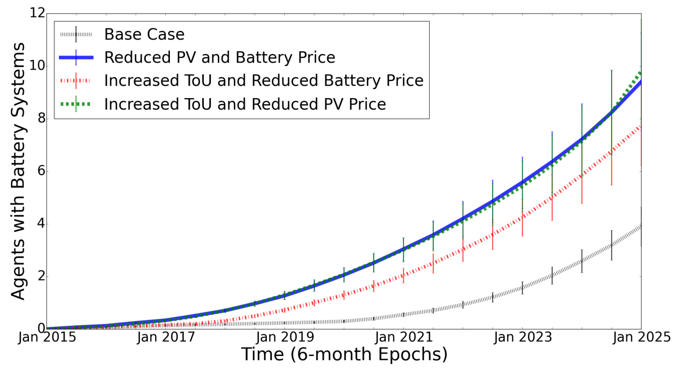


Figure 2.15: Battery Adoption in Different Scenarios with Multiple Variables Changed from Base Case

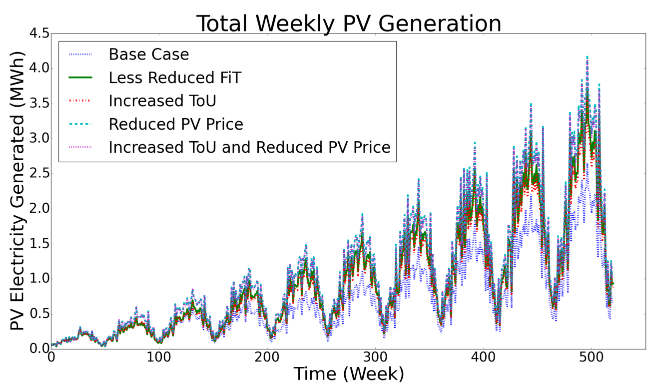


Figure 2.16: PV Electricity Generation

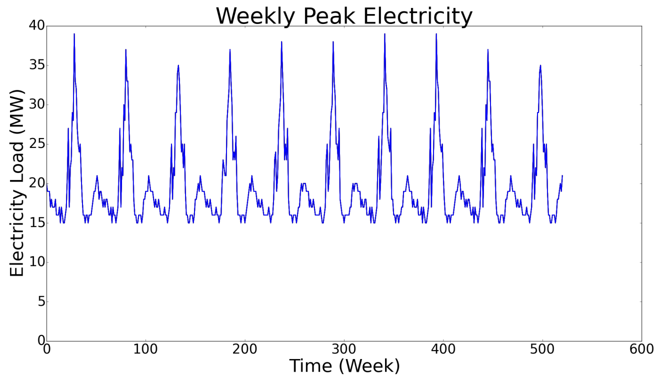


Figure 2.17: Weekly Peak Loads

and Figure 2.17 shows the weekly peak loads. The weekly peak loads about the same in all scenarios while the PV generation increases in proportion with PV adoption. After looking closely at the load values, we found only a 0.2% reduction in daily peak load in the scenarios with the most adoption. This shows that, barring a concentration of PV systems within a particular geographical area, utilities would not have to worry about an unstable electric grid resulting from high levels of intermittent PV generation for the next decade.

2.4 Related Work

In this section, we discuss prior studies that forecast solar PV adoption using ABMs.

Robinson et al. [111] develop an ABM to study the adoption of solar panels by households in Austin, Texas. This work uses the Theory of Planned Behaviour (TPB) in combination with social influence to model agent decisions to purchase solar panels for their homes. Our work goes further by introducing battery adoption and studying the impact of solar panel adoption on the electric grid.

Palmer et al. [102] study the adoption of solar panels by residences in Italy. Here, factors that influence solar panel adoption include the payback period, social influence, income, and environmental concerns. The adoption decision is represented by an utility function. They also segment the market based on socio-economic properties of households, with categories such as innovators, early adopters, early majority, etc. The results show that income has the most significant impact on adoption. However, this work does not include the adoption of batteries and electric grid impacts.

Murakami [91] focuses on the impacts of social policies and interactions in PV system adoption. This study also pays attention to the technical limit of PV penetration in a distribution system by incorporating power flow analysis in the model. Here, batteries are used to compensate for locations with solar PV generation restrictions. Our work differs from this by considering the adoption of storage in association with PV systems, and evaluating policies that may affect the adoption of PV-battery systems.

Iachini et al. [62] study the impact of incentives on PV adoption. This work focuses on economic and social factors that affect how each household may adopt PV systems. In building social networks, this work incorporates household locations and similarities in household attributes. Here, the decision to buy a PV system is dependent on income, payback of the PV system being considered, environmental concern, and social influence. Each of these factors is modeled as a utility and each utility adds to the agent's decision function. Using the Emilia-Romagna region in Italy as a case, the authors validate their approach by matching simulated adoption with historical adoption. Our work improves on this study by incorporating battery adoption and estimating the impact of the PV-battery system adoption on the electric grid, with a case study on Ontario.

Zhang et al. [147, 146] use an ABM to study two policies: subsidizing system costs and giving out PV systems for low-income households. A household's (agent's) PV purchase decision is a logistic regression model based on the Net Present Value (NPV) of the PV system, and the number of installations in close proximity of the household. Using San Diego in a case study, the results show that adoption is favored more by a policy to give out PV systems to households in order to spur the PV market. As with most other referenced studies, our work improves on this study by incorporating battery adoption and estimating the impact of the PV-battery system adoption on the electric grid, with a case study on Ontario.

Zhao et al. [148] combine system dynamics and agent-based modeling to study PV-related policies in a hybrid model, where they focus on FiT and Investment Tax Credit (ITC). Here, the factors that influence adoption are the payback, income, level of advertisements, and residential location. When an agent considers a purchase, the payback of the PV system is estimated based on the agent's energy consumption patterns, electricity prices, and reductions from incentives. This study also incorporates willingness to purchase as a parameter, that enables an agent to purchase a system if a certain threshold is met. This is similar to the approach in our work. Our study differs and improves on this study by including battery systems, effects of PV-battery systems on the electric grid, and an Ontario case study. From the case studies done by Zhao et al., it was found that residents in larger cities are less responsive to PV adoption incentives than those in smaller cities.

It is important to note that the results from these prior studies depend critically on the jurisdiction, since this determines the rules of interconnection, the installation costs, and feed-in tariff values. Our work differs from prior work in that (a) it focuses on Ontario, (b) it takes into account the adoption of battery storage and potential benefits from incorporating storage on the electric grid, and (c) it studies the grid impact of PV-battery system adoption.

2.5 Limitations

The limitations of this study are as follows:

- The survey data was quite noisy – due to a wide range of respondent preferences – and since it is difficult to tell what level of innovation each survey respondent falls in, with respect to PV adoption, the 95% confidence intervals are quite large. However, since the agent purchase decision variables were carefully selected, we believe that the relative differences in scenarios are still valid and provide useful information for policymakers and industry stakeholders.
- While estimating the electricity bill from load traces, we applied the ToU pricing scheme. However, in reality, there are additional charges in electric bills such as delivery and clean energy charges, but it is unclear how these charges are estimated. Consequently, we excluded these charges from our electricity bill calculations. We also assume that the relative proportions of ToU prices will be maintained in the future.

2.6 Policy Implications

Increasing the ToU prices further could drive PV-battery system adoption as consumers seek alternatives to grid electricity. However, an effective reduction in PV-battery system prices would encourage PV-battery adoption better than a ToU price policy that is focused solely on reducing peak loads. Given the current drive to reduce peak loads in Ontario via the ToU scheme, a policy that combines increased peak-to-off-peak price ratios with discounts for PV-battery systems could create a more stable grid, where peak loads are reduced and the intermittency of solar PV generation is stabilized by the presence of batteries. Also, consumers can use their batteries for ToU bill management which further reduces peak loads.

We also suggest that FiT reduction over time should be executed carefully. We find that slowly reducing the FiT (30% difference from the base case after 10 years) would result in an increase of about 20% in PV adoption after 10 years. A cancellation of the FiT program should occur when the effective ToU price per kWh for most consumers is higher than the FiT; at this point, consumers can purchase PV-battery systems with a net metering contract.

Given the overall low adoption levels, barring a concentration of PV systems within a particular geographical area, utilities would not have to worry about high levels of PV penetration for the next decade. Thus, policy makers need not seek to compensate utilities for grid support of renewables.

Above all, with the large confidence intervals resulting from different agents having different social thresholds for adoption, a policy action such as a publicity campaign that inform customers about the benefits of PV-battery systems and endears customers towards purchasing the systems would reduce the overall social threshold in the population, and would therefore improve PV adoption regardless of other policies discussed.

2.7 Summary

In this work, we study the adoption of PV-battery systems in Ontario using an Agent Based Model. We create an ABM with agents that consume electricity and can also choose to generate and store electricity using PV-battery systems. In addition, we attempt to base agent decisions on rational components such as price and system payback periods, and irrational components using Affect Control Theory. Using a data-driven approach for our study, we conduct a survey in Ontario and ask respondents about their attitudes towards PV-battery systems and what systems they might purchase under different market conditions. From analyzing our survey results, we find that the estimated deflections from ACT does not fit our logistic regression decision model, suggesting that people are typically rational with respect to significant financial expenses. However, we find that the system price, payback period, respondents' maximum budget for PV-battery systems, and the inclusion of a battery influence the decision to purchase systems. Populating our ABM with responses from the survey, we consider different scenarios and observe the changes in PV-battery system adoption, and the resulting impact on the electric grid.

First, the results show that there is likely to be no sudden increase in PV adoption if policies stay the same and prices change at the current rate. Also, we find that the most effective way to increase PV-battery system adoption is to reduce system prices, and this could be aided by informing customers about the benefits of PV-battery systems. Furthermore, increasing the ToU prices can also serve to drive customers towards PV-battery systems. We also find that net metering is likely become more attractive to consumers over time, as the ToU price increases gradually and PV-battery system prices decline. Furthermore, due to the low levels of PV adoption at the time of this study – about 0.4% of households – we find that the Ontario population does not have a generally innovative attitude towards PV systems. The impact on the electric grid is also minimal, given the levels of adoption in future scenarios – about 11% in the scenario with highest adoption – and utilities would not have a problem with the intermittency of PV electricity generation, barring a geographic concentration of PV installations.

Areas of consideration for future research include the sole adoption of batteries and motivations for consumers to purchase batteries, and modeling the impact of publicity campaigns to raise awareness about PV systems.

Chapter 3

Electric Vehicle Ecosystem Model

Publication References[1]:

- A. Adepetu, S. Keshav. "The Relative Importance of Price and Driving Range on Electric Vehicle Adoption: Los Angeles Case Study." *Transportation* (2015): 1-21.
- A. Adepetu, V. Arya, S. Keshav. "An Agent-Based Electric Vehicle Ecosystem Model: San Francisco Case Study." *Transport Policy* 46 (2016): 109-122

The widespread commercial availability of plug-in Electric Vehicles (EVs) in recent years motivates policies to encourage EV adoption and infrastructure to cope with the increasing number of EVs. We present an agent-based EV ecosystem model that incorporates EV adoption and usage, spatial and temporal considerations, that can aid different EV industry stakeholders such as policymakers, utility operators, charging station planners, and EV manufacturers. The model is used to determine how different policies and battery technologies affect EV adoption, EV charging, and charging station activity. We conduct two case studies focused on San Francisco and Los Angeles. With the agent-based EV ecosystem model, we simulate the impact of rebates, availability of workplace charging, public awareness of lower EV operational costs, and denser EV batteries on the EV ecosystem[2].

[1] The research work from these papers that is included in the thesis was carried out and documented by the author of this thesis.

[2] The ABM simulation code can be found at bitbucket.org/adeda/ev-ecosystem

3.1 Technology Overview

Here, we briefly explain the technological terms used in this chapter.

- **Electric Vehicle (EV):** This is a vehicle that runs on electricity. In this thesis, EV refers to an electric car.
- **Battery Electric Vehicle (BEV)**: This is an EV that runs completely on electricity. It contains a battery that is charged by plugging the car to an electricity source and the battery is discharged when the car is used.
- **Hybrid Electric Vehicle (HEV)**: This is an EV that runs partially on gasoline and electricity. It contains a battery that is typically charged via regenerative braking. However, the HEV cannot be plugged to an electricity source.
- **Plug-in Hybrid Electric Vehicle (PHEV)**: This is an EV that runs partially on gasoline and electricity. It also contains a battery that is charged by plugging the car to an electricity source and the battery is discharged when the car is used. Whenever the battery can no longer supply energy to the car, the gasoline is used to run the car's engine.
- **Internal Combustion Engine Vehicle (ICEV)**: Also known as a conventional vehicle, this is a car that runs completely on gasoline.

3.2 Introduction

In recent years, there has been an increase in the market penetration of Electric Vehicles (EVs) in countries such as Norway, Estonia, and the United States (US) [37, 55, 89]. Despite the well-documented barriers to EV adoption [18], including high initial costs, range anxiety, and the perceived scarcity of adequate charging infrastructure, EV adoption is increasing. For example, the number of Plug-in EVs (PEVs) in the US increased from zero to more than 165,000 in just 3 years from 2010 to 2013 [37]. In September 2013, the Tesla Model S, an electric car, was Norway's best-selling car, and in November 2013, more than 10% of cars registered in Norway were electric [68].

This success is partly due to government policies such as EV purchase rebates, EV Supply Equipment (EVSE) rebates, high-occupancy lane access for EVs, free parking, removing import taxes, educating the general public about emissions, and encouraging businesses to have charging terminals at work. It is noteworthy that California, which has several policies that encourage EV adoption [8], also has one of the highest EV adoption rates in the US [73, 98].

Although rapid EV adoption is a generally desirable outcome, it has some potential drawbacks, including increasing grid load and the need to provision expensive charging stations. Moreover, it is not obvious which policies are most responsible for increasing EV adoption. What is needed, therefore, is a tool that carefully models the EV ecosystem to allow the exploration of 'what-if' scenarios. Using an agent-based EV ecosystem model that captures EV adoption and usage, we present a tool that can be used by policymakers, electric utilities, charging station planners, and battery manufacturers for purposes such as the following:

- Policymakers can estimate the impact of different policies on EV adoption.
- Electrical utilities can estimate the spatial and temporal changes in electrical load resulting from different levels of EV adoption and different EV technologies.
- Charging station planners can estimate how different levels of EV adoption affect public charging station activity.
- Battery manufacturers can determine how battery sizes would affect EV adoption and electrical load.

We have used our tool to study EV adoption and usage in San Francisco and Los Angeles, California. Drawing upon the results of a comprehensive study of driving habits in this city [23], we study the impact of policy and technology changes on future EV penetration, presenting results that are likely to be of interest to each of the stakeholders above.

3.3 Related Work

This section presents a number of studies on EV adoption and usage in the research literature.

3.3.1 EV Adoption Models

An EV adoption model seeks to model the EV purchase decision. There are three major types of adoption models: ABMs, consumer choice models, and diffusion rate models [7]. Al-Alawi and Bradley [7] provide a detailed review of different EV adoption models in each of these three categories.

In EV diffusion rate models, EV adoption is estimated based on the Bass diffusion model [15]. Here, consumers are segmented based on their attitude towards an innovation: early adopters, early majority, late majority, and laggards [112]. Consumer choice models forecast adoption based on the vehicle preferences of a particular population. This often involves the use of logit models and discrete choice mathematical models. While diffusion rate and consumer choice models have their benefits, ABMs utilize the bottom-up system approach that enables us to understand how a system reaches a certain state, based on interactions between agents and with the environment. Since our work involves the development of an agent-based EV ecosystem model, we focus on these models next.

Eppstein et al. [39] and Pellon et al. [105] study the adoption of EVs by modeling agents (people) that choose between ICEVs, HEVs, and PHEVs. For each agent, factors such as age, income, house location, expected years of vehicle use, mileage, etc., are considered. Network externalities are modeled based on an agent's susceptibility to media campaigns and social influence. This work also spreads out agents over a geographical area. This spatial orientation is used in conjunction with social networks to estimate agent network externalities. This work serves as a basis for our model and is discussed in more detail in Section 3.4.

Shafiei et al. [117] also present an agent-based EV adoption model. In order to estimate the probability of a person buying a particular vehicle out of a pool of vehicles, an agent's willingness to pay for the vehicle is combined with customer preferences and vehicle attributes. This work also uses a refueling effect variable to incorporate the availability and acceptability of public charging stations that is linearly proportional to the market share of EVs. The results show the potential impacts of changing EV and gas prices on EV adoption. However, since this work focuses on EV adoption, it does not incorporate a detailed EV usage model.

The approach by Schwoon [115] estimates the availability of hydrogen refueling stations for fuel cell vehicles, based on the penetration of these vehicles and the maximum possible increase in hydrogen refueling stations over a period of time. This work does not focus on EVs but serves as a basis for agent-based EV adoption models.

Sweda and Klabjan [127] present an ABM focused on the deployment of charging infrastructure, and the ABM includes an EV adoption model. Agent properties include income, vehicle class preference, range anxiety, and preferred vehicle longevity. An agent buys a vehicle based on price, fuel cost, greenness, social influence, long distance penalty, and infrastructure penalty. The study, however, does not detail how these variables are quantified. The model also includes three drive cycles for each agent: local, work, distant. We use a similar approach in our work.

Sullivan et al. [125] model PHEV penetration using an ABM. In addition to EV owners, the model represents the government, fuel producers, and vehicle producers as agents. This paper stresses that the budget of an agent is the most important factor considered when buying a car. It also adds that agents are likely to buy vehicles 'proportional' to their income and area of residence. Each agent has specific home and work addresses, income, budget for transportation, driving cycles, and preferred vehicle longevity. The study further mentions that the vehicle choice is dependent on an agent's willingness-to-pay and peculiar preferences. According to Al- Alawi and Bradley [7], this is one of the most detailed agent-based EV adoption models. However, including governments and fuel producers as agents gives the modeler less control on estimating the sensitivity of EV adoption towards government policies or fuel producer decisions. As a result, we structure our model to provide insight on the impacts of different policies and EV technologies that are exogenous to the model.

Shepherd et al. [121] study the factors affecting EV adoption using a systems dynamics approach. Using the UK as a case study, they focus on the impact of factors such as rebates, EV range, and charging availability on EV sales and reduction of CO2 emissions. This work, however, does not comprise a detailed EV usage that is, a driving and charging model.

Lin and Greene [83] use a Nested MultiNomial Logit (NMNL) model with variables such as customer driving needs and availability of refueling to forecast PHEV adoption. The potential customers are segmented based on factors including location of residence, ability to charge at work, and affinity for new technology. The results show that PHEV adoption is influenced the most by availability of charging stations. This study, however, models only PHEVs and does not detail EV usage.

Brown [20] studies the influence of factors such as financial incentives and vehicle range on the market penetration of PHEVs and BEVs, using an ABM with a mixed logit approach for agent vehicle choices. Our study takes a step further by estimating the energy impacts of EV penetration based on agent driving and charging decisions.

Table 3.1 shows a summary of these vehicle adoption studies and how we improve on each study. Our EV ecosystem model attempts to improve on existing EV adoption and usage models by combining EV adoption and use. Specifically, our model integrates daily drive cycles with real-world trip characteristics (duration and distance), public charging stations, policies, and EV loads. Using an ABM provides granularity; each agent makes purchase, driving, and charging decisions, and this results in additional electrical load on the grid.

Table 3.1: Comparing Agent-Based EV Adoption Models

Study	**Contribution**	**Drawbacks**
Eppstein et al. [39]	This study focuses on the adoption of HEVs and PHEVs. Also uses spatial data and network externalities.	It assumes that the EV is charged only once a day. As a result, it does not properly consider the impacts of EVs on the grid and the availability of charging on agents. In addition, it focuses on only the electrical range of a vehicle as its benefit. We study both home and workplace charging. We consider both range and fuel economy as EV benefits.
Shafiei et al. [117]	This is an agent-based study that focuses on BEVs and includes refueling effects.	It does not look at impact of the EV adoption rate on infrastructure.
Schwoon [115]	This focuses on the adoption of fuel cell vehicles.	The methods used for refueling cannot be necessarily applied to EVs because of refueling time which is a very significant variable.
Sweda and Klabjan [127]	Rather than focusing directly on adoption, this paper focuses on the impact of EV adoption on grid infrastructure in order to develop a charging infrastructure deployment plan.	It does not include spatial distribution of EV adoption and it focuses on siting public charging stations.
Paevere et al. [101]	This study focuses on temporal and spatial changes in EV charging demand based on different adoption scenarios.	It only looks at the eventual impact of EV rebates on charging demand. We focus on other policy and vehicle battery impacts.

Cui et al. [30]	This paper models PHEV adoption and how different charging schemes can be used to manage EV charging demand.	It focuses more on charging schemes rather than EV adoption under different scenarios.
Sullivan et al. [125]	This is about the most complete EV study out there. It uses an agent-based approach.	It studies only PHEV penetration. It also models government, fuel producers, and vehicle producers as agents. However, we model these as driving variables since the actions of these agents do not necessarily depend on only the EV ecosystem.
Shepherd et al. [121]	Focusing on a UK case study, this work models EV adoption using system dynamics. It focuses on the influence of rebates, EV range, and charging availability on EV sales.	The model focuses on EV adoption and does not comprise a detailed EV usage model.
Brown [20]	This study focuses on the influence of factors such as financial incentives and vehicle range on the market penetration of HEVs, PHEVs and BEVs.	Our study takes a step further by estimating the energy impacts of EV penetration based on agent driving and charging decisions.
Lin and Greene [83]	This paper uses a choice model to forecast PHEV adoption. It has a very detailed and useful market segmentation.	Since it does not use an agent-based approach, it is difficult to simulate driving and charging, hence the impact on the grid.

3.3.2 Impact of EV Usage on the Grid

Paevere et al. [101] focus on the temporal and spatial distributions of the impact of EV charging demand. Focusing on Victoria, Australia they study scenarios with different rebates and EV penetrations, as well as different charging schemes, and how the resulting load adds to the existing residential load. This is similar to our approach since one of the cases it focuses on is the impact of EV purchase rebates on EV adoption, and the resulting electrical load. We go further by considering the impacts of other policies: encouraging workplace charging stations and educating the population on estimating the Total Cost of Ownership (TCO) of vehicles. There are other studies ([105, 11]) that also focus on the impact of different fixed EV penetration scenarios and charging rates on the daily load profile. For example, Acha et al. [1] use an ABM to combine EV trips and charging with optimal power flow analysis.

Cui et al. [30] focus on how the distribution of PHEVs affects the grid via power line congestion and transformer overload, and how charging schemes can be used to manage these effects. In this study, an ABM with decisions based on a NMNL approach is used to determine EV adoption; this approach is similar to that used by Shafiei et al. [117].

These studies provide the context for our work, presenting some of the electrical load impacts of EVs, including the spatial and temporal distributions of EV electricity consumption at different scales.

3.4 ABM for EV Ecosystem

We present the details of the agent-based EV ecosystem model. Our model is an EV ecosystem model because it goes beyond EV adoption and incorporates EV usage, that is, both driving and charging. This provides a more complete model for estimating the impacts of EVs within a socio-technical system. For example, our model can forecast the number of EVs bought each year to allow electric grid operators to gauge the increases in electrical load at different parts of the grid corresponding to home and work locations. In addition, our model takes an agent-based approach, where the agents are people who decide whether to buy EVs or not, and use the EVs according to their driving needs.

We should note that the agent-based EV ecosystem model does not strictly follow the approach discussed in Chapter 1; instead of creating a new survey, we use a survey conducted by the National Renewable Energy Laboratory's (NREL's) secure transportation data project [23]. As a result, we do not execute feature selection for agent vehicle purchase decisions and do not base the adoption function on a regression model. Therefore, we make some assumptions about EV adoption that are described subsequently. In addition, we base our EV adoption model on the work done by Eppstein et al. [39].

The Eppstein et al. agent-based EV adoption model is focused on PHEV and HEV adoption. The two specific additions we make are to model the adoption of BEVs, and to incorporate vehicle range and fuel economy as attributes that affect agent purchase choices. We now discuss the simulation parameters used in our model (Tables 3.2 and 3.3)[3]. In order to determine agent behaviour, each agent is initialized with a number of characteristics as seen in Table 3.2. Work days represent the days of the week during which an agent goes to work. This is necessary for activating either a workday or non-workday drive cycle each simulation day. Also, the age and fuel type of each agent's vehicle are defined at the beginning of each simulation run.

Table 3.2: Agent Variables (DS = Dataset; E = Estimated; I = Independent)

Variable	**Source**			
	DS	**E**	**I**	**Description**
Age	X	X		Each resident in surveyed households is listed in an age bracket, within which we uniformly assign a particular age.
Income	X	X		Each household is listed in an income bracket, within which we uniformly assign a particular income. We divide the income among each household's working residents, if necessary.
Work days	X			These are the days of the week that a person goes to work. In cases where it is not specified in the data, we assume work days of Monday - Friday.
Home location	X	X		The household location of each respondent is anonymized but listed as a zip code. Even though zip codes are not areas, we uniformly assign locations close to the centers of these zip codes within a 1 km radius, by obtaining the central geographical coordinates of each zip code.
Work location	X	X		The work location is obtained similarly to the home location.
Vehicle fuel type and age	X			Each surveyed household has a list of vehicles already in use, with details such as the model year and fuel type assigned.
Workday and non-workday drive cycles	X	X		The drive cycles are based on expected trips to and from home locations, work locations, and random locations of interest. See Tables 3.4 and 3.6.

[3]'DS' implies that the variable was informed using a dataset; 'E' implies that the variable was estimated; 'I' implies that the variable was assumed to be an independent variable.

Desired vehicle range	X	X		This is the farthest daily driving distance, estimated based on daily drive cycles.
Desired vehicle fuel efficiency	X			This is assumed to be the highest vehicle efficiency available in the market today [136]. See Table 3.5.
Cost Sensitivity G		X		G is correlated with income with some noise included. See Eq. 3.8.
Social threshold T			X	T is the fraction of an agent's social network that must own EVs in order for that agent to buy an EV. By default, the percentages of agents classified as early adopters, early majority, and late majority are 16%, 34%, and 50% respectively [83, 113, 112].
Social network		X		Each agent's social network is selected from other agents with similar ages($\pm$5 years), incomes($\pm$\$10,000), and residential locations ($\pm$2 km). Each agent is assigned a number of social connections, randomly chosen with minimum and maximum sizes of 1 and 14 respectively.
Ability to estimate TCO			X	This is a binary variable that determines if an agent can estimate the TCO of a vehicle. This is used to evaluate the impact of a policy to educate people on EVs and TCO. By default, 20% of agents are assumed to be capable of estimating TCO.
Option to charge at work			X	This is a binary variable that determines if an agent has a charging terminal available at the work place. By default, 20% of agents can charge at work [83, 13].
Desired vehicle longevity	X	X		This the number of years an agent decides to use a vehicle before selling it off. For each agent, this variable is obtained from a normal distribution with an average of 11 years [74] and a standard deviation of 1 year.

Table 3.3: Environment Variables (DS = Dataset; E = Estimated; I = Independent)

Variable	**Source**			
Cost of gas	X			This is the equivalent cost in \$/kWh obtained from the cost in \$/gallon [21] and the energy content of gasoline: 1 gallon of gasoline contains 33.7 kWh of energy [9].
Cost of electricity	X			This is the average cost of electricity in San Francisco [21].
Existing rebates	X		X	This is a reduction in the effective cost of an EV, based on federal and state policies [135, 22].
Public charging stations	X	X		Real-world map and specifications of public charging stations [109]. This includes level 2 and 3 charging stations, scaled according to the number of agents in the simulation. See Figure 3.3.
Vehicle types and specifications	X			See Table 3.5 [136].
Trip duration and distance		X		We use MapQuest Route Matrix to obtain driving distance and duration [87].
Discount rate	X			This is the interest rate used to estimate the present cost of future expenditure. This is useful for TCO estimation. Typical discount rates fall between 2% and 10% [38]. We set this variable at 8%; note that changing the rate to 5% or 10% did not significantly change outcomes.

An important agent variable, G, is the cost sensitivity ($0 \leq G \leq 1$) that represents an agent's tendency to purchase a vehicle with a lower carbon footprint as against its cost. However, G is not the only parameter that influences an agent's decision to purchase an EV. We also model the influence of an agent's social network on the agent's decision to adopt new technology (EVs). Each agent is assigned a threshold T ($0 \leq T \leq 1$) (following [39] and [17]); T must be equaled or exceeded by the fraction of an agent's social network that own EVs in order for the agent to buy an EV. In other words, an agent with $T = 0$ is considered to be an early adopter, since it can buy an EV regardless of the EV-owning proportion of its social network; as T increases, an agent tends towards being a late adopter. The social network of an agent is selected uniformly randomly from agents within the same age or income brackets, and from agents living within a specific spatial radius. On the other hand, agents in the same social network do not talk to one another since more modeling details would be required to adequately represent social network interactions and the resulting influences. The environment variables (Table 3.3) are used to represent different simulation scenarios, and these variables affect EV adoption and usage, as described next.

EV Adoption

In our model, vehicle purchases are considered by agents every three months. We define the vehicle purchase process for each agent as follows:

1. Determine which vehicles on the market the agent can afford: we assume that an agent cannot spend more than 20% of its annual income on purchasing a vehicle [39].

2. Determine which BEVs can meet the agent's daily trip requirements, such that the agent would not get stranded in transit with a fully-discharged EV (this check is required for BEVs only).

3. Rank the affordable vehicles according to desirability. Desirability is a function of benefits and costs of different alternatives (discussed in more detail below).

4. Buy the most desirable vehicle.

5. If, for any reason, no suitable vehicle to purchase is found, keep using the existing vehicle.

6. Overall, if the EV-owning fraction of an agent's social network is less than the agent's social threshold T, then the agent does not buy an EV.

In our model, vehicle purchases are executed quarterly, and an agent chooses from three different vehicle types: ICEV, PHEV, and BEV. For each agent, the relative desirability D_{ij} of each pair of vehicles is obtained based on their benefits and costs [39], where these depend on the agent's cost sensitivity G and social threshold T, described next (also see Figure 3.1).

G is used to model the degree to which an agent values a vehicle's benefits such as a long driving range and high fuel efficiency, over its costs. For example, if an agent has $G = 0$, then that agent would rank a vehicle's desirability based only on its costs, but if

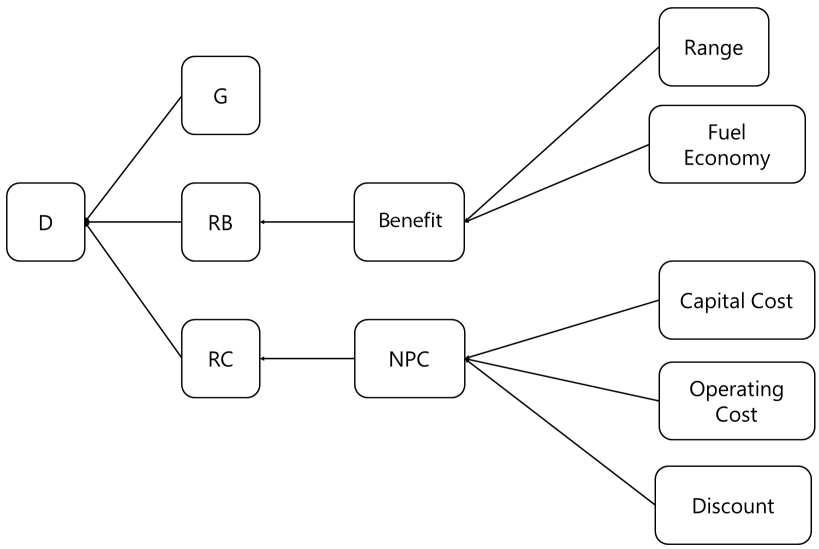


Figure 3.1: Derivation of Desirability D; G is the cost sensitivity of the agent; RB is the relative benefit of compared vehicles; RC is the relative cost of compared vehicles; NPC is the net present cost of each vehicle in consideration.

$G = 1$, the agent would rank a vehicle's desirability based only in its benefits regardless of its costs. The relative desirability D is computed as the weighted difference between the relative benefit RB and relative cost RC of each pair of vehicle choices, scaled by the agent's cost sensitivity G. The computation of RC and RB is discussed below.

T determines the degree to which an agent is an early adopter and is used to model social influence on vehicle purchase decisions. For example, if an agent has $T = 0.1$, the agent will buy an EV only if at least 10% of its social network already owns EVs. The distribution of G among agents determines how many agents buy EVs, and T determines when EVs are bought based on EV penetration in the agent population. The social threshold is included in the model in order to determine the impact of social networks on agent decisions. This is similar to the work by He et al. [57] that incorporates social network influence in a discrete choice model with a case study on HEV adoption in California.

The desirability of a vehicle j over i, D_{ij}, is a function of the relative cost RC_{ij} and relative benefit RB_{ij} [39]. Specifically, the relative desirability of two vehicles is given by:

$$D_{ij} = G \times RB_{ij} - (1 - G)RC_{ij} \tag{3.1}$$

The most desirable vehicle is purchased by the agent.

The relative cost is given by:

$$RC_{ij} = \frac{C_j - C_i}{C_j} \tag{3.2}$$

where C_i is the cost of car i. C is either the sticker price or TCO of a vehicle, because not all vehicle purchasers fully consider the expected lower operational costs of EVs [18, 38]. For estimating the TCO, we use the Net Present Cost (NPC), which is given by:

$$NPC = \sum_{t=0}^{N} \frac{C_t}{(d + 1)^t} \tag{3.3}$$

where N is the number of years, C_t is the net cost in year t, and d is the discount rate. In the current version of our model, the recurring costs consist, solely, of fuel costs. Also, the sticker price of a vehicle is the only initial cost. However, the model provides room for a more detailed cost estimation process if desired. Our model does not consider financing options as part of the vehicle purchase process.

The relative benefit RB_{ij} is given by:

$$RB_{ij} = \frac{B_j - B_i}{B_j} \tag{3.4}$$

where B_i is the benefit of car i. Here, the benefit of using a car is dependent on two attributes: range and fuel economy. For estimating the fuel economy of PHEVs, the fuel efficiency of the electrical and combustion engines in a PHEV are scaled with respect to the ratio of the charge-sustaining and charge-depleting distances traveled during an agent's typical drive cycle. The benefit of a vehicle, then, is given by [115]:

$$B = 1 - \frac{1}{n}\sum_{i=1}^{n}(max(0, \frac{pref_i - v_i}{pref_i})) \tag{3.5}$$

where $pref_i$ is the agent's preference for attribute i, and v_i is the value of the vehicle's attribute i. Figure 3.1 shows the relationship between all the variables used to define desirability D, and Algorithm 2 shows the pseudocode for the EV purchase process.

EV Usage

The aspects of EV usage included in our model include EV charging at home, at work, and at public charging stations and driving (discharging). Each agent is assigned a workday drive cycle and a non-workday drive cycle. The current version of our model does not include long-distance trips. These drive cycles are used to represent the typical trips a person takes each week. These include trips to work, public charging stations, and other Locations of Interest (LoI) used to represent places such as a shopping mall. Each agent is uniformly assigned two LoIs, out of a set of possible LoIs within the city. Also, all daily drive cycles start and end at home. An example of a drive cycle is shown in Table 3.4.

Each trip destination has spatial coordinates, used to estimate driving distance and time between locations; we employ the MapQuest Directions API [87] by providing the geographical coordinates. We use the Route Matrix request option to obtain the trip information, which is provided by OpenStreetMap©. The start time for each trip after the first trip of the day is updated based on the arrival time and duration of stay at the destination of the prior trip. The energy consumed for each trip E_{trip} is obtained by

$$E_{trip} = EV\ efficiency \times distance\ traveled \tag{3.6}$$

Similarly, the charging time for an EV is a function of the energy required to fill the battery and the charging level.

Algorithm 2 The EV Purchase Process

```
function PurchaseCar(Agents, Cars)
    for all agent ∈ Agents do
        SocialEV ← (number of friends with EV) / (total number of friends)

        if agent.EV is ∅ and agent.T ≤ SocialEV then
            for all car ∈ Cars do
                DesirabilityCount[car] ← 0
            end for

            for all car ∈ Cars do
                for all otherCar ∈ Cars; car ≠ otherCar do
                    D ← CompareDesirabilities(car, otherCar)        ▷ Equation 3.1
                    if D > 0 then
                        DesirabilityCount[car] ← DesirabilityCount[car] + 1
                    end if
                end for
            end for

            agent.Car ← car with max(DesirabilityCount)
        end if
    end for
end function
```

Table 3.4: Example of a Workday Drive Cycle

Trip Number	**Start Time**	**Trip Destination**	**Stay (hours)**
1	8:00 AM	Work	8
2	–	Mall	1
3	–	Home	–

$$Charging\ time = Energy\ required \times Charging\ level \tag{3.7}$$

For agents with BEVs, it is crucial not to get stranded in transit due to inadequate charge. As a result, before a BEV-driving agent executes its drive cycle for a particular day, it checks that the EV State-of-Charge (SoC) is sufficient. If not, it chooses to visit a public charging station close to its route or doesn't drive the EV that day if the EV cannot reach any charging station.

One benefit of using a spatially-oriented model is the ability to accurately model public charging stations. Each public charging station is defined by its location, charging capacity, and number of charging terminals. In our model, only BEV owners visit public charging stations since PHEV owners do not need to visit public charging stations. EVs drive to the closest charging station to get charged, regardless of its load. A future refinement would be to include the option of going to a more distant but less busy charging station. Typically, agents do not visit public charging stations except in two cases: when the agent cannot make the next trip due to insufficient battery SoC for the remainder of its drive cycle or the trip to the public charging station has been added at the beginning of the day (also due to insufficient battery SoC). Also, a public charging station trip can only be added once a day, except in cases where an agent searches for alternative public charging stations as discussed above. At a public charging station, an agent is modeled to charge its EV just enough to complete its drive cycle for that day. That is, it does not charge to the full battery level.

3.4.1 Model Verification

To verify our model, we conduct the following verification tests:

- A single-agent simulation to ensure that agents are initialized with all the appropriate and required parameters.

- A test simulation to ensure that the environment variables are initialized correctly.
- A simulation to test adoption in edge cases; one scenario with an exorbitantly high EV price and another with an EV price of $1. The adoption is expected to vary significantly with the system price.
- A test simulation to verify the scheduling of EV charging at public charging stations.
- A test simulation to ensure that agents complete daily drive cycles.
- A debug simulation to ensure that results are presented correctly.

3.5 San Francisco Case Study

In this section, we discuss the San Francisco case study and show results from different simulated scenarios. First, we explain the process of tuning agent behaviour.

3.5.1 Experiment

We focus on San Francisco as a case study for evaluating the impacts of EV-related policies on EV adoption. The city of San Francisco was studied since it is one of the cities with the highest penetration of EVs [98].

Data Description

The data used to populate the ABM model in this study was obtained from a survey conducted by NREL's secure transportation data project [23]. The survey comprises anonymized household data: home and work zip codes, work days, vehicle specifications of the residents in each surveyed household, as well as total household income. The survey was carefully chosen to be representative of California's population. This is crucial for our study since our estimations for EV adoption are extrapolated from this survey sample. It should be noted that San Francisco is a spatially compact city, resulting in shorter driving distances compared to more spatially distributed cities. The effect of the short distances traveled in some of the results is discussed in Section 3.5.3.

The ratio of the actual population of San Francisco population in reality to the number of participants in the survey is about 366. In order to have adequately detailed EV ecosystem dynamics, but without having to simulate the entire population of the city, we duplicated each agent 10 times with the same income, vehicle type, and home and work zip code values, but with different values for G and T (explained in Section 3.5.2); the number of agents in the simulation is 6,100. This enables us to achieve finer and more detailed simulation results. Therefore, the magnitudes of EV adoption and load values obtained in this study are at a scale of about 1:37 to reality. This scaling is also reflected in the number of public charging stations and their locations (i.e., we scaled down the true number of charging stations and the number of charging points at these stations by a factor of 37).

Simulation Description

The characteristics which define the behaviour of an agent in the EV ecosystem model are listed in Section 3.4, and these characteristics are obtained from the data survey and resulting correlations. All members of a family household were considered to be a single agent in the simulation since families typically purchase vehicles together, and the corresponding household income was used as the agent's income. On the other hand, the income of non-family households were divided equally by the number of workers in each of such households, and each worker is represented by an agent. In each family household, the effective agent age is set to be the age of the household's survey respondent. Also, persons or households without vehicles were not included in the simulation, since the reason for not owning a vehicle could not be modeled and these agents could skew the results.

Each agent is also initialized to have a range preference equal to its maximum daily driving distance and a fuel economy preference equal to the best possible fuel economy in the modeled vehicle market (5.55 km/kWh). Each vehicle type in the model is shown in Table 3.5. The rebates are based on the US and California EV rebate programs while the sticker price, engine efficiency, and battery capacity of each vehicle closely tracks real-world values [136]. The combustion engine efficiency of the ICE and PHEV in Table 3.5 is based on fuel energy content conversions [8].

The workday drive cycles are similar to Table 3.4 and non-workday drive cycles are shown in Table 3.6. However, all agents do not start their daily trips at the same time as one another. The workday drive cycles are randomized to start between 5 AM and 10 AM while non-workday drive cycles are randomized to start between 6 AM and 12 Noon, with start times chosen uniformly randomly in this range. In order not to skew results such as the daily load profiles, each agent has a fixed start time for each daily drive cycle in all simulated scenarios. Figure 3.2 shows the maximum driving distance for each agent – about 88% of the population can use the BEV modeled after the Chevrolet Volt to meet their driving needs.

Table 3.5: Vehicle Models

Vehicle Type	Combustion Engine Efficiency (km/kWh eq.)	Electrical Efficiency (km/kWh)	Battery Capacity (kWh)	Existing Rebate ($)	Sticker Price ($)	Vehicle Make (2013)
ICEV	1.4	–	–	0	16,230	Toyota Corolla
PHEV	2.34	5.55	6.7	4,500	32,000	Toyota Prius
BEV	–	5.55	24	7,500	28,800	Nissan Leaf
BEV	–	4.60	60	10,000	69,900	Tesla Model S

Table 3.6: Non-Workday Drive Cycle

Trip Number	**Start Time**	**Trip Destination**	**Stay (hours)**
1	10:00 AM	LoI	2
2	–	LoI 2	1
3	–	Home	–

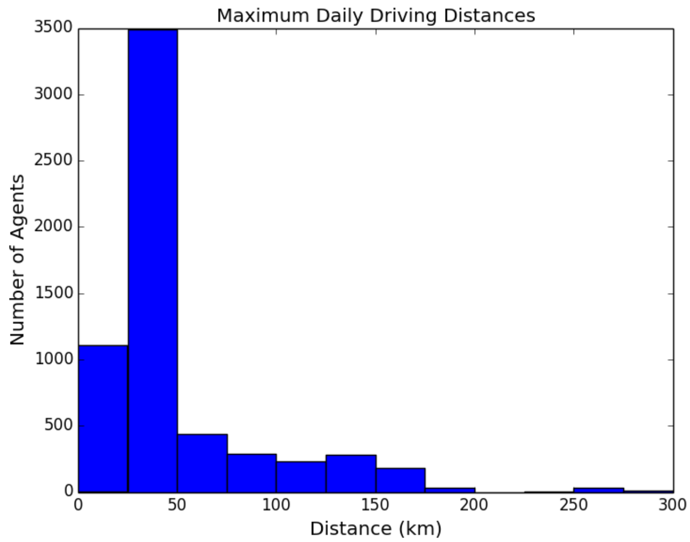


Figure 3.2: Maximum Daily Driving Distances of All Simulated Agents

In addition, eight level-2 public charging stations and one level-3 public charging station are also spatially distributed according to the public charging stations already present in the San Francisco area (Figure 3.3 [109]). All agents can charge at home, with a capacity of 3.3 kW (Level 1) while chargers at workplaces are set at 10 kW (Level 2). Also, the preferred vehicle longevity, i.e., the number of years which agents own a car before selling, was obtained from a normal distribution with an average of 11 years [74] and a standard deviation of 1 year. Other environment variables are initialized as follows: cost of gas = 0.107 \$/kWh (eq.); cost of electricity = 0.221 \$/kWh; and discount rate = 8%.

3.5.2 Parameter Tuning

In our adoption model, an agent's decision to purchase a vehicle is dependent on the agent's income, its cost sensitivity G, social network threshold T, and typical driving behaviour, as well as the prices and attributes of the vehicles on the market. We realize that G and T are essentially unknowable quantities. However, in order to achieve realistic results, we tune the G and T of the agent population such that the predicted EV adoption matches what was observed in practice in San Francisco. Specifically, the distribution of G determines the fraction of the agent population that buy EVs, and T determines the rate at which these agents purchase EVs. Tuning these two parameters in the agent population enables

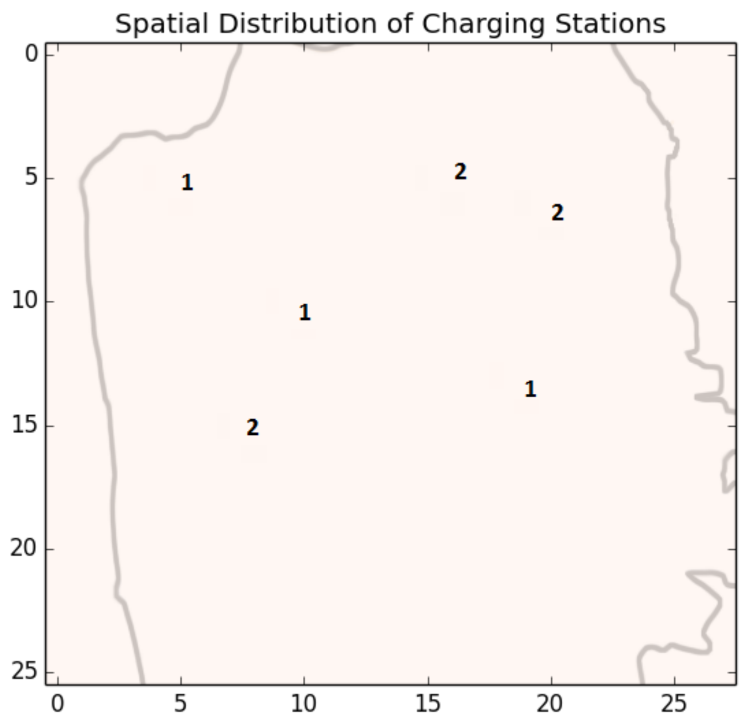


Figure 3.3: Public Charging Station Locations Scaled from Real-World Locations [109]. The scale on both axes is km.

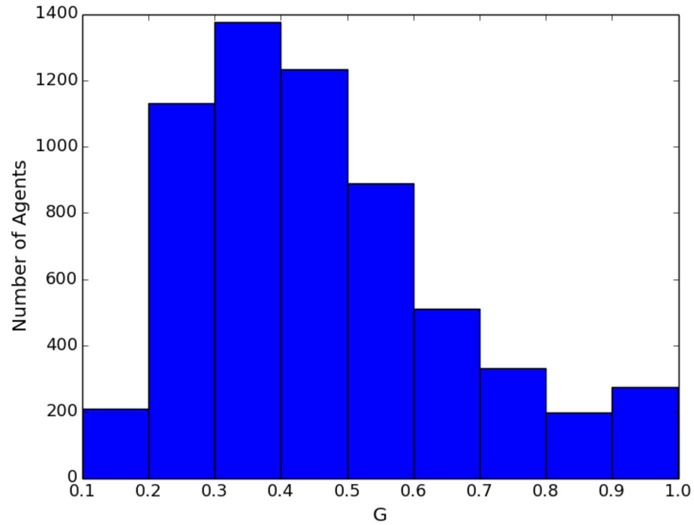


Figure 3.4: Distribution of G by Number of Agents

an approximate estimation of system dynamics.

Figure 3.4 shows the distribution of initial values for for San Francisco, where G has been estimated from agent annual income. Specifically, G can be positively correlated with each agent's income; each agent's G_i is obtained via

$$G_i = (m + \omega) \times (income_i + K) \tag{3.8}$$

where $income_i$ is the agent's income, K is a scaling constant, m is the slope of the G and income axes as seen in [39], and ω is a random variable drawn from a uniform distribution. Eq. 3.8 is defined such that agents with high incomes are more variable in their cost sensitivity while agents with lower income are more focused on the cost of a vehicle rather than its benefits. Figure 3.6 shows the income distribution of agents.

We classify agents based on their inclination towards EV adoption (Table 3.2) as follows: early adopters (16%), early majority (34%), and late majority (50%) [83, 113, 112]. Based on the survey data, 260 out of 6,100 agents own EVs. Since we do not have access to San Francisco EV sales data, we assume a plug-in EV adoption growth in San Francisco that is similar to the US [37] between 2011 and 2014. With a target EV number of 260, we define T for early adopters, early majority, and late adopters as 0, 0, and 0.04 respectively. These low T values were necessary to match the penetration of EVs that we obtained from

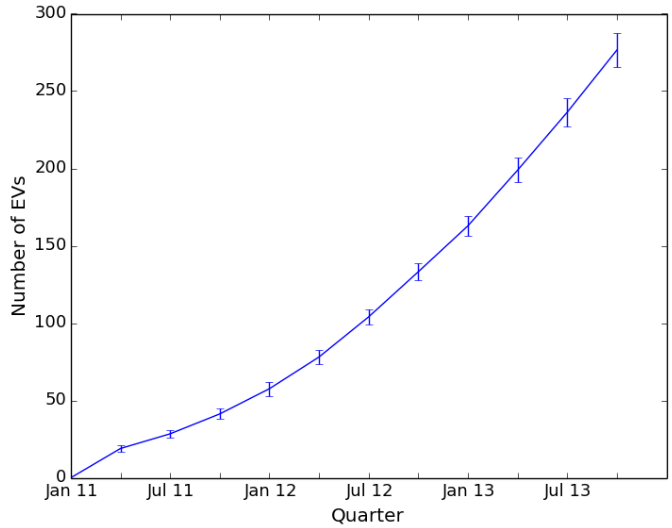


Figure 3.5: EV Adoption Parameter Tuning

the data. Figure 3.5 shows the EV adoption, averaged over 20 simulation runs with these T values and similar G distributions (Figure 3.4). To summarize, we obtain the G values from Equation 3.8 and the income data from the survey, and we then find a value of T such that the forecast adoption of EVs matches reality.

We evaluated the usefulness of our approach by studying outcomes that may be of interest to each potential user of the model: policy makers, utilities, and battery manufacturers. The impacts of different policies are evaluated in different simulation scenarios. The policies considered are as follows:

1. Reducing the effective costs of EVs via rebates, therefore making EVs affordable for more people and making EVs more competitive with ICEVs.

2. Encouraging the availability of charging stations at the work place. The EVSE rebate provided by the Los Angeles Department of Water and Power [8] is an example of a policy that provides incentives for charging station installation.

3. Educating the population on TCO estimation.

Also, the impacts of different battery sizes on EV adoption are estimated by multiplying the existing EV batteries by factors of 1.25, 1.5, and 2. Each scenario is simulated over a

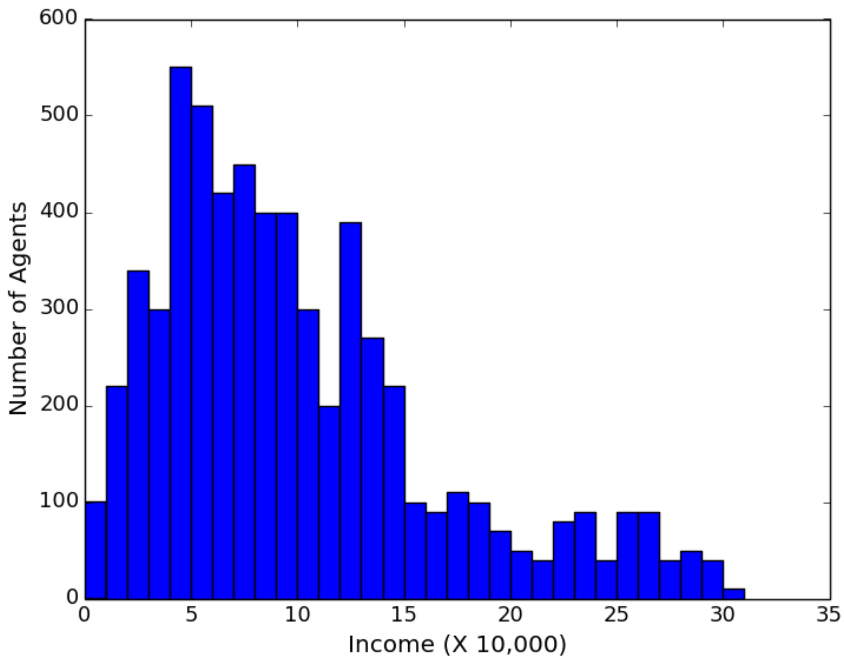


Figure 3.6: Income Distribution

periods of 5 years (2014 - 2018). It is noteworthy that all the results have been averaged over 20 simulation runs and each data point shows the 95% confidence interval.

3.5.3 Policies

The results from different policy scenarios are compared and discussed here. In the base case, the rebates are defined as seen in Table 4. Also, we assume that 20% of agents can charge at work, and that 20% of agents are able to estimate vehicle TCO.

EV Rebates

In addition to the base case, two scenarios are considered:

- No rebates for EVs.
- An additional rebate of $ 2,000 for all EVs.

These scenarios determine the possible impact of removing EV rebates as well as increasing the existing rebates by a fixed value. Figure 3.7 shows the sensitivity of EV adoption to rebates. As expected, more EVs are bought when rebates are increased by $2,000 and the growth of EV penetration is reduced when rebates are removed. Clearly, EV rebates should not be canceled anytime soon since they are still required to encourage the adoption of EVs, given the current EV prices. However, EV price reductions would reduce the need for rebates especially as batteries become cheaper.

Figure 3.8 shows the spatial distribution of home locations of EV owners in each scenario. This also informs public charging station planners on where stations should be sited. Figure 3.9 shows the spatial income distribution, and this provides an overview of the relationship between agent income and EV adoption. We find that there is more adoption at the center of the city even though wealth is not concentrated there. The electrical load impacts are discussed in Section 3.5.3.

Charging at Work

The two scenarios to study the impact of different percentage of agents that can charge at work are

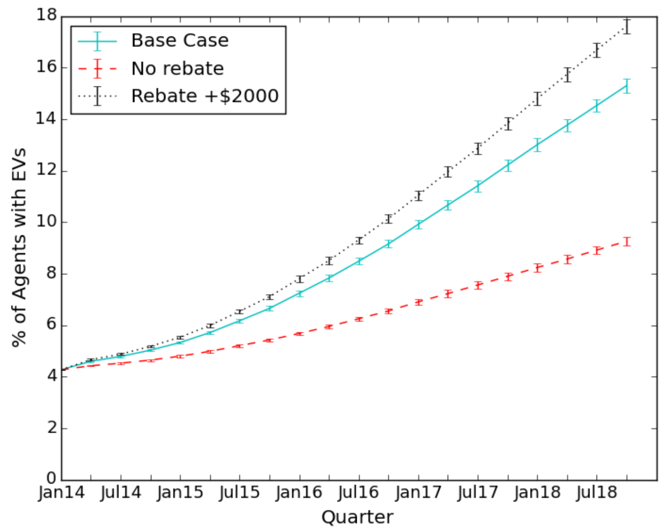


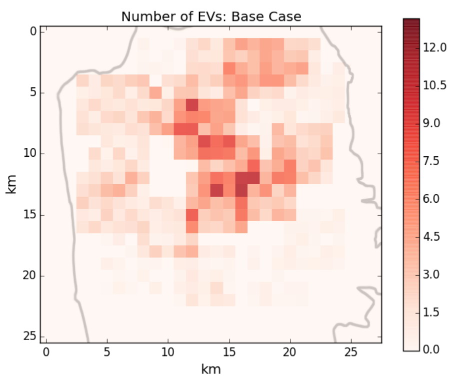
Figure 3.7: EV Adoption; Sensitivity to Rebates

- 40% of agents with a charge-at-work option (base case has 20%).
- 60% of agents with a charge-at-work option.

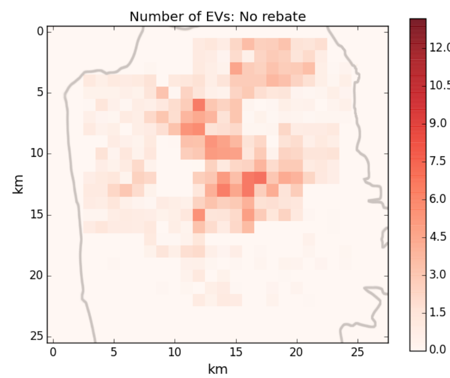
To our surprise, increasing the number of agents that can charge at work does not appear to have a significant impact on EV adoption. This is due to the combined effect of San Francisco being a spatially compact city short distances traveled (Figure 3.2) and the possibility of charging at work not being a significant aspect of the EV purchase decision. However, there are impacts on the grid and these are discussed in Section 3.5.3.

Estimating the Total Cost of Ownership (TCO)

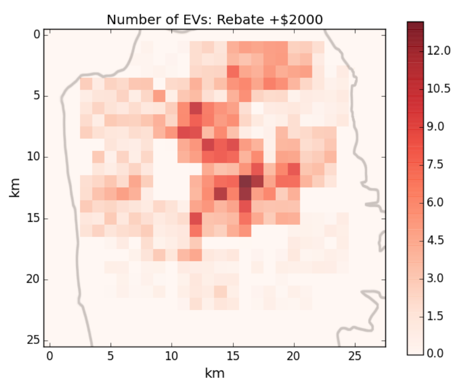
Figure 3.10 shows the sensitivity of EV adoption to the percentage of the population that can estimate the TCO. Two additional scenarios are executed where 40% and 100% of agents can estimate the TCO of a vehicle (base case has 20%). There is a slight but insignificant increase in EV adoption when more people know the TCO of a vehicle. This slight increase results from short distances traveled within the city; making the gain in TCO smaller than in a city with longer driving distances. Given that policy makers and EV manufacturers spend quite a bit of money on consumer education, this is an interesting



(a) Base Case



(b) No Rebates



(c) Additional Rebate of $2,000

Figure 3.8: Spatial Distribution of EV Adoption; Sensitivity to Rebates

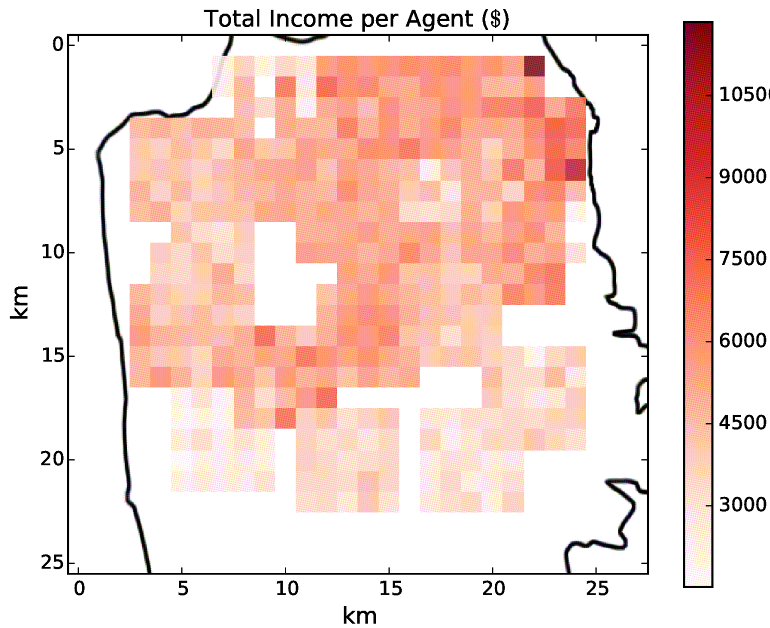


Figure 3.9: Total Income per Agent in each Location

result. This result also emphasizes the need to focus on reducing the selling price of EVs as the most viable method to encourage EV adoption.

Charging Station Planning

Figures 3.11 and 3.12 show the average daily EV arrivals summed over all public charging stations for rebate and battery size scenarios. Figure 3.11 shows an expected increase in public charging station activity over time that is proportional to EV growth (Figure 3.7). Figure 3.12 shows an interesting behaviour in public charging station activity as battery sizes are changed. This reduction in public charging station visits results from larger batteries, which indicates that as battery sizes increase, the need for public charging stations may disappear over time or charging stations may be useful only with Level 3 chargers. It is also clear that EV owners will change their charging and driving behaviours as battery technologies improve.

Figures 3.13 to 3.15 show the average hourly arrival profile at the public charging stations in the last simulated month in different scenarios. It should be noted that these profiles are dependent on the drive cycles of the agents. The charging activity seen in

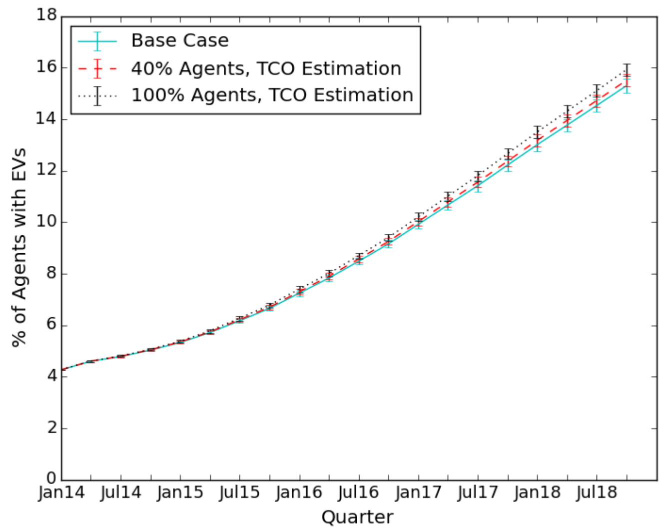


Figure 3.10: EV Adoption; Sensitivity to TCO estimation

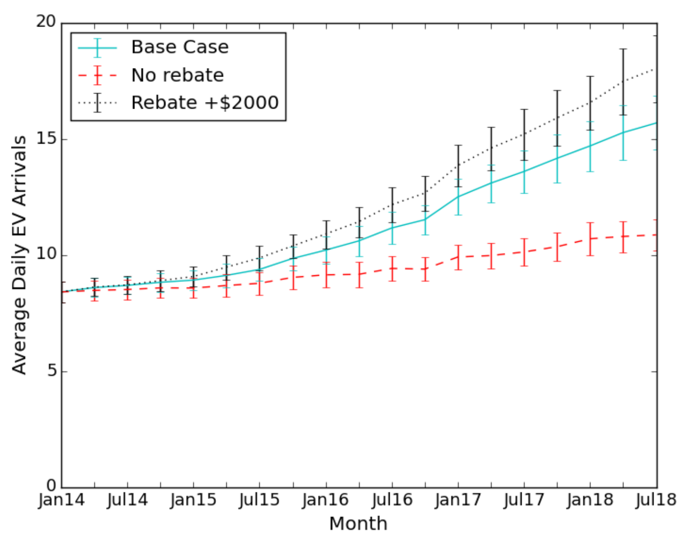


Figure 3.11: EV Arrivals at Public Charging Stations; Sensitivity to Rebates

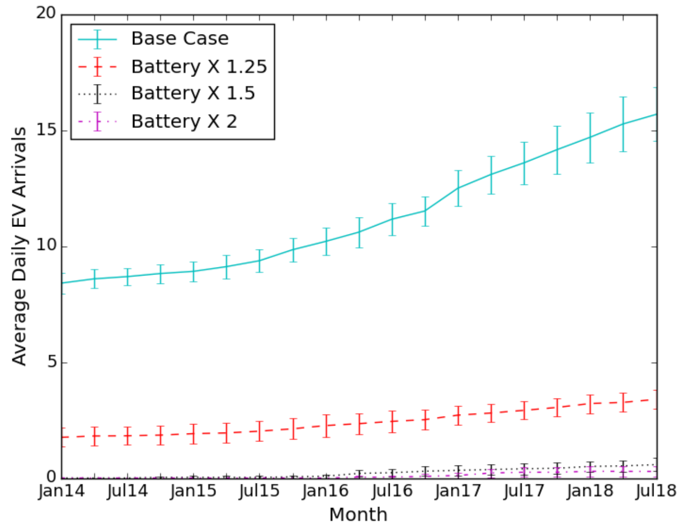


Figure 3.12: EV Arrivals at Public Charging Stations; Sensitivity to Battery Size

Figure 3.13 corresponds to the rebate-effected changes in EV adoption seen in Figure 3.7. In addition, Figure 3.14 shows that charging at work has no significant impact on public charging station usage. As seen in Figures 3.12 and 3.15, the battery size increase has a significant impact on charging station activity.

Battery Sizing

To study the effect of battery size on EV adoption and usage, we have simulated scenarios where batteries can hold 1.25, 1.5, and 2 times more energy than in the base scenario. However, we have not increased EV prices accordingly and we do not model the increased usage of an EV if it has a bigger battery (i.e., we are assuming that the drive cycle is independent of battery size, which is admittedly a naive assumption). With bigger batteries, EVs have improved electric range. Figure 3.16 shows that increasing battery sizes, thereby increasing the electrical range of the EVs, does not significantly change EV adoption in the San Francisco area mostly likely due to the short distances traveled daily. As a result, we have EV adoption curves similar to the base case. It should be noted that agent range preferences are set at the maximum distance covered daily. The load impact of EVs with larger batteries is discussed in Section 3.5.3.

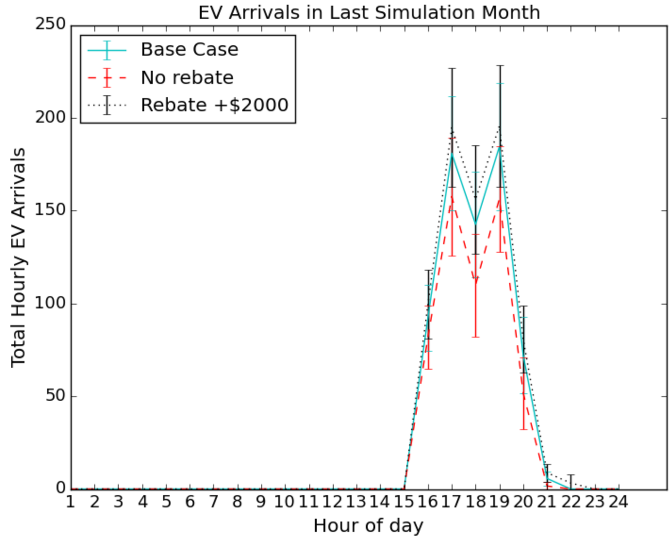


Figure 3.13: Total Hourly EV Arrivals at Public Charging Stations in Last Simulation Month; Sensitivity to Rebates

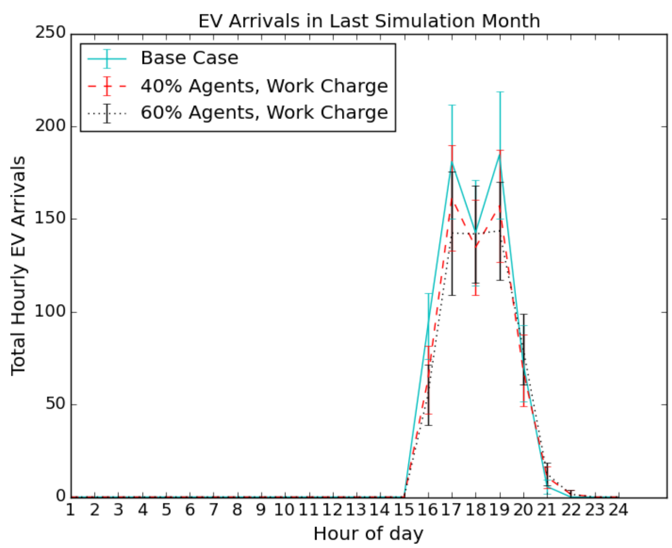


Figure 3.14: Total Hourly EV Arrivals at Public Charging Stations in Last Simulation Month; Sensitivity to Charging at Work

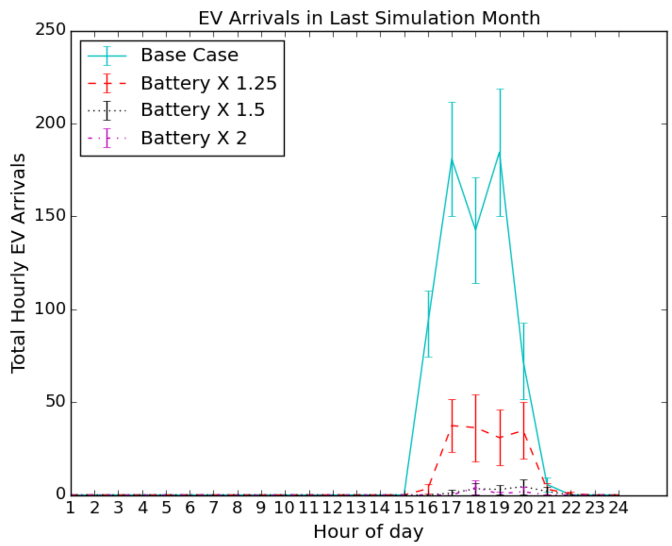


Figure 3.15: Total Hourly EV Arrivals at Public Charging Stations in Last Simulation Month; Sensitivity to Battery Size

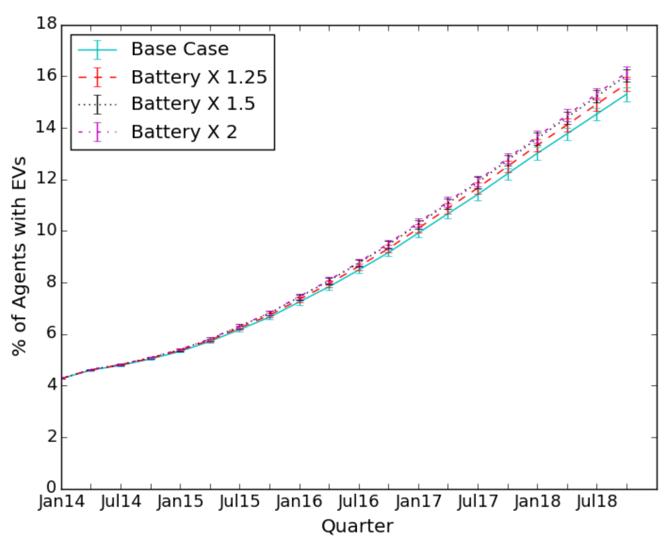


Figure 3.16: EV Adoption; Sensitivity to Battery Size

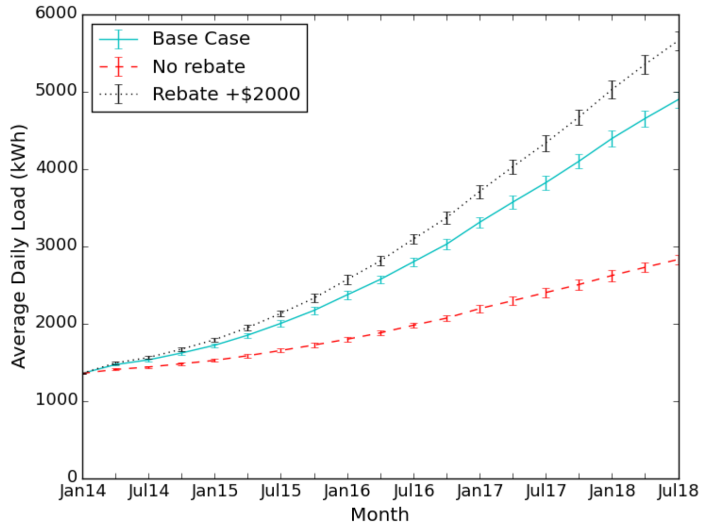


Figure 3.17: Load Growth; Sensitivity to Rebates

Impact on Utilities

Figures 3.17 to 3.20 show the EV load growth over time for different scenarios. In Figure 3.17 and 3.19, we see a load growth proportional to the growth of EVs. Focusing on charging at work, Figure 3.18 shows an increase in the charging load due to the increased number of EVs and the higher use of electricity by PHEVs, since more agents can charge at work. Also, Figure 3.20 shows that there is approximately 30% increase in load for doubling the battery size, even though this change in battery size results in about 5% additional EV adoption. Larger batteries mean PHEVs using less gasoline and more electricity, hence, the increase in load.

Figures 3.21 to 3.23 show the hourly EV load profile in the last simulated month in different scenarios. In Figure 3.21, we see higher loads as the number of EVs increases with additional rebates, and Figure 3.22 shows that charging at work may not be an adequate scheme for leveling the charging load. Also, increasing battery sizes slightly increases the duration of the peak charging period at the end of the day (Figure 3.23). Even though long-distance trips are not included in our model, larger batteries could result in more long-distance trips, hence, more load on the grid. All improvements in battery technology point towards more load on the grid, and this should be taken into consideration as EVs become more prevalent.

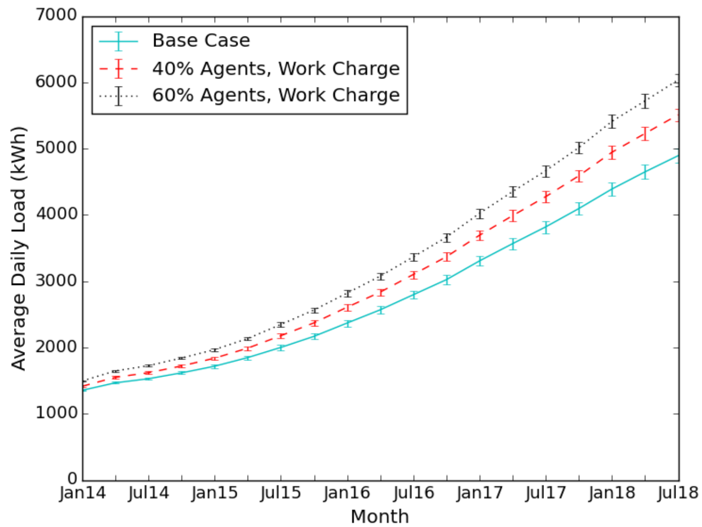


Figure 3.18: Load Growth; Sensitivity to Charging at Work

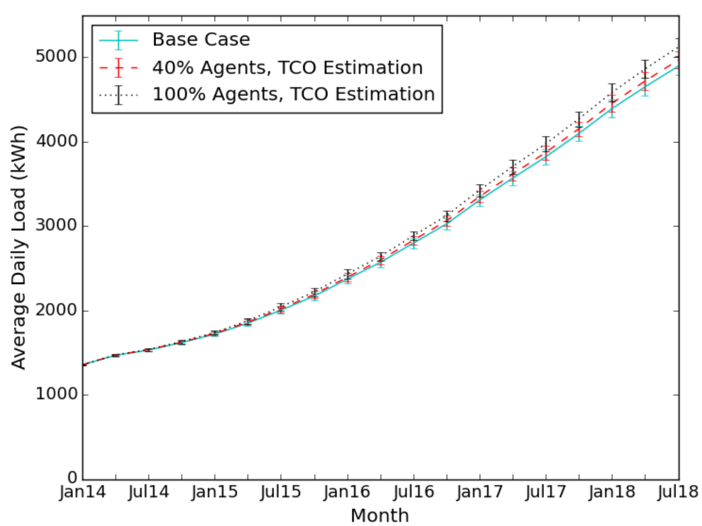


Figure 3.19: Load Growth; Sensitivity to TCO Estimation

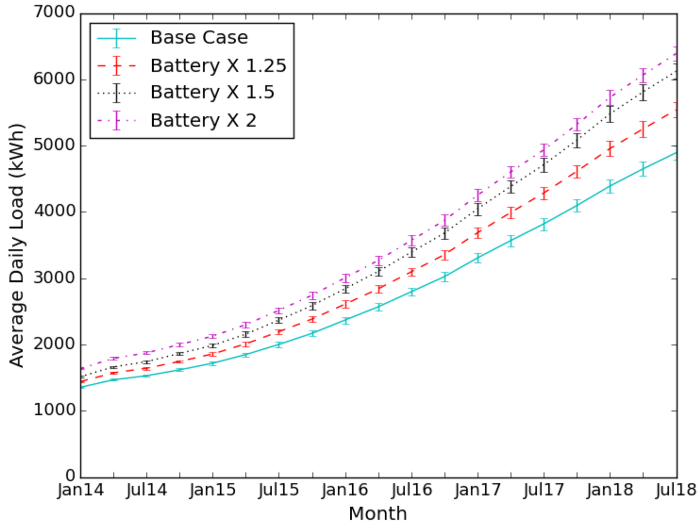


Figure 3.20: Load Growth; Sensitivity to Battery Size

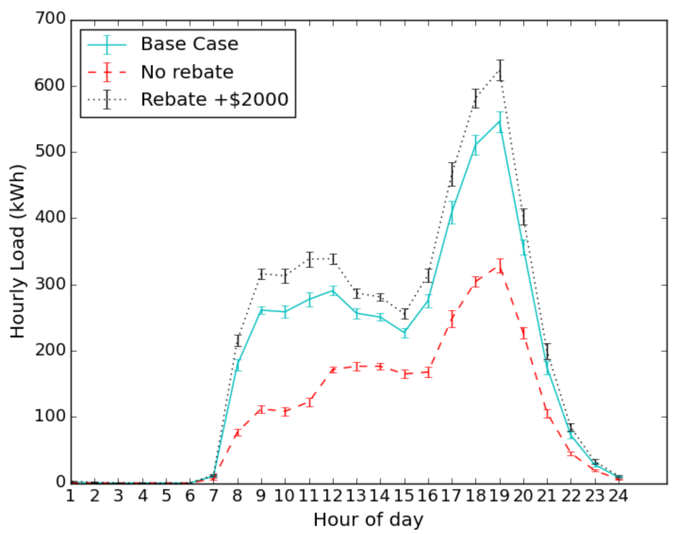


Figure 3.21: Average Daily Load Profile in Last Simulated Month; Sensitivity to Rebates

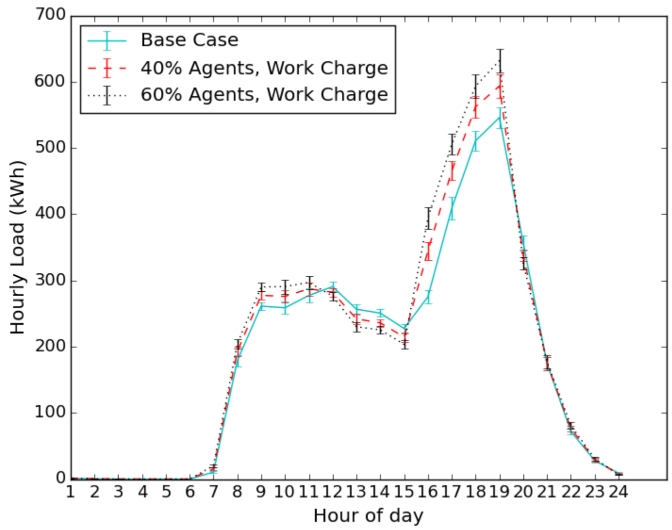


Figure 3.22: Average Daily Load Profile in Last Simulated Month; Sensitivity to Charging at Work

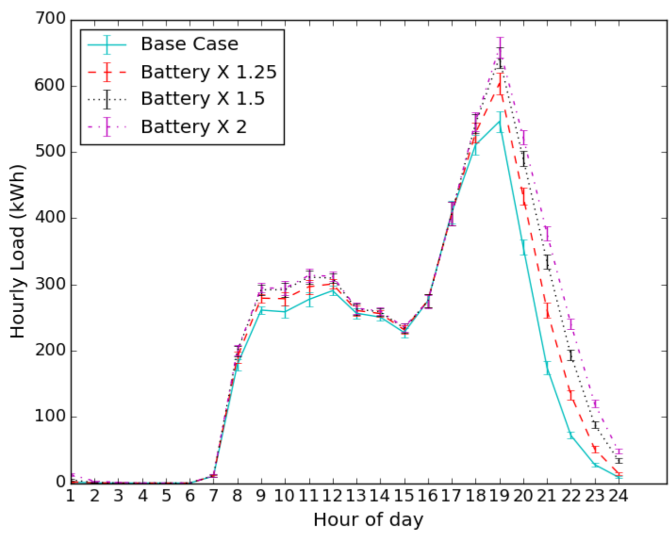


Figure 3.23: Average Daily Load Profile in Last Simulated Month; Sensitivity to Battery Size

3.5.4 Policy Implications

Here, we discuss the effects of the EV-related policies on the EV ecosystem.

Rebates

Canceling EV rebates at a point in time when EVs are not cost competitive with ICEVs would result in a steep reduction in EV adoption. On the other hand, increasing current rebates in San Francisco by $2,000 would not result in a significant increase in EV presence. The current subsidy level is nearly optimal. EV technologies should be allowed to mature until they can effectively compete with ICEVs in terms of range and costs before rebates are removed. Furthermore, while policies are put in place to provide rebates, public charging stations need not be subsidized in order to support the expected increase in EV adoption.

Informing the Population on the Total Cost of Ownership (TCO)

The primary advantage of EVs over ICEVs is fuel efficiency, and the degree of this advantage is dependent on the mean distances traveled: the longer this distance, the more energy saved per km, resulting in lower fuel costs. In the case of San Francisco, educating people on the importance of TCO will not increase EV adoption, considering the spatial compactness of the city. Educating people on TCO would be more apt in locations where longer distances are traveled.

Charging at work

We find that in the case of San Francisco, although subsidizing workplace charging stations may reduce public charging station activity, it is not likely to reduce peak charging loads. The presence of workplace charging stations would encourage more EV adoption, albeit slightly, resulting in slightly higher loads especially at peak periods. The hourly EV charging profiles show that there is no EV charging during the early hours of the day. EV peak load reduction approaches such as Time-of-Use (ToU) pricing, or incentivizing EV owners to charge their EVs during off-peak periods, may be more effective in moving peak loads to these early hours. Moreover, the effectiveness of increased workplace charging in reducing peak loads is dependent on the percentage of residents that work within the city.

Battery Size

In San Francisco Bay Area, 81% of EV charging is done at home [31]. Increasing battery sizes would result in fewer public charging station visits per car since EV owners can charge more at home. In this study, we have focused on short-distance trips, but larger batteries may result in more EVs being used in long distance trips due to increased range. As a result, installing Level 3 public charging stations may become more useful than installing Level 1 and Level 2 public charging stations. Policymakers need to make decisions on subsidizing charging station installations based on the dynamics between battery size and typical distances traveled: the larger the battery size, the greater the mean distance traveled and the greater the need for Level 3 charging stations (in contrast to Level 1 or Level 2 stations).

3.6 Los Angeles Case Study

We carry out a case study to forecast the impact of EV rebates and EV battery technology improvements on patterns of EV adoption and EV usage. Agents are initialized based on a transportation survey of residents in Los Angeles with a focus on transportation. It should be noted that we made a change to the EV adoption model in the Los Angeles case study. While comparing driving range of vehicles, we incorporate the non-linearity of the relationship between driving range and customer vehicle valuation derived from a study by Daziano [32]; the study by Daziano is based on a survey focused on vehicle purchase decisions, with respondents from California. As a result, each agent's range preference is represented by the agent's Willingness To Pay (WTP) for a vehicle with a particular range. According to Daziano [32], the WTP per unit distance has a non-linear relationship with vehicle range. Therefore, an agent's valuation of a vehicle's range is given by:

$$WTP = WTP_{per\ unit\ distance}(range) \times range \tag{3.9}$$

We use the average values in the fixed parameter logit analysis from the work by Daziano [32] to model the agents in our simulations. It should be noted that Equation 3.9 is only an approximation of an integral. Next, we describe the Los Angeles Li-500 case study in more detail.

3.6.1 Experiment

In this section, we provide details of the Los Angeles case study.

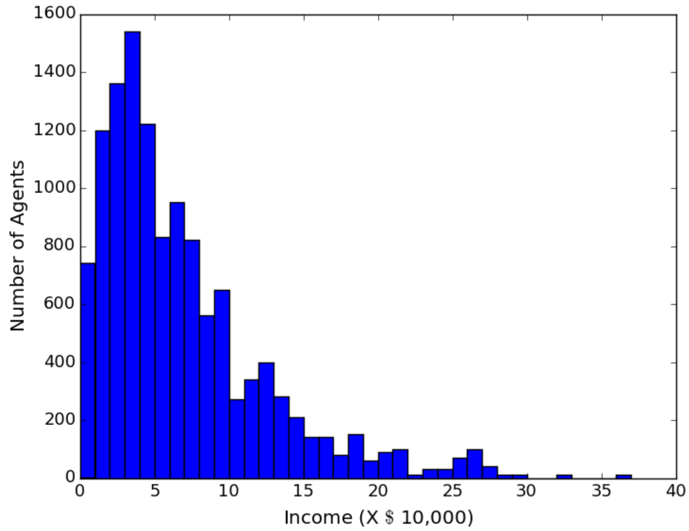


Figure 3.24: Agent Income Distribution

Data Description

We focus on Los Angeles in this study due to its overall spatial sparseness (though it is known to have a dense urban core) and high-penetration of EVs [98]. Similar to the San Francisco case study, the data used to populate the ABM in this study was obtained from the survey conducted by NREL's secure transportation data project [23]. For each household surveyed, the data provides home and work zip codes (i.e. coarse-grained geographical locations), work days, and vehicle specifications of the residents, as well as total household incomes.

The ratio of the actual population of Los Angeles, to the number of participants in the survey is about 1:789. In order to have adequately detailed EV ecosystem dynamics, but without having to simulate the entire population of the city, we duplicated each agent 10 times. This enables us to achieve finer and more detailed simulation results. Therefore, the magnitudes of EV adoption and load values obtained in this study are at a scale of about 1:80 to reality. This scaling is also reflected in the number of public charging stations and their locations (i.e., we scaled down the true number of charging points at these stations by a factor of 80).

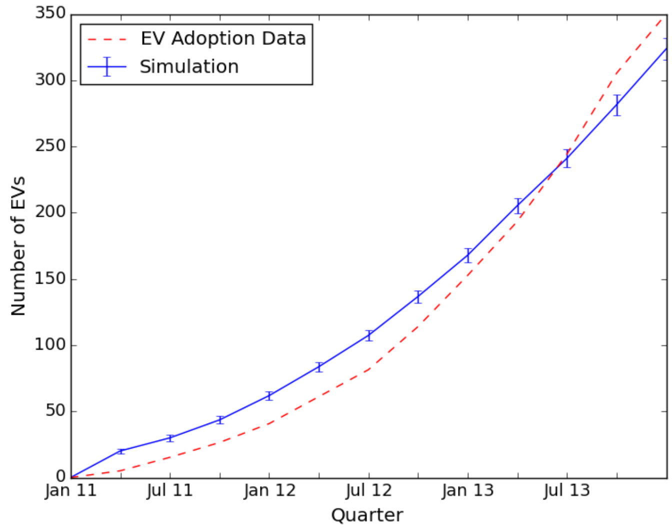


Figure 3.25: Parameter Tuning Results

Parameter Tuning

We apply a parameter tuning approach, similar to the approach described in Section 3.5.2. Specifically, each possible combination of G and T distribution means was simulated nine times and the squared errors of EV adoption were averaged. Figure 3.25 shows the simulated adoption with the closest fit to historical adoption; it is noteworthy that all the results have been averaged over 20 simulation runs and each data point shows the 95% confidence interval. Also, Figures 3.26 and 3.27 show the selected G and T distributions respectively.

Simulation Description

Here we discuss the initialization of other agent and environment variables. We use the same vehicle models used in the San Francisco case study (Table 3.5). Figure 3.28 shows the typical daily driving distances of the agents, using the drive cycle seen in Tables 3.4 and 3.6. Also, the full set of charging stations within the Los Angeles area was obtained from Plugshare [109], and the number of stations was scaled down eight-fold as discussed earlier. Furthermore, we assume that 20% of agents can charge EVs at work and 20% of agents can estimate the TCO of EVs. These assumptions were not changed in the different

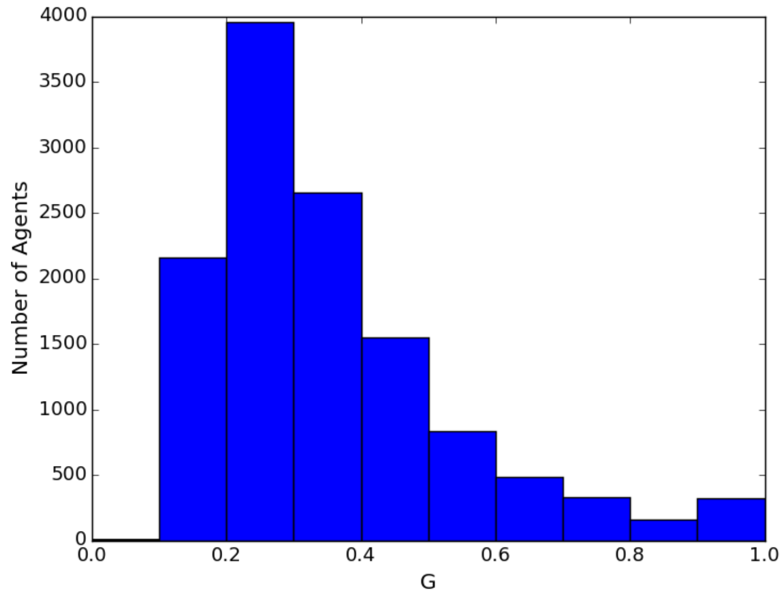


Figure 3.26: Distribution of G by Number of Agents

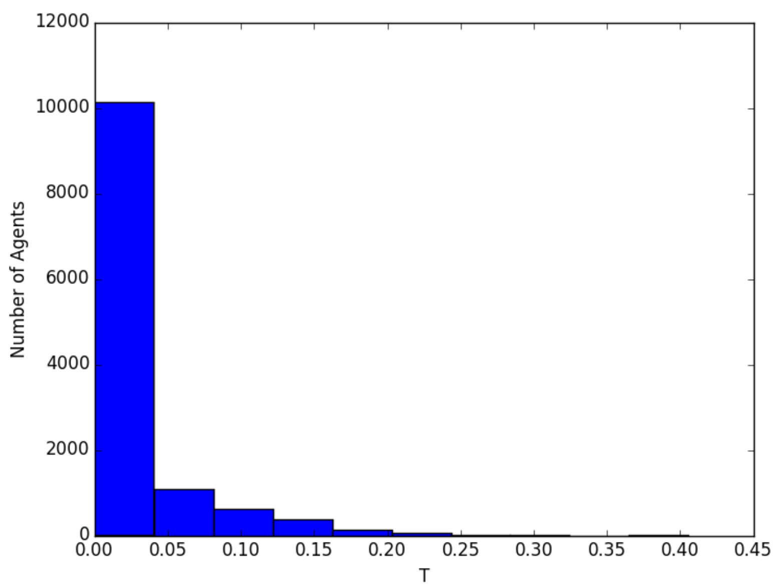


Figure 3.27: Distribution of T by Number of Agents

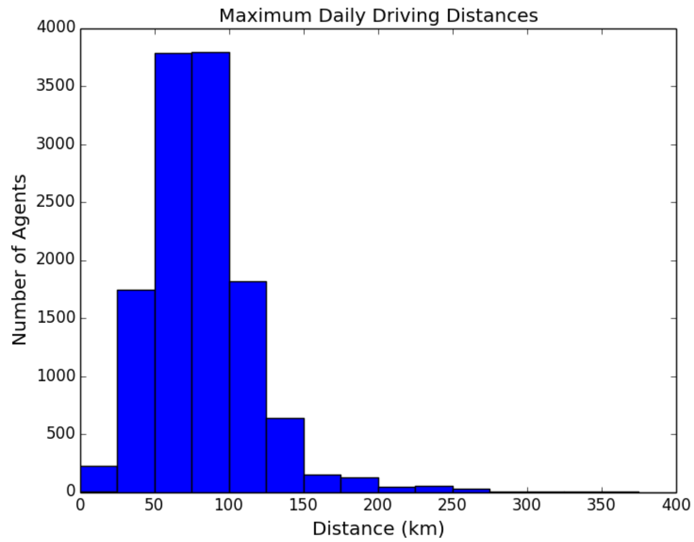


Figure 3.28: The Distribution of Driving Distances in the NREL Secure Transportation Dataset. Note that most distances are under 100 km.

scenarios, since the focus in this study is on the impact of price and driving range.

We studied four scenarios in addition to the base case:

- Case 1: Li-500 battery technology is supposed to improve the energy density of the batteries, approximately, by a factor of 5 [63]. Therefore, we increase the battery sizes of all EVs in Table 3.5 by a factor of 5 but without increasing the EV price.
- Case 2: The existing EV rebates are increased by $2,000. We execute this scenario in order to compare the impacts of reductions in price and improved batteries.
- Case 3: The existing EV rebates are increased by $4,000.
- Case 4: The EV batteries are increased by a factor of 5 and the existing rebates are increased by $2,000.

3.6.2 Simulation Results

Here, we look at the temporal and spatial changes in EV adoption, electrical load, and charging station activity in the different simulated scenarios.

EV Adoption: Range vs. Price

The adoption of EVs is influenced by the costs and benefits associated with each EV. Figure 3.29 shows EV adoption over the simulated period of 5 years across the four simulation scenarios. We see that the additional rebate of $4,000 results in the highest EV adoption. Surprisingly, increasing the battery size alone does not result in a significant improvement in EV adoption. Factors that lead to this insignificant change in EV adoption include the large proportion of agents that cannot afford EVs, and the parameter tuning process that found that, historically, most agents have focused more on vehicle costs than benefits (Figure 3.26).

However, reducing the EV price by means of a $2,000 rebate and increasing battery size shows a significant increase in EV adoption; in the base case about 7% of the population own EVs at the end of the simulation, whereas, about 9% of the population own EVs when batteries are better and the rebate is higher. This suggests that for increasing EV adoption in Los Angeles, improved batteries should not be at the expense of increased EV costs.

To get more insight into our results, compare the electric range of each EV in Table 3.5 with the driving distances seen in Figure 3.28. We can see that, surprisingly, even for a spatially spread-out city like Los Angeles, current EV technology can already meet existing daily driving distances. This is because most of the wealthy people in LA, who can afford EVs, live and work in the downtown core. A relatively inexpensive EV such as the Nissan Leaf can meet the driving requirements of about 70% of the agents. Considering that Los Angeles already has a high penetration of EVs compared to the rest of the US, we can draw the conclusion that improved range alone cannot bring about significant improvements in EV adoption: improvements in battery technology are better used to reduce costs rather than increase range.

Figure 3.30 shows the spatial adoption of EVs based on the home locations of agents in three different cases. The difference in EV adoption between scenarios can be seen spatially as the battery size and EV rebates are increased. Also, more EVs are adopted in the central area, where wealth is concentrated (see Figure 3.31); this informs charging station planners of the locations that may require public charging stations and the number of charging stations required.

Electrical Load

EV adoption will add to the overall electrical load. We now study the areas in LA that could be affected due to EV adoption. Figure 3.32 shows the electrical load growth from

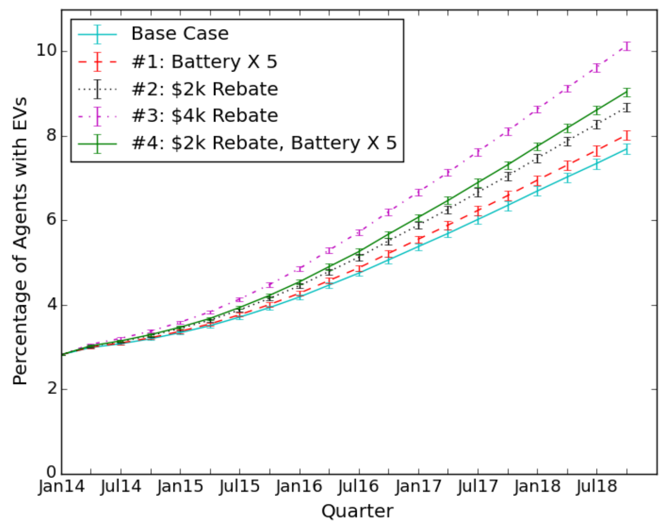


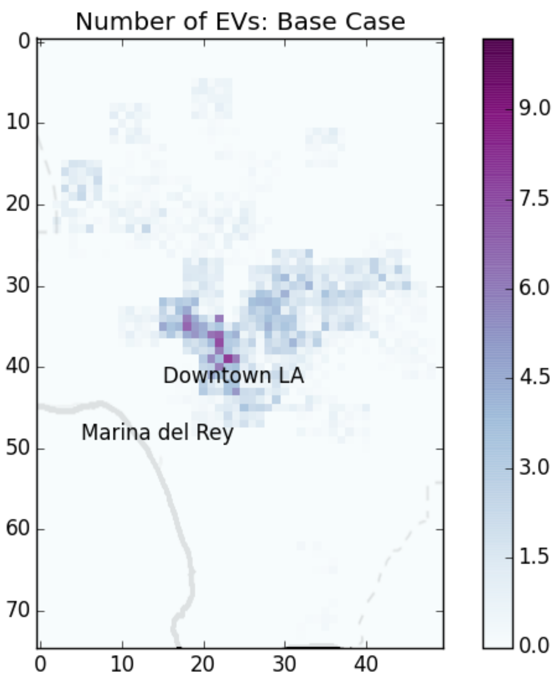
Figure 3.29: EV Adoption

EV charging over the simulated years. Increased batteries result in more electrical load over time, especially due to PHEVs using more electricity and less gasoline. Comparing Figure 3.29 and Figure 3.32, larger batteries would have more significant impacts on EV charging than on EV adoption, as expected.

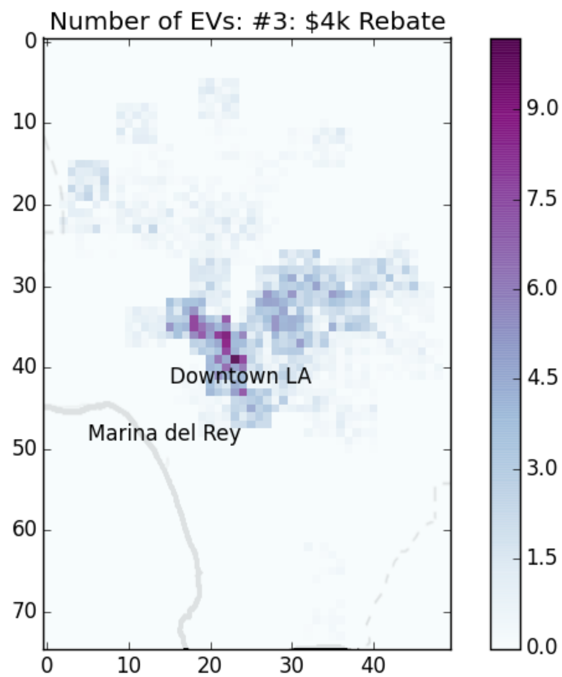
Figure 3.33 shows the total EV charging load profile from charging at home, work, and public charging stations. For all cases, the peak charging loads are proportional to the number of EVs. The larger batteries in Case 1 also result in higher electrical loads. The evening charging load peak would help utilities to know how much additional load to plan for, and the locations of these loads. If the time of the existing daily load peak in a particular location coincides with the time of the charging load peak, utility operators might have to improve the existing distribution infrastructure. It should be noted that the daily charging profile shown in Figure 3.33 is dependent on the trip structure (Table 3.4).

Figure 3.34 shows the spatial distribution of EV charging load in three different cases. The variations in load between the different scenarios are more evident at the central areas of the map. This indicates that changes in EV adoption from rebates and batteries could result in a need for grid infrastructure upgrades. Also, the load increase in the simulated cases see here is consistent with the annual load increase (Figure 3.32) and the spatial distribution of EV adoption (Figure 3.30).

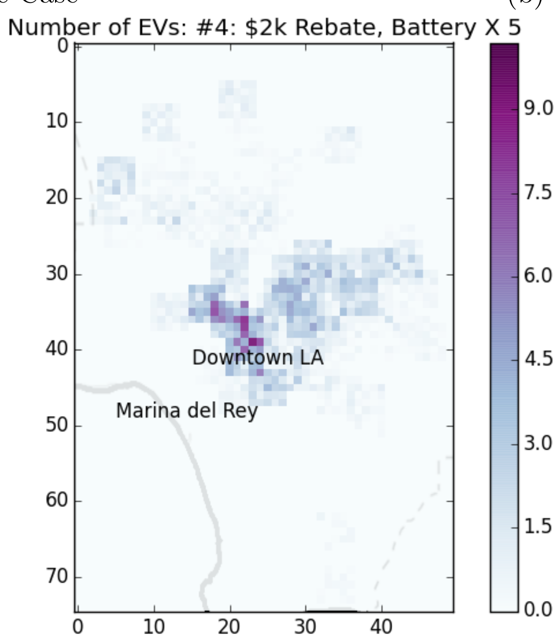
Figure 3.35 shows the number of EV arrivals at public charging stations in the last



(a) Base Case



(b) Case 3



(c) Case 4

Figure 3.30: Spatial EV Adoption at the end of the Simulations

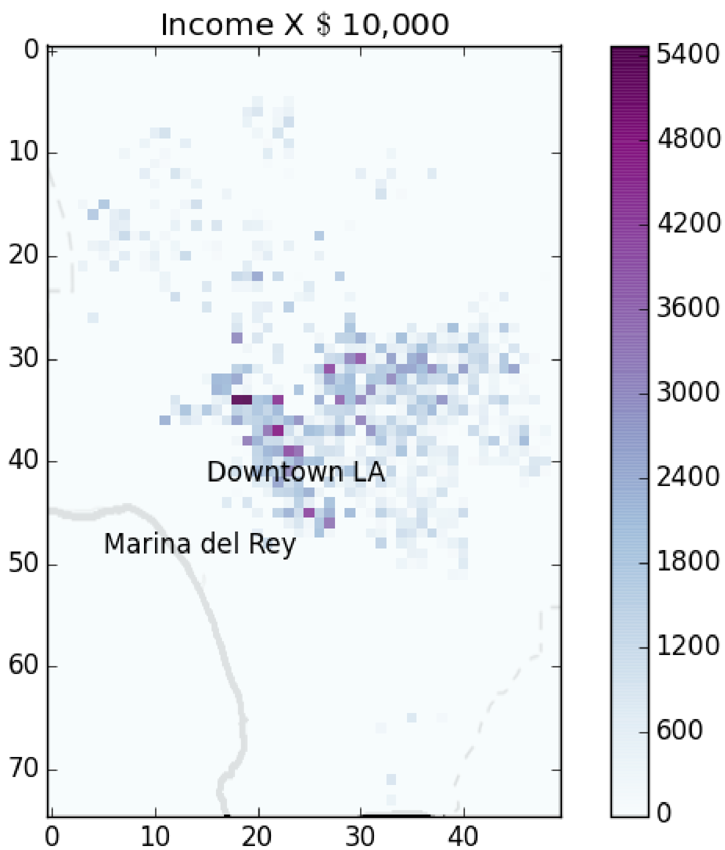


Figure 3.31: Spatial Distribution of Income

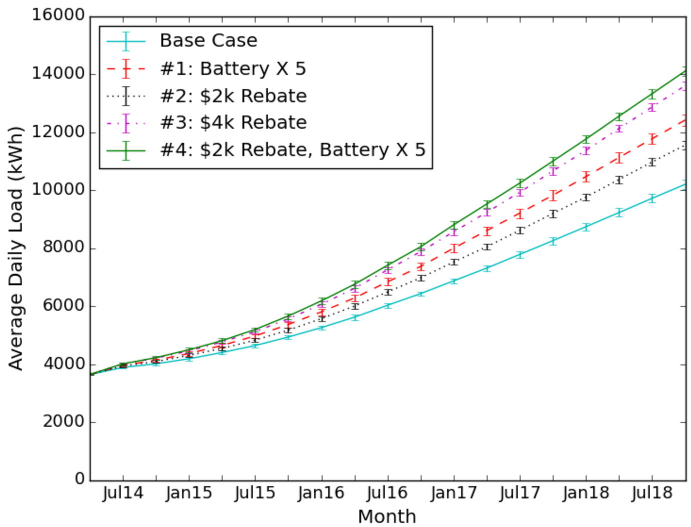


Figure 3.32: Charging Loads

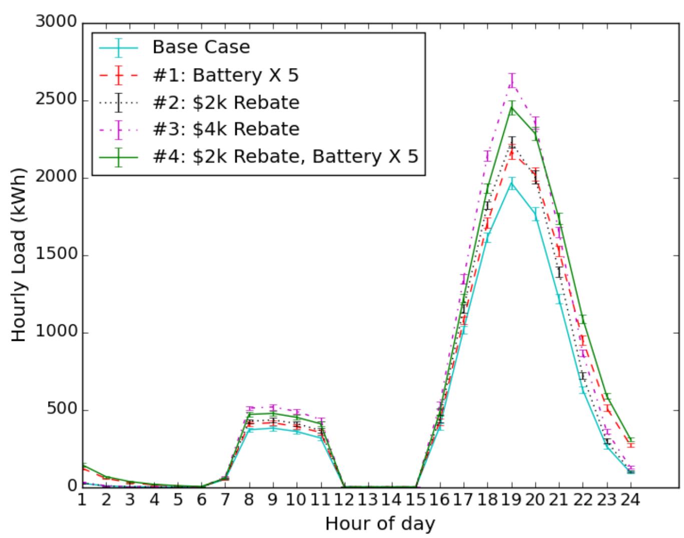
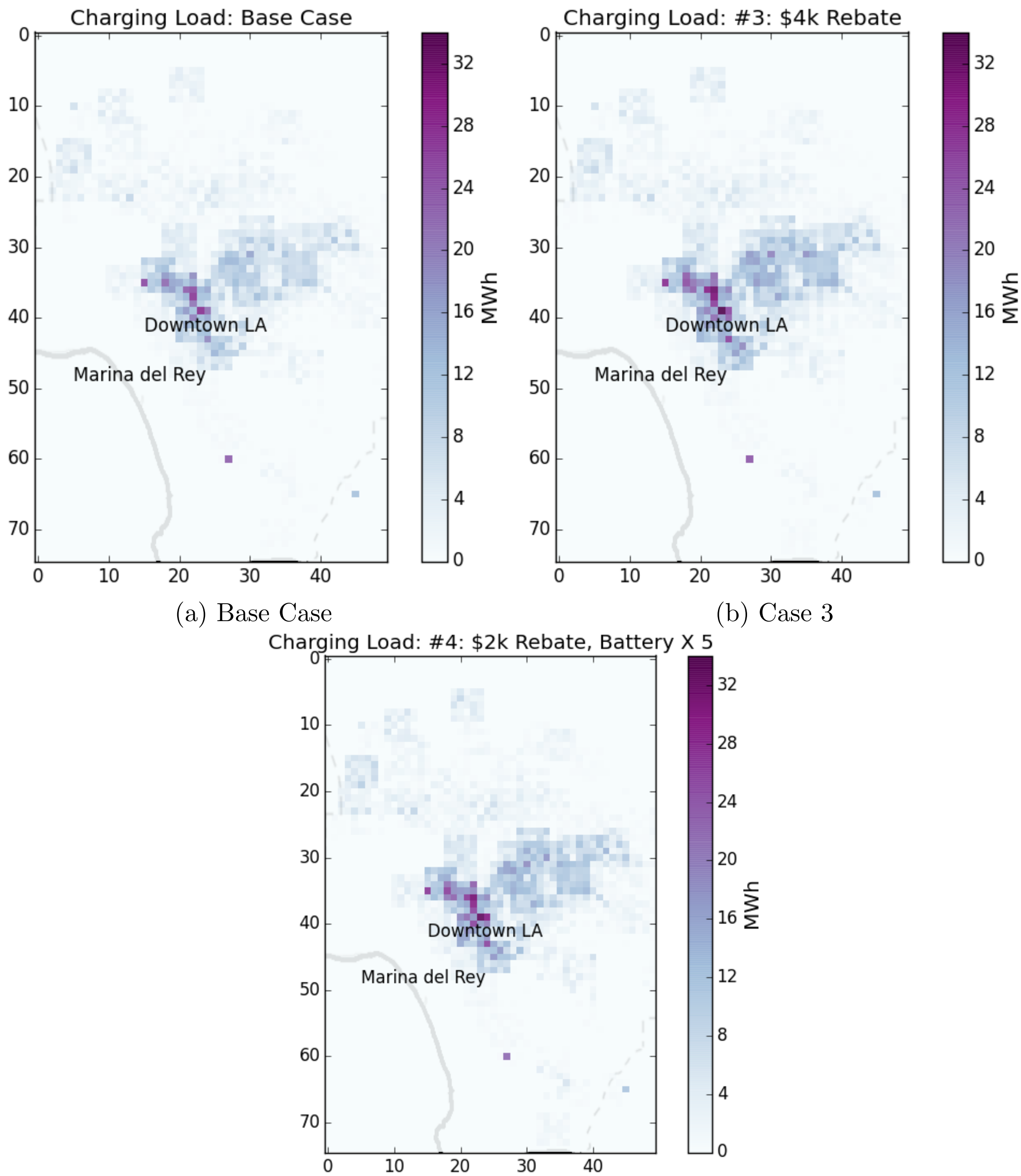


Figure 3.33: Hourly Charging Loads in the Last Simulation Month



(a) Base Case

(b) Case 3

(c) Case 4

Figure 3.34: Spatial Loads in Last Simulation Year

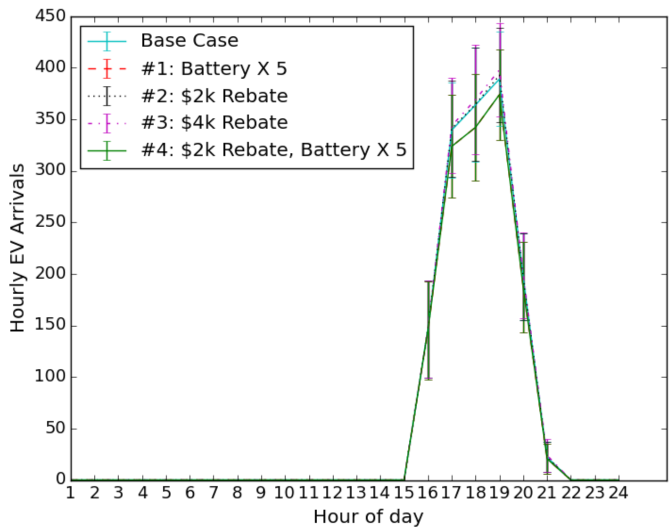


Figure 3.35: EV Arrivals at Public Charging Stations in Last Simulation Month

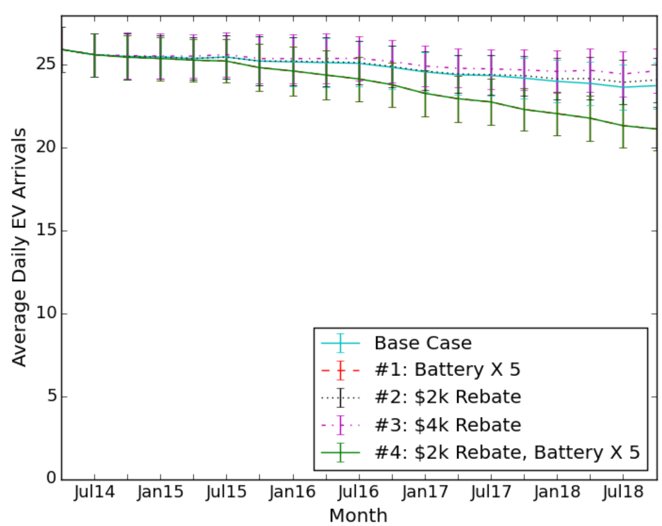


Figure 3.36: EV Arrivals at Public Charging Stations

simulated month. There is no significant change in public charging station activity in the different scenarios. Figure 3.36 shows the change in public charging station activity over the years, and a slight decrease in charging station arrivals can be seen. It should be noted that in the EV ecosystem model, only BEVs visit public charging stations, therefore, Figures 3.35 and 3.36 represent the expected minimum charging station activity for each scenario.

3.6.3 Policy Implications

The results show that a high capacity battery would increase EV adoption slightly, but EVs are still too expensive for a significant increase in adoption. Increasing EV rebates shows significant improvements in EV adoption. We find that the cost-competitiveness of EVs is a more significant barrier to EV adoption than range anxiety. While increasing the capacity of EV batteries would reduce range anxiety and make EVs more attractive for purchase, the current costs are still prohibitive. In order to encourage EV adoption, EV costs should be reduced in tandem with battery improvements. Since there is already a high penetration of EVs in Los Angeles, the need for joint EV cost and battery improvements can be generalized.

In order to improve cost competitiveness of EVs, policies could be implemented to systematically reduce EV costs. For example, an EV rebate program focusing more (even more than current policies) on the battery cost component of an EV, rather than the whole cost of the EV, would abate the higher costs resulting from larger battery capacities. Furthermore, with fluctuating gas prices, EVs could struggle against ICEVs for some time. Lower gas prices and more efficient combustion engines would make the fueling cost of EVs less of an advantage, unless people take overall environmental friendliness into consideration in their vehicle purchase decisions.

Also, with an increase in battery size, there is a proportional increase in electrical load on the grid over time. However, larger batteries and the corresponding increase in EV adoption result in higher electrical loads since PHEVs use more electricity in place of gas. In addition, we find that the evening charging load peak would increase in proportion to EV ownership. Incentives that encourage EV owners to charge at off-peak periods or charging schemes that coordinate EV charging within a particular electricity distribution area are options for managing this change in electrical load.

In summary, we find it surprising that vehicle affordability is a greater determinant of EV adoption than range, even in a geographically dispersed city such as Los Angeles. However, our results point to the need for EV policies supported by data that can be used to drive the EV industry into a mature phase, where EVs are cost-competitive with conventional vehicles. With battery technology improving consistently, EVs with driving ranges closer to that of a typical ICEV will be readily available, and the stakeholders in the EV industry should ensure that the cost of such EVs are not prohibitive enough to discourage EV adoption.

3.7 Limitations and Future Work

We have designed a simple yet effective EV ecosystem model that uses realistic data (see Tables 3.2 and 3.3) to assess the impact of changes in policies and technology on EV adoption and use. Any model abstracts certain aspects of reality; ours does too. Specifically, our model suffers from the following limitations:

- A simple TCO estimation process.
- Lack of a financing option for EV purchase.
- Only two vehicle preferences (range and fuel economy) are used in the agent EV purchase decision. Other EV benefits such as free parking and allowance for high-occupancy vehicle lanes could be modeled.
- Linear estimation of battery charging and discharging, without considering acceleration or auxiliary energy consumption in EVs, e.g., cooling or heating.
- A price learning process that can model the impact of adoption on prices.
- We do not consider the impact of long-distance trips on the purchase decision.

Areas of future work include:

- Forecasting EV adoption by fleet services. The criteria for individuals and fleet services to purchase EVs differ, therefore, posing an interesting research question. Also, we realize that many of our conclusions are a direct consequence of the compact geographic size of San Francisco.
- Estimating the impact of demand response policies and distributed generation resources on EV adoption.

- Estimating how public charging stations might be affected by larger batteries as well as the availability of cheaper fast charging stations to home owners.
- Exploring the interrelationship between the adoption of home solar systems and EV adoption.
- Evaluating the impact of improved batteries on driving behaviour – we would study the changes in daily trips when people drive EVs with a larger battery 'buffer' as well as the use of EVs in long-distance trips.

3.8 Summary

In this chapter, we have detailed the agent-based EV ecosystem model and carried out case studies. We have used our framework, albeit not strictly, to develop this EV ecosystem ABM. The results show what policies might be effective in improving EV adoption, with cost reduction the most effective. In addition, the results show the resulting challenges of EV adoption such as the need for more public charging stations and increased charging load peak, especially in the evening.

Chapter 4

Time-of-Use Electricity Pricing

Publication Reference:

A. Adepetu, E. Rezaei, D. Lizotte, S. Keshav. Critiquing Time-of-Use Pricing in Ontario. *2013 IEEE International Conference on Smart Grid Communications*[1].

Time-of-Use (ToU) electricity pricing is an electricity pricing scheme where consumers are charged at a rate that is dependent on the time of electricity consumption. This pricing scheme is often implemented to match the cost of generating electricity and to make consumers defer appliance usage, in order to reduce the daily electricity consumption peak which can both reduce the cost of generation and its carbon footprint. We first critique the current ToU scheme in Ontario and make recommendations to improve it. Subsequently, we create an ABM to study ToU pricing and its effectiveness in reducing peak loads, which allows us to evaluate the benefit of our recommendations[2].

4.1 Introduction

ToU electricity pricing commenced in Ontario in 2006, and this was accompanied by the deployment of Advanced Metering Infrastructure (AMI) also known as 'smart meters.' Electricity generation systems are typically sized for the peak consumption periods and

[1] The research work from this paper that is included in the thesis was carried out and documented by the author of this thesis.

[2] The ABM simulation code can be found at `bitbucket.org/adeda/tou`

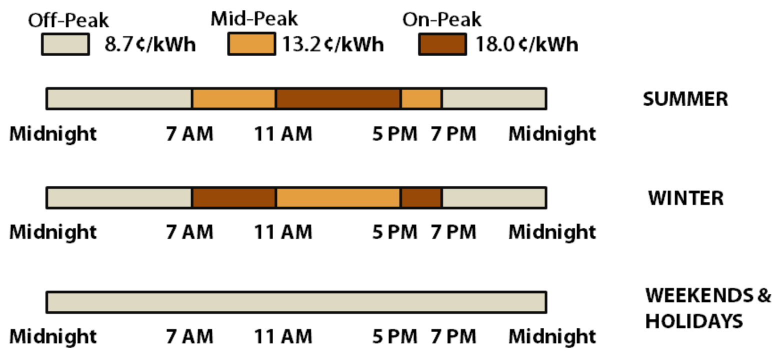


Figure 4.1: Ontario ToU Pricing Scheme [99]

as a result, the generation systems are not used to their maximum capacity during other periods. This causes a *wastage* of generation capacity. To have a more efficient system, electrical loads should be deferred from the peak periods. To do so, the utility can charge a higher rate for electricity consumption during these periods to motivate consumers to defer their loads.

Figure 4.1 shows the current ToU pricing scheme in Ontario. The peak, mid-peak, and off-peak periods are different for each of two seasons. For utilities, an ideal scenario would be one where the consumption is the same throughout the day, resulting in a flat electrical load profile.

In prior work [4] (which is also presented in part in Section 4.2), we empirically studied the impact of ToU pricing in Ontario and evaluated the aptness of the pricing scheme for Ontario. We found that, as of that time, there had been no reduction in the Peak-to-Average Ratio (PAR) of the Ontario electricity consumption. In addition, we found that the peak periods of the electrical load data and the ToU scheme do not match (See Section 4.2). As a result, we made the following recommendations to improve the electricity pricing scheme:

1. If the two-season ToU scheme is to be maintained, the start dates should be moved back in time by two weeks. Furthermore, the peak, mid-peak, and off-peak periods should be changed to the time periods shown in Table 4.2.

2. The ToU scheme should comprise four seasons. The recommended start dates and daily period divisions are shown in Figure 4.2.

We should note that in a study by Navigant [94] using electrical load data from households in Ontario, it was found that there has been a 3.3% reduction in household electrical

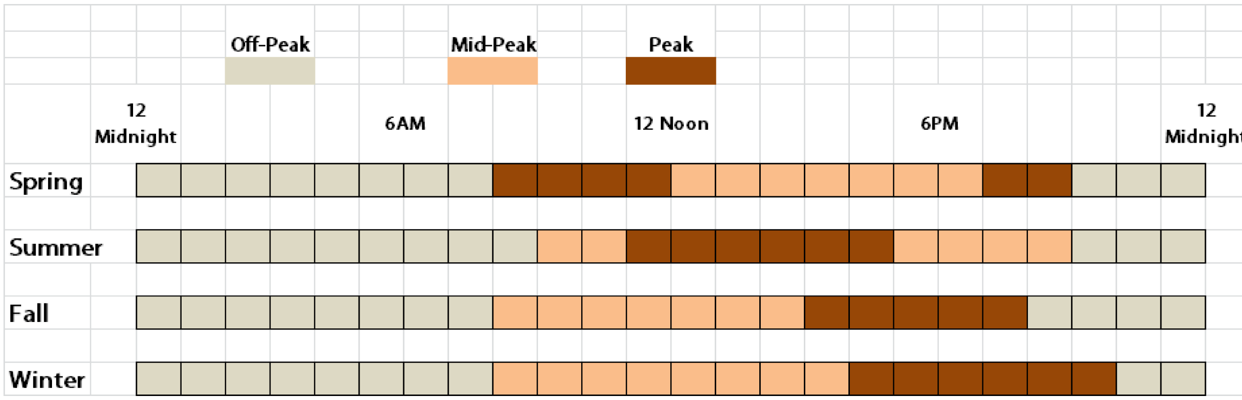


Figure 4.2: Daily Periods of the 4-Season TOU Scheme

peak load between 2009 and 2013[3]. However, this does not validate the assigned peak, mid-peak, and off-peak periods; indeed, we believe that even greater reductions are possible with better alignment of load and price peaks, as we demonstrate in Section 4.4.

To evaluate ToU pricing in Ontario and identify a ToU scheme that is fit for purpose, we create an ABM that models the residents of Ontario, and how they use deferrable loads such as washing machine, clothes dryer, and dishwasher.

4.2 Critique of Ontario ToU Scheme

In this section, we evaluate the ToU scheme in Ontario. Specifically, we ask the questions:

1. Do loads exhibit seasonality, and if so, how many seasons are present in the load data?

2. If the current ToU season length of 26 weeks is maintained, when should each season start and what are the appropriate peak, mid-peak, and off-peak periods?

We answer these questions by applying the time series clustering approach to the Ontario load data between 2003 and 2005.

[3]ToU pricing was initiated in Ontario in 2006 but some jurisdictions in Ontario did not implement it until 2010.

4.2.1 Data

Our study is based on the publicly available Ontario hourly aggregate load demand between 2003 and 2005 [65]; this is just before the commencement of ToU electricity pricing in Ontario. This load data comprises electricity loads from residential, commercial, and industrial consumers. This load data is ideal since it enables the evaluation of electrical load seasonality and peak periods in Ontario as a whole[4]. In order to compare data across years, we aligned data from each week of the year by discarding the last day of each year (and last two days for each leap year) to get exactly 52 weeks.

4.2.2 Time Series Clustering

We determine the seasons in a set of load profiles using clustering by exhaustive search. Our approach is similar to that of Inniss [69].

Enumerating all Possible Seasons

To identify this seasonality in load data, we first define the concept of a *season* with respect to load data. A season is a continuous period of time, measured in weeks, represented in this study with hourly load data. Therefore, we define a *seasonal sequence* as a set of contiguous seasons that sum up to 52 weeks, with the conditions that a season spans at least 4 weeks and at most 40 weeks, and seasons can 'wrap around' the year.

For example, a seasonal sequence $S = [a, b, c, d]$ would refer to 4 ordered seasons with lengths of a, b, c, and d weeks, but where the start date of the first season is undefined. Therefore, we can enumerate *all* feasible seasons by cyclically permuting all possible seasonal sequences for all possible start points $k = (1, 2, ..., 52)$ in a year. For example, Figure 4.3 shows the cyclic permutation process for $S = [10, 6, 19, 17]$ in a 4-season scenario. The seasons are shifted by 1 week to move from one permutation to the next, up to the 52nd permutation.

Table 4.1 summarizes the progression of the possible seasonal sequences for a 4-season scenario. Each row in the table represents the number of weeks in a season. The same approach is used to enumerate all possible seasons for different numbers of seasons. To save computation time, repetitions resulting from cyclic permutations are removed. For

[4]Note that the dataset includes one anomalous day: the large-scale blackout on August 14, 2003. We replaced data from this day with data from a similar weekday – August 13, 2003.

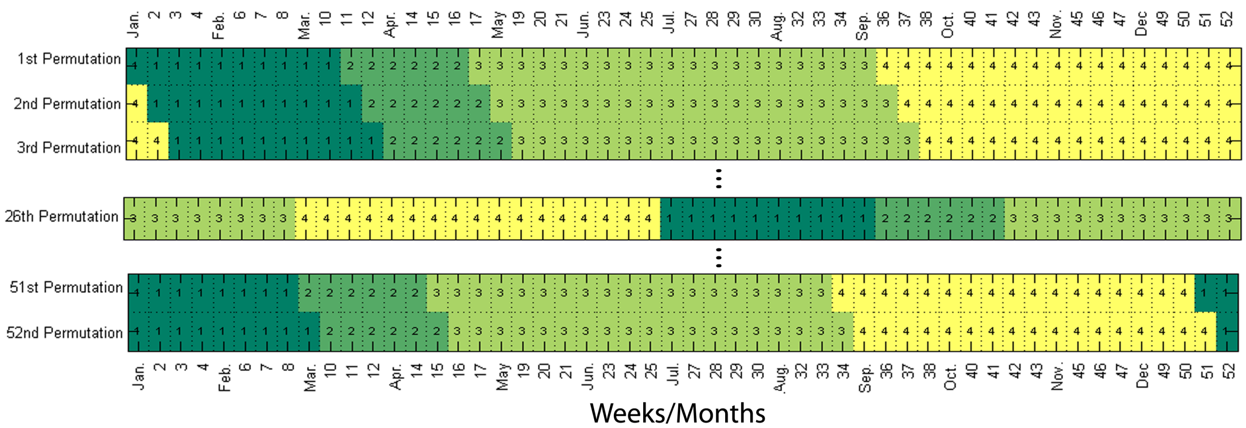


Figure 4.3: Cyclic Permutations for Seasonal Sequence $S = [10, 6, 19, 17]$

example, a seasonal sequence $S = [10, 6, 19, 17]$ that starts on the first week of the year is the same as a seasonal sequence of $S = [6, 19, 17, 10]$ that starts on the 11th week of the year.

Feature Representation

Given that ToU electricity pricing aims to reduce the load during peak periods, we define the data features based on the peak, mid-peak, and off-peak periods. In the current Ontario ToU scheme, there are six peak hours, six mid-peak hours, and 12 off-peak hours. Using this same approach, let the daily load at hour h be denoted $L(h)$, $h = 1...24$. We define a 24-element daily feature vector ϕ^D whose hth element ϕ^D_h is given by:

$$\phi^D_h = \begin{cases} 1 & \text{if } L(h) \geq P_{75} \quad (h \text{ is Peak}) \\ 0.5 & \text{if } P_{50} \leq L(h) < P_{75} \quad (h \text{ is Mid-Peak}) \\ 0 & \text{if } L(h) < P_{50} \quad (h \text{ is Off-Peak}) \end{cases} \tag{4.1}$$

where P_{50} and P_{75} are the 50th and 75th percentiles respectively of the load for that day.

Furthermore, we define the basic unit of time for defining a season as one week. By concatenating the aforementioned daily feature vectors ϕ^D in the jth week of the year, we obtain a 168-element feature vector $\phi^W(j)$ for week j. We cluster weeks into seasons based on $\phi^W(j)$.

Table 4.1: Seasonal Sequences for a 4-Season Scenario

Season 1	Season 2	Season 3	Season 4
4	4	4	40
4	4	5	39
4	4	6	38
...			
5	5	5	37
5	5	6	36
...			
13	13	13	13

Seasonal Sequence Score

We measure the validity of a seasonal sequence based on the R^2 cluster validity index [78, 84]. Higher R^2 values indicate better clusters. The R^2 value of a seasonal sequence, for a sequence with K seasons, is given by:

$$R^2 = 1 - \frac{\sum_i^K \sum_{j \in C_i} (\phi^W(j) - \bar{\phi}_i)^2}{\sum_{j=1}^{52} (\phi^W(j) - \bar{\phi})^2} \tag{4.2}$$

where C_i is the set of weeks in the ith season and $\bar{\phi}_i$ is the centroid of the ith season, that is, the average load vector over the season. $\bar{\phi}$ is the centroid over the entire dataset. This is easily extended to compute the score of a seasonal sequence over multiple years (in this case, C_i refers to the ith season in multiple years.) Note that the difference between ϕ^W vectors is calculated using the Euclidean distance.

4.2.3 Clustering Results

We now discuss the clustering results.

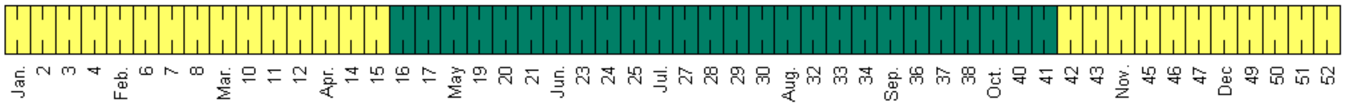


Figure 4.4: Clustering for Two 26-Week Seasons

Table 4.2: 2-Season 26-Week TOU Scheme

	Summer	**Winter**
Start Date	April 15	October 13
End Date	October 14	April 14
Peak Period	11 AM – 5 PM	4 PM – 9 PM
Mid-Peak Period	9 AM – 11 AM5 PM – 9 PM	8 AM – 4 PM
Off-Peak Period	9 PM – 9 AM	9 PM – 8 AM

Selecting Two 26-Week Seasons

First, we estimate the R^2 value over all possible seasonal sequence permutations for two 26-week seasons. Figure 4.4 shows the start dates for each season. The results show that the ToU scheme should have been implemented with each season starting two weeks earlier. However, we do not believe this to be significant with respect to changes in peak load. More importantly, the results show that the peak, mid-peak, and off-peak periods should be structured as shown in Table 4.2. This is based on the number of times each hour of the day is above or below the $75th$ percentile and the $50th$ percentile as described in Equation 4.1.

Number of Seasons

For each scenario with a particular number of seasons $N \in \{2, 3, 4..., 7\}$, we estimate the R^2 value over all possible seasonal sequence permutations. Figure 4.5 shows the best R^2 value for a particular value of N as a function of N. We select the best number of seasons based on the point where there is an elbow in the R^2 graph. As a result, four seasons in a year would appropriately represent the seasonality in Ontario load data. Figure 4.6 shows the duration of each season given different number of seasons per year.

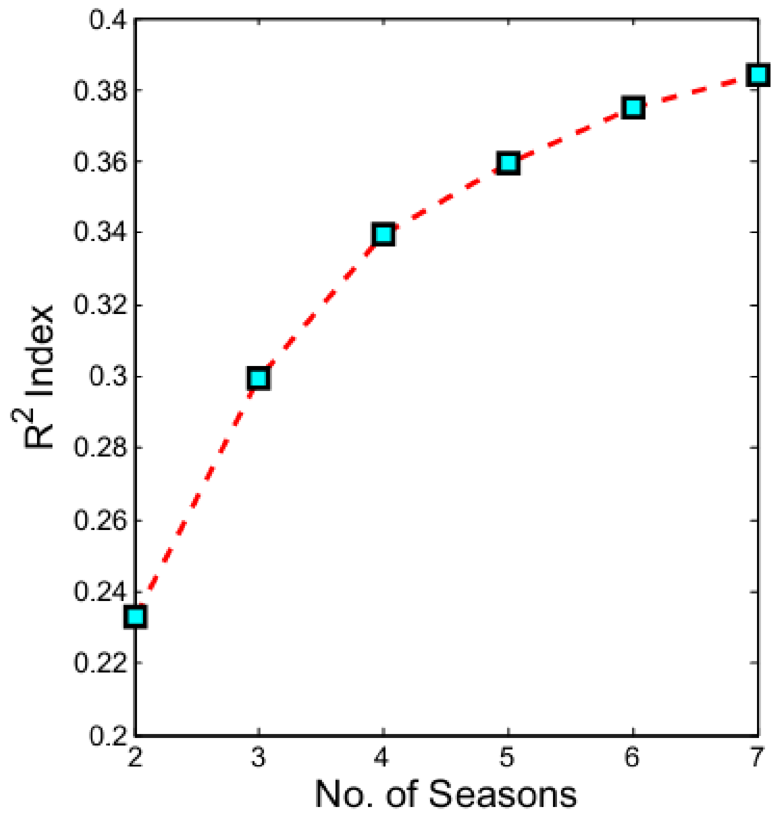


Figure 4.5: R^2 Index for Different Numbers of Seasons

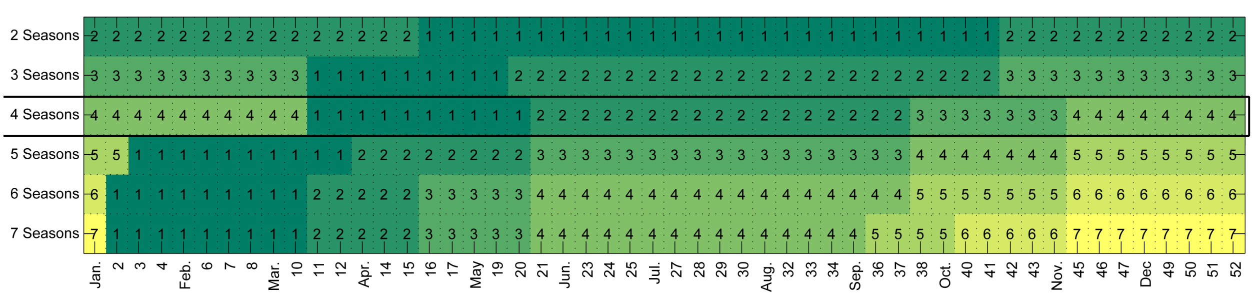


Figure 4.6: Optimal Seasonal Sequences for 2-7 Seasons

4.3 ABM for ToU Electricity Pricing

In this section, we describe the ABM for evaluating the gains from using our recommendations for ToU electricity pricing.

4.3.1 ABM Design

To study the response of households to ToU prices, we design an ABM where the residential electricity demand comes from agents which are household residents that choose to use appliances to meet different needs. Typical household electrical appliances in Ontario are shown in Table 4.3 [85, 131]). These include air conditioners, televisions, light appliances, dishwashers, washing machines, clothes dryers, etc. Of these, we consider the dishwasher, washing machine, and clothes dryer to be the most flexible loads. This is because for most of the appliances listed in Table 4.3, deferring appliance loads would be inconvenient or impossible due to usage patterns. For example, houses have to be nearly continuously cooled in summer and nearly continuously heated in winter. As a result, the ABM focuses on how agents choose to use only the three most easily deferred appliances.

We do not model social interaction between agents in the model. This is for several reasons. First, unlike the technology adoption case studies where the adopted technologies such as solar panels and EVs are publicly visible, the use of electronic appliances is not publicly evident. Therefore, the decision of an agent to defer appliance use is not likely to be affected by decisions made by other agents. Second, deferring appliance use to save money is a personal matter, and not something that is discussed socially, at least in Ontario. This also argues for agent decisions to be independent of each other.

We believe an ABM approach can be used to compare different ToU policies. In our approach, the agents decide when to use their appliances in response to different electricity pricing schemes. That is, agents can defer appliance usage from peak and mid-peak periods to off-peak periods in response to ToU prices. Note that only agents that pay their own bills in proportion to their usage are modeled as capable of deferring appliance loads. In contrast, an agent who pays a fixed amount to their landlord is modeled as not changing appliance usage since it does not have any impact on their bill.

To understand the determinants of agents' behaviour in response to ToU price signals, we conducted a literature review. We find that different studies on ToU pricing and have identified different reasons for agents' response to ToU pricing. These include the following household and system variables:

Table 4.3: Typical Household Appliances [131, 85]

Appliance	**Flexible**	**Non-flexible**
Air conditioner		X
Dehumidfier		X
Furnace fan		X
Swimming Pool		X
Swimming Pool Heater		X
Ceiling Fan		X
Fan (Portable)		X
Block Heater		X
Electric Heater (portable)		X
Furnace Fan Motor (Intermittent)		X
Oil Furnace (Burner)		X
Heat Recovery Ventilation		X
Humidifier (Portable)		X
Lighting appliances		X
Air Cleaner (Room and Furnace)		X
Clothes Dryer	X	
Washing Machine	X	
Computer (Monitor and Printer)		X
Dishwasher	X	
Food Freezer		X
Microwave oven		X
Stove (Oven)		X
Fridge		X
Television		X
Water Bed Heater		X
Water Heater		X
Kitchen Appliances		X

- Level of education [35]: This corresponds to the highest level of formal education achieved by the resident, ranging from primary school to graduate level.
- Income [88, 35]: This is the annual income of the respondent or respondent's family income. We bin this variable in groups of $25,000.
- Electricity bill payment: This is a binary variable that indicates whether a respondent pays monthly electricity bills based on meter readings or not. We believe that only those who pay based on usage would be motivated to change appliance usage to save money.
- Daytime occupancy [88, 132]: This is a binary variable representing the typical presence or absence of occupants in the house between 9 AM and 4 PM.
- Presence of school age children [35, 14]: This is a binary variable that indicates the presence of children aged between 6 and 12 years. Electricity demand price elasticity has been found to vary with different household types, including those with children. We aim to see if this is the case with ToU electricity pricing in Ontario.
- Number of residents [88]: This is the number of people dwelling in a household.
- Average monthly electricity bill in summer and winter: We suspect that consumers monthly electricity bill could impact how they respond to ToU electricity pricing. We add these variables to test this possibility.
- Peak-off-peak price ratio [42]: Faruqui et al. review different ToU schemes and state that a higher peak-off-peak price ratio of 4:1 is much better than lower ratios. In the survey, we pose a question to evaluate the degree to which a change in the peak-to-off-peak price ratio elicits a behavioural change.
- Change in electricity bill due to deferring appliance usage: This is the amount saved monthly by shifting all instances of peak-period appliance usage to off-peak periods.

We use the survey responses to define the agent properties and decision functions.

4.3.2 Data and Survey Description

In this study, besides survey results, our data sources include smart meter readings from households in a region of Ontario, and data from electric utility websites. For our analysis and simulations, we use actual hourly load data from anonymized smart meter readings in 100 residences in Ontario, Canada. This data has been provided by a local electric utility. In addition, we obtain data on typical household appliances and their typical electricity consumption from different utilities [85, 131, 129].

We conducted a survey targeted at Ontario's residents. The survey focused on the following:

- The respondents' knowledge if the current ToU pricing scheme such as expected monthly savings from load deferral and peak-to-off-peak ratio.
- The respondents use of appliances in response to the ToU scheme.
- The respondents typical use of washing machines, clothes dryers, and dishwashers.
- Possible motivations for changing appliance usage patterns.

The survey was distributed online using Crowdflower [29], with a restriction that it only accepts respondents in Ontario. We also added test questions to check if respondents were paying attention to the questions and used only those surveys that answered the test questions correctly. There were over 500 responses to the survey collected over a period of two months, with 206 valid responses due to geographical location and filters for correctly answering test questions.

Two important questions from the survey are shown in Tables 4.4 and 4.5. The survey can be found in Appendix B.

4.3.3 Feature Selection and Logistic Regression

To predict the usage of appliances, we attempt to fit responses to the two questions presented above in the survey to a logistic regression equation. That is, we try to predict the actual survey response to shift each appliance based on factors such as the level of education, income, average monthly bill in summer and winter, number of residents, etc. We also tested if the peak-to-off-peak ratio or the expected monthly saving is influential in people's decisions to defer each of the three appliances considered in this study. Since the exact amount saved monthly is not clear from the ToU electricity pricing scheme, those consumers who cannot estimate savings would have to make decisions based on the peak-off-peak price ratio alone. Otherwise, if the consumers can estimate monthly savings, they

Table 4.4: Survey Question on Peak-Off-Peak Price Ratio: *What difference between the day price and night price would urge you to change how you use each appliance?*

Peak-Off-Peak Price Ratio	**Washing Machine**	**Clothes Dryer**	**Dishwasher**
None			
Day price is 1.5 times as expensive as night price			
Day price is 2 times as expensive as night price			
Day price is 3 times as expensive as night price			
Day price is more than 3 times as expensive as night price			
Cannot say			

Table 4.5: Survey Question on Monthly Savings: *How much monthly savings from your appliance would urge you to use it at night or during weekends?*

Monthly Savings	**Washing Machine**	**Clothes Dryer**	**Dishwasher**
None			
$5 per month			
$10 per month			
$15 per month			
$20 per month			
More than $20 per month			
Cannot say			

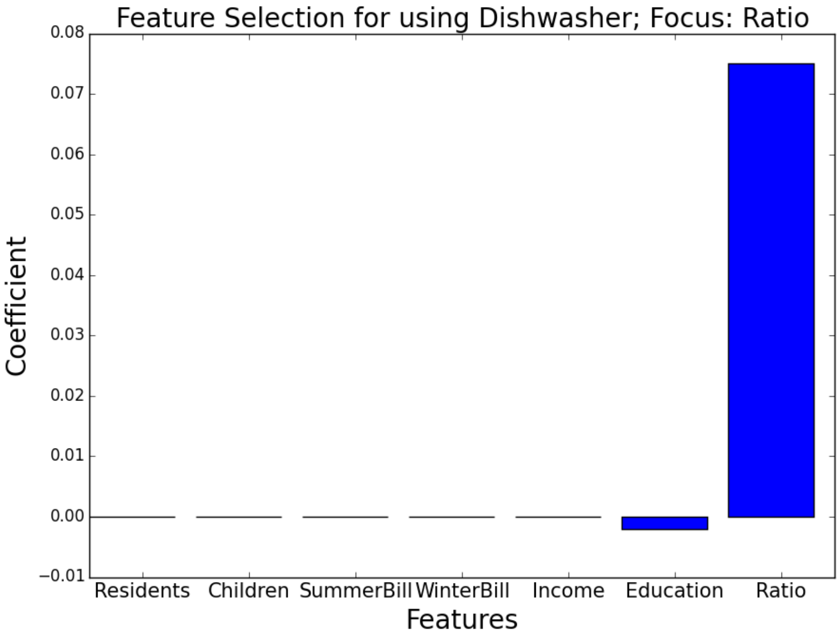


Figure 4.7: Feature Selection for Dishwasher Usage with the Peak-Off-Peak Price Ratio as a ToU Variable

would make decisions based on the monthly savings. We take this approach in the agent decision model.

We found that the logistic multiple regression algorithm did not generate a regression equation that could predict the ground truth responses with sufficiently high confidence (i.e., 95%). When selecting features for washing machine and clothes dryer usage with the peak-off-peak price ratio as a ToU variable, only the peak-off-peak price ratio was selected as a significant feature. Figures 4.7 to 4.10 show other feature selection results, using Lasso LARS with a seven-fold cross validation. Given the lack of correlated variables in feature selection for washing machine and clothes dryer usage, we do not use logistic regression analysis in these cases. Figure 4.7 shows the feature selection result for dishwasher usage with peak-off-peak price ratio as the determinant ToU variable; Table 4.6 shows the corresponding logistic regression results. The *education* variable and the intercept do not fall within the 95% confidence interval.

In Figures 4.8 to 4.10 there are variables that are correlated with the decision to defer appliance usage. However, the logistic regression results show that these variables cannot be

Table 4.6: Logistic Regression Result for Dishwasher Usage with the Peak-Off-Peak Price Ratio as a ToU Variable

Variable	**Coefficient**	**Standard Error**	z	$P > \lvert z \rvert$
Intercept	0.1194	0.900	0.133	0.895
Ratio	0.9382	0.347	2.707	0.007
Education	-0.1618	0.121	-1.338	0.181

Table 4.7: Logistic Regression Result for Washing Machine Usage with the Monthly Savings as a ToU Variable

Variable	**Coefficient**	**Standard Error**	z	$P > \lvert z \rvert$
Intercept	-0.6648	0.682	-0.975	0.330
Monthly Savings	0.0933	0.019	4.880	0.000
Summer Bill	-0.0925	0.152	-0.609	0.542
Winter Bill	-0.1416	0.161	-0.881	0.378
Education	0.0995	0.089	1.122	0.262

fitted with a 95% confidence interval. Tables 4.7 to 4.9 show the logistic regression results. Given that the logistic regression functions did not predict the ground truth responses with sufficiently high confidence (i.e., 95%), the agent decisions are encoded directly from the responses to the questions in Table 4.4 and 4.5. We discuss this next.

4.3.4 Agent Parameters and Behaviours

Table 4.10: Agent Parameters

Variable	**Definition**	**Source**
Appliances	Each agent can own three appliances: washing machine, clothes dryer, and washing machine.	Survey.

Bill Payment	Each agent is classified based on how they pay electricity bills. This variable is *True* if an agent pays bills based on usage. Otherwise, it is set at *False*	Survey.
ToU Know How	This determines if an agent knows how to estimate savings from a ToU scheme. This is set at *False* by default and is only *True* in information scenario campaign simulations.	–
Appliance Weekday Usage	This is the number of times each appliance is used on weekdays each week.	This is obtained from the survey. If the respondent did not provide any option but the agent owns an appliance, the usage is determined to have a value between *1* and *5* using a uniform random function.
Appliance Usage Hours	These are the periods of the day during which an agent typically uses each appliance.	Survey.
Knowledge of ToU impact	This is a variable that determines if an agent is aware of ToU electricity pricing. Only those who are aware can respond to ToU pricing scheme.	Survey.
Home Control Device Usage	This states if an agent is willing to use automatic home control devices with their appliances	Survey.
School Age Children	This is the number of school age children residing in the agent's household.	Survey
Off-Peak Appliances	These are the appliances used by the agent in response to the current ToU scheme	Survey.
Critical Savings	This is the stated monthly saving from using each appliance under the ToU scheme that would make an agent to change appliance usage.	Survey.

Critical Ratio	This is the stated peak-off-peak price ratio that would make an agent to change appliance usage.	Survey.
Electric Load (kWh)	This is the amount of electricity consumed by the agent during each hour in a year.	Electrical load data from some households in Ontario.

Table 4.10 shows the agent parameters and Table 4.11 shows the environment variables. In this ABM, the only agent behaviour is the use of appliances. This appliance usage is scheduled based on the agent's appliance usage pattern. This includes the number of times each appliance is used on weekdays and the typical usage hours. For each time an agent uses each appliance it owns, the hour of usage is randomly selected from the agent's typical usage hours using a uniform distribution. If this hour falls within the peak or mid-peak period, the agent decides to defer the load. The decision to defer appliance usage is determined based on the peak-off-peak price ratio or the estimated monthly savings as follows:

- If an agent cannot estimate monthly savings from appliance deferral (*ToU know how* variable), the decision to defer appliance usage is based on the peak-off-peak price ratio. If the ToU peak-off-peak price ratio is higher than or equal to the ratio stated in the survey, the agent will defer appliance usage.
- Else, if the agent can estimate monthly savings, the decision is based on the stated monthly from the survey. For example, if a respondent mentions that only a monthly saving of $10 would make them change their dishwasher usage, the corresponding agent would only change dishwasher usage if the agent can save that amount of money from using its dishwasher.

Algorithm 3 shows the appliance usage process.

We should note that once an agent decides to defer a particular appliance, the agent will always defer that appliance if it falls within the peak or mid-peak periods. The appliance usage in the simulation is structured as follows. For each appliance an agent owns and for each weekday usage of that appliance:

- A time of use is selected from the agent's typical hours of usage using a uniform random function.

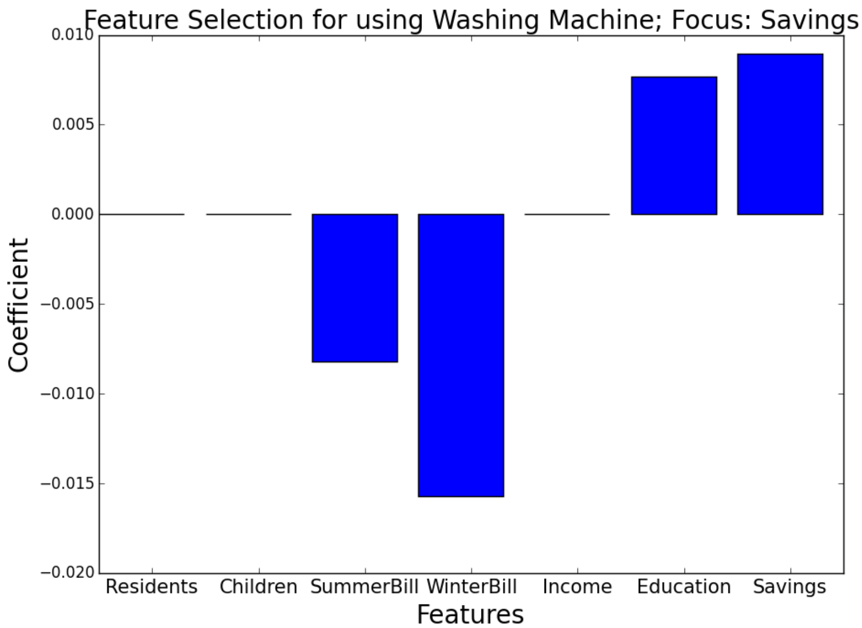


Figure 4.8: Feature Selection for Washing Machine Usage with the Monthly Savings as a ToU Variable

Table 4.8: Logistic Regression Result for Clothes Dryer Usage

Variable	**Coefficient**	**Standard Error**	z	$P > \|z\|$
Intercept	-0.3564	0.737	-0.484	0.629
Monthly Savings	0.0809	0.020	4.082	0.000
Summer Bill	-0.1406	0.160	-0.879	0.379
Winter Bill	-0.0695	0.166	-0.419	0.675
Education	0.0578	0.094	0.616	0.538

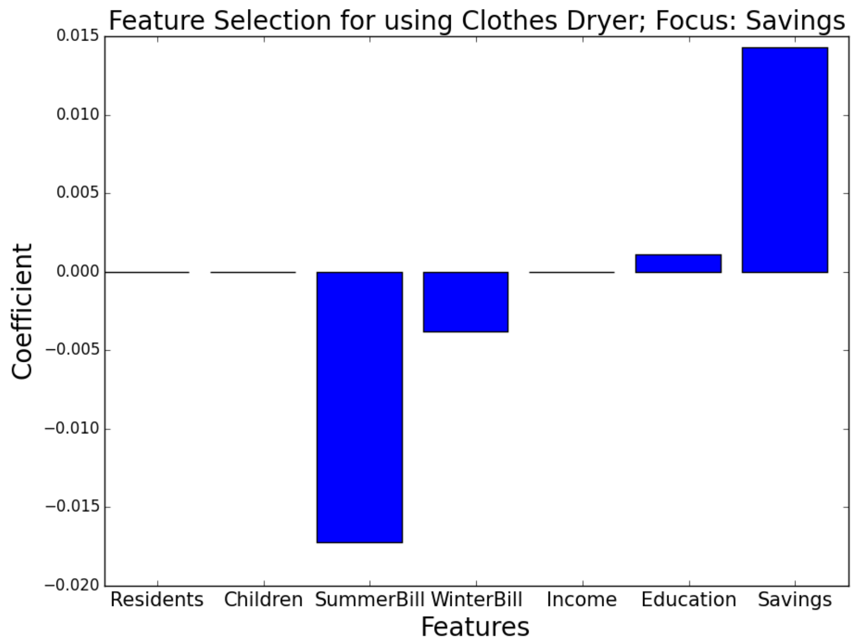


Figure 4.9: Feature Selection for Clothes Dryer Usage with the Monthly Savings as a ToU Variable

Table 4.9: Logistic Regression Result for Dishwasher Usage

Variable	**Coefficient**	**Standard Error**	z	$P > \|z\|$
Intercept	0.0319	0.500	0.064	0.949
Monthly Savings	0.0781	0.022	3.593	0.000
Winter Bill	-0.1889	0.134	-1.407	0.159

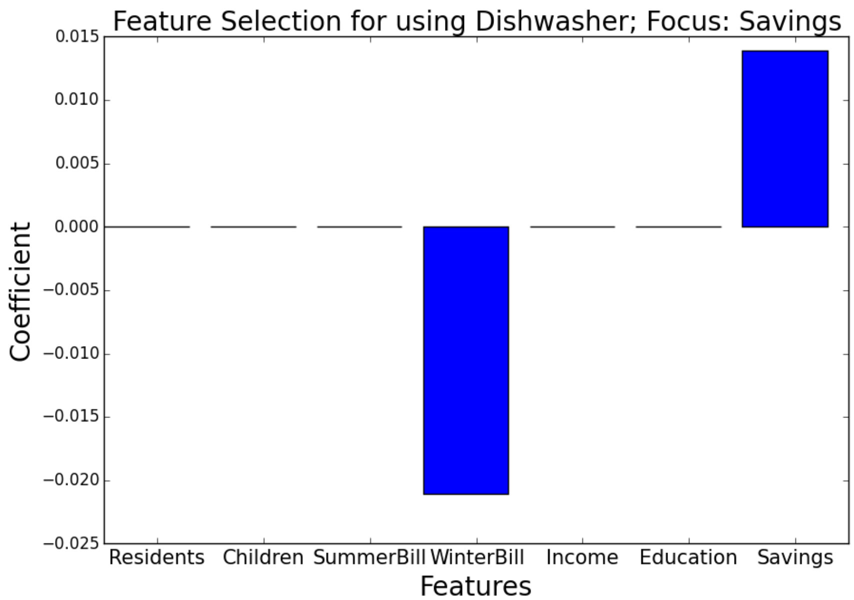


Figure 4.10: Feature Selection for Dishwasher Usage with the Monthly Savings as a ToU Variable

Table 4.11: Environment Parameters

Variable	**Definition**	**Source**
ToU Electricity Price	In the ToU pricing scheme, electricity consumers are charged at a rate based on the season and the time of day.	Figure 2.1 shows the ToU pricing scheme in Ontario (at the time of writing).
Appliance Loads (kWh)	The dishwasher consumes about 1 kWh per use; The washing machine and clothes dryer each consume about 3.5 kWh per use	The appliance load values were obtained from a appliance wattage listing [129].

Algorithm 3 Appliance Usage Process

```
function UseAppliances(Agents)
    for all agent ∈ Agents do
        if agent.Appliances ≠ ∅ and agent.PaysOwnBills then
            for all appliance ∈ agent.Appliances do
                UsageCount ← 0

                while UsageCount < agent.WeeklyUsageFrequency[appliance] do
                    UsageTime ← random(agent.TypicalUsagePeriod[appliance])

                    if UsageTime ∈ Peak ∪ MidPeak and agent.WillShiftLoad then   ▷ Agent will shift load based on ToU ratio or savings preferences.
                        UsageTime ← random(OffPeak)
                    end if

                    agent.UseAppliance(UsageTime, Appliance)
                    UsageCount ← UsageCount + 1
                end while

            end for
        end if
    end for
end function
```

- If the selected time of use falls within the peak or mid-peak periods and the agent decides to shift the load, an off-peak hour is selected using a uniform random function. The change in load is estimated by subtracting the appliance consumption from the originally intended hour of use and adding the appliance consumption to the selected off-peak hour.

4.3.5 Verification

To verify our model, we conduct the following verification tests:

- A single-agent simulation to ensure that agents are initialized with all the appropriate and required parameters.
- A test simulation to ensure that agent appliance usage is estimated scheduled correctly. We also verify that appliance loads are transferred from TOU scheme peak and mid-peak periods are to the off-peak periods.
- A test simulation to ensure that ToU seasons cover the assigned number of weeks, and that these seasons are changed accordingly in the simulation.
- A debug test of the survey importation to ensure that data from the survey are interpreted appropriately.
- A test simulation to check the estimation of values such as the electricity bill from appliance usage and monthly savings from ToU.

4.4 Results

We consider several scenarios to determine what ToU electricity pricing scheme might be effective. In the simulations, we compare the performance of different pricing schemes over the course of a year. We consider the following policy scenarios:

- Base Case: This is the scenario with the current ToU scheme.
- *Peak4*: ToU scheme with a peak-off-peak ratio of 4:1. Faruqui et al. [42] mention that a peak-off-peak price ratio of 4:1 is more effective than a ratio of 2:1.

- *Opt2*: A ToU scheme with two seasons but with seasons and periods shown in Table 4.2.

- *Opt4*: A ToU scheme with four seasons. We set the ToU scheme as shown in Figure 4.2.

- *Info*: Informing all residents about estimating monthly savings.

- *Auto*: Provision of home control devices that would schedule appliance usage. We asked survey respondents whether they would be willing to use home control devices to schedule the operation of appliances. In this scenario, if an agent is willing to use this device, the appliance loads would be deferred to the off-peak periods.

- *Opt2Auto*: A ToU scheme with two seasons combined with the use of home control devices; periods shown in Table 4.2. This is a combination of the *Opt2* and *Auto* scenarios.

We use household data from a region in Ontario to visualize the changes in load in each scenario. We find that changing the peak-off-peak ratio (*Peak4*) does not result in any change, therefore, increasing the ratio would not make an impact in Ontario. Given the current (high) level of participation in appliance usage deferral due to ToU pricing (78% of responses), this is not a surprising result. We conclude that a peak-off-peak ratio of 2:1 is sufficient to make Ontario residents defer appliance usage.

Figure 4.11 shows the average daily load profile in winter and summer seasons for the base case and *Opt2* scenario. Compared with the base case, there is a shift in the evening peaks to the right (later in the day) in the *Opt2* scenario. This shows that given the appliance usage patterns of Ontario residents, simply changing the peak and mid-peak periods could lead to a change in usage patterns, driving usage to a time where electricity is generally cheaper than during the middle of the day. Also, in the *Opt2* scenario there is an increasing local peak in the morning period. With such a policy, the changes in electricity consumption over time should be monitored to ensure that the ToU scheme does not result in the formation of a new load peak in the morning. The PAR of the winter season load profile increases from 1.75 in the base case to 1.76 in the *Opt2* scenario; for the summer seasons, the PAR reduces from 1.68 in the base case to 1.66 in the *Opt2* scenario.

As seen in Figure 4.12 a four-season scenario could also result in an increased morning peak in the spring and winter seasons. This should be taken into consideration as a new peak in the load profile may require yet another change in the ToU scheme. Also, there is a shift of the evening peak in winter and spring seasons. However, there does not appear to

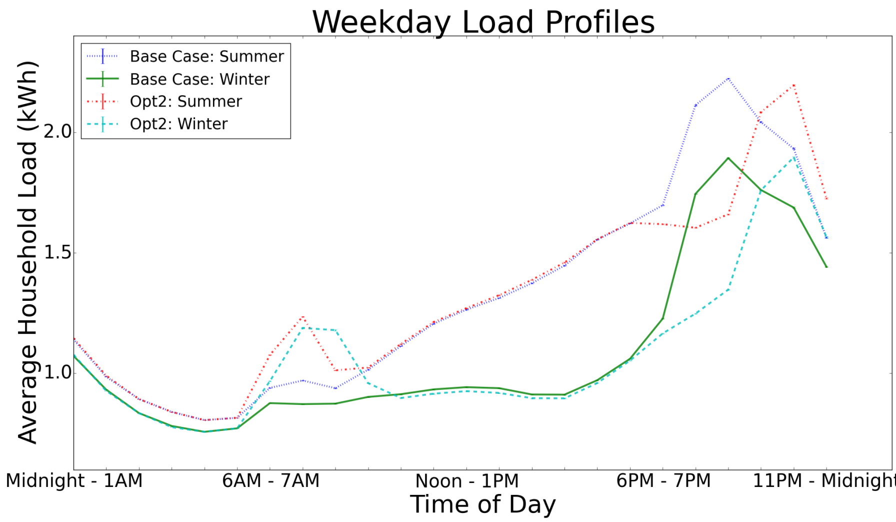


Figure 4.11: Average Weekday Load Profiles: *Opt2* Scenario

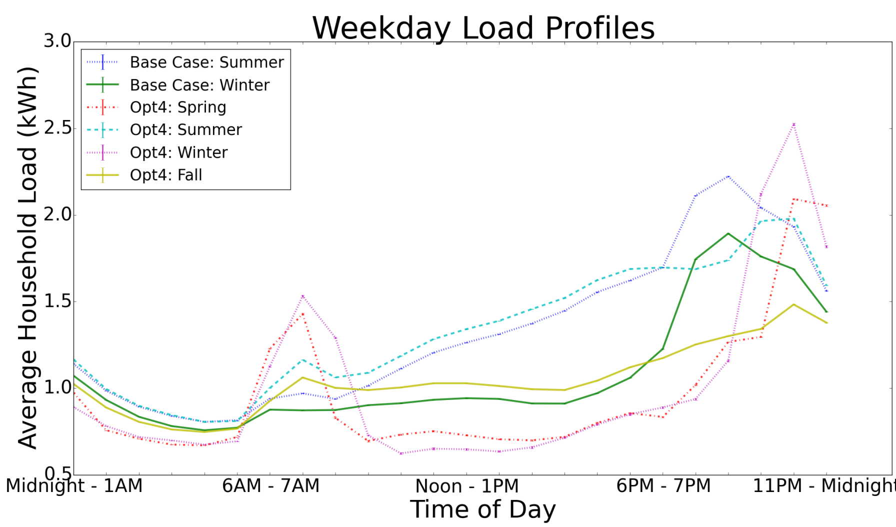


Figure 4.12: Average Weekday Load Profiles: *Opt4* Scenario

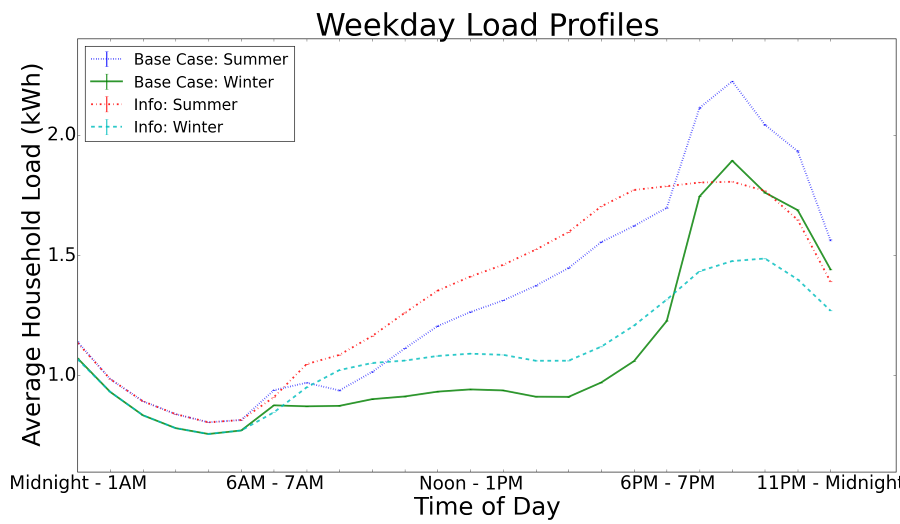


Figure 4.13: Average Weekday Load Profiles: *Info* Scenario

be any clear benefit of a four-season ToU scheme over the optimal two-season scheme; in the *Opt4* scenario, the PARs in spring (2.16) and winter (2.5) are higher than the PARs in the base case while the PARs in summer (1.49) and fall (1.42) are lower. Further analysis on the cost of generating electricity during each season might be more indicative of what scenario is better for the electric grid. In addition, the frequent changes in behaviour required in managing a four-season ToU scheme could be challenging for electricity consumers.

In Figure 4.13, we see that informing residents about actual ToU savings could lead to loads not being deferred; the base case load is higher during the peak periods in both winter and summer. This result is not surprising given that out of the respondents who stated expected monthly savings in the current ToU scheme, 64% expect to save above $10 each month by deferring loads; deferring the three appliance loads would not result in monthly savings of more than $10 in the current ToU scheme. This is a good example of perverse incentives, where knowledge of the low cost of not deferring appliance usage results in the usage not being deferred!

In the *Auto* scenario, more loads are deferred to the off-peak periods. This inference is based on the increase in the evening peak as seen in Figure 4.14; 56% of responses stated the willingness to use home control devices and this high percentage is reflected in the results. Comparing the base case with the *Opt2Auto* scenario (Figure 4.15), we see that there is a significant load shift to the later off-peak periods in the alternative scenario. Also, more loads are shifted than in the base case, hence, the higher late night peak. This

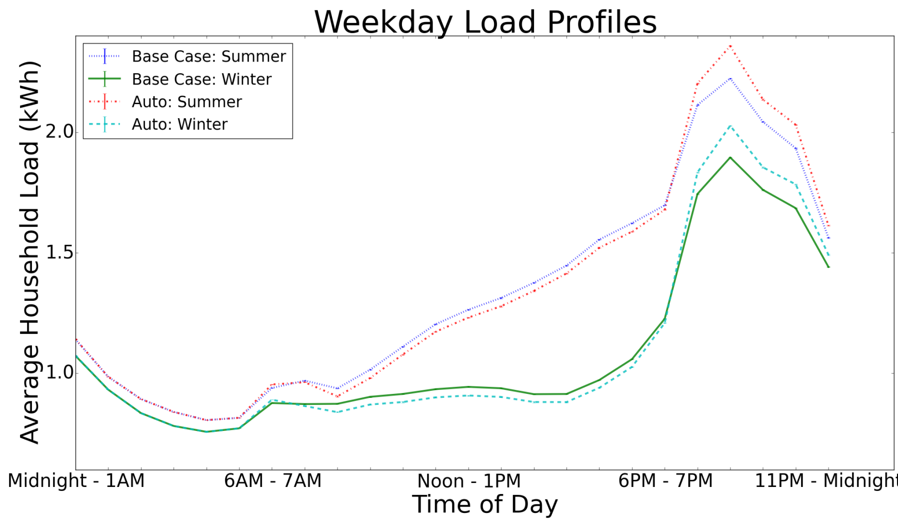


Figure 4.14: Average Weekday Load Profiles: *Auto* Scenario

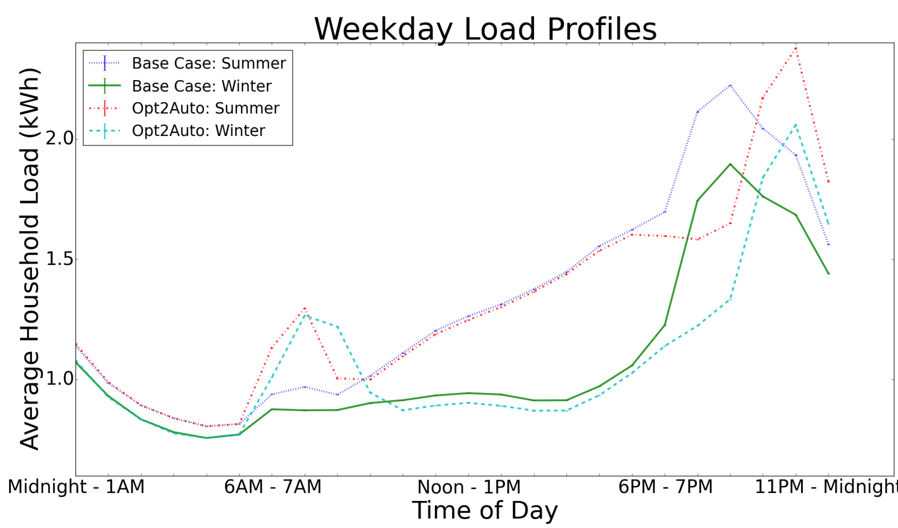


Figure 4.15: Average Weekday Load Profiles: *Opt2Auto* Scenario

is beneficial given that electricity is much cheaper during these periods than the load profile peak period in the base case.

Policy Implications

The results show that ToU electricity pricing can be effective in deferring loads. Indeed, 78% of respondents already defer appliance usage in response to the current ToU scheme in Ontario. Moreover, we find that a 4:1 peak-off-peak price ratio would not result in any significant changes in load in Ontario. This is not surprising considering the current response to ToU in Ontario.

A viable policy approach would be to change the ToU scheme to that used in the *Opt2* scenario. The shift in peak to a later period is beneficial to the Ontario grid as a whole. For such a policy to be implemented, it would be important to consider the actual cost of generating electricity during these periods and compare that with the inconvenience of late-evening off-peak periods to consumers. In addition, the *Opt2Auto* scenario could also be viable. The results show that, in comparison to the base case, more loads are deferred to later in the evening; 56% of respondents stated that they are willing to use home control devices for their appliances while 31% were undecided. The cost of obtaining and providing residents with home control devices should be compared with the additional benefits of such a scheme.

Informing consumers on exact savings from ToU might be counterproductive. 64% of responses stated an expectation of more than $15 monthly savings from deferring appliance usage in the current scheme. However, with typical appliance usage, only about $10 can be saved in the current ToU scheme. With much lower savings, consumers might not be motivated to defer appliance usage.

Regardless of the ToU scheme implemented, the changes in load should be continuously monitored to ensure that the ToU scheme is synchronized with the electricity consumption dynamics. For example, we see that in the *Opt2* scenario there is an increasing peak in the morning periods in both summer and winter. This could be a cause for concern over time.

4.5 Related Work

There have been studies that review the effectiveness of ToU pricing and other DR programs [42, 95]. Faruqui et al. [42] mention that for ToU pricing to be effective, changes should be made to existing schemes such as increasing the peak-to-off-peak price ratio, reducing the length of peak-periods, and using ToU only in summer.

In a Navigant study [94] sponsored by the IESO, the Ontario ToU scheme is analyzed. Using econometric analysis and comparing household load profiles before and after ToU implementation, while controlling for temperature, a 3.3% reduction in peak was found in the aggregated household weekday load. While this shows that ToU has impacted electricity consumption in Ontario, it is worth studying the impact of alternative ToU policies.

Similarly, Miller [90] studies the effectiveness of ToU electricity pricing in Ontario. This work uses smart meter load data from a jurisdiction in Ontario and compares load before and after ToU implementation, while controlling for the effect of temperature. The results show that there is a 0.8% reduction in the PAR. In addition, Miller's analysis found a 2.6% reduction in peak-period demand.

Torriti [132] studies the impact of occupancy on the response to ToU pricing. Using a town in Italy as a case study, Torriti suggests that there is a loose relationship between ToU pricing and electricity consumption. They find that the weather and active occupancy determine consumption. Di Cosmo et al. study the impact of ToU pricing on 5,000 households in Ireland. Using results from a ToU pilot study, they find that ToU reduces the peak loads but incremental changes made to ToU pricing do not have any significant impact. Next, we focus on studies with approaches similar to agent-based modeling.

Yang et al. [144] use a game theory approach to evaluate ToU pricing scheme. This study considers ToU pricing for residential, commercial, and industrial consumers, generating decision functions for each type of customer. Customers have a cost function comprising payments for electricity and satisfaction with electricity usage. Each customer has a set of reactions, i.e., shifting loads to different electricity prices at different times. Also, the electrical utility company is designed to make profits and meet electricity demand. This study, however, does not base consumer behaviour on data, therefore not incorporating energy culture.

Jia-hai [70] presents an ABM for estimating the response of customers to different ToU pricing schemes. Agent types include utility and consumer agents, with different objective functions. In order for a customer agent to shift its load, it estimates the losses from using electricity at peak periods and if the loss is significant (represented by fuzzy variables), the customer agent shifts its electrical load to off-peak periods. However, this work does not consider crucial factors such as customer income, age, and how these influence the agent's behaviour. Also, the Jia-hai model represents the electrical utility company as an agent; we design our model such that utility operators are exogenous to the model.

4.6 Limitations and Future Work

In this study, we use our ABM approach to evaluate ToU pricing policies. The limitations are as follows:

- Given the lack of historical data on the uptake of ToU electricity pricing in Ontario over time, we were unable to validate our model. As a result, we cannot forecast the impact of ToU over time as changes are made to the ToU scheme; we can only study the specific policies in the survey.
- The online survey might not be representative of the Ontario population since it is done online. We should note that the cost of conducting in-person surveys is beyond the scope of this thesis.

Some areas of consideration for future work are as follows:

- Other demand response schemes such as the Critical Peak Pricing (CPP) can be studied and compared to ToU electricity pricing.
- Using phone and in-person survey interviews would provide more confidence in the survey.

4.7 Summary

In this chapter we have discussed the ABM for evaluating ToU policies. We critique the correctness of the ToU scheme in Ontario with respect to the selection of seasons and daily peak, mid-peak, and off-peak periods. Subsequently, we make recommendations on improving ToU scheme in Ontario. Using our ABM framework, we have designed an ABM where agents use appliances in response to ToU electricity prices. We populate this ABM with responses from an online survey focused on Ontario residents and simulate different policies, including the aforementioned ToU scheme recommendations.

The results show that a two-season ToU scheme with a later peak period as seen in Table 4.2 could be more effective than the current ToU scheme. In addition, we found that combining this ToU scheme with the use of automatic home control devices could further improve the effectiveness of ToU pricing. Also, a ToU scheme with a peak-off-peak price ratio of 4:1 would not be more effective in Ontario than the current ToU scheme, since there is already a high participation in load deferral due to ToU pricing. In fact, a policy that informs consumers about the monthly savings from deferring appliance usage to off-peak periods would be counterproductive; according to the survey, most respondents expect to save more than they can realistically save.

Chapter 5

Conclusion

This chapter concludes the thesis. In Section 5.1 we summarize our contributions. We discuss possible areas of future work in Section 5.2 and we present concluding remarks in Section 5.3.

5.1 Summary

In recent years, there have been significant changes in energy systems resulting from new or improved technologies, dynamic energy consumer behaviour, and new policies. Policies, in particular, are used to guide system transition towards a desired state and energy systems are no different. Before an energy policy is implemented, it needs to be evaluated. A common approach is to conduct pilot studies. However, these studies are very expensive and can be limited with respect to the range of policy scenarios that can be conveniently studied. A cheaper and more viable alternative is the use of system model simulations to test policies.

The focus of this thesis has been on devising a structured approach for evaluating energy policies using ABMs. We discuss and justify the choice of ABMs as a system modeling option. Using a data-driven approach, we introduce a novel framework based on best practices for agent-based modeling, survey design and collection, and data analysis. We show how an energy system problem can be analyzed, and how the possible policies are explored. With this framing of the energy system problem, an ABM can be created and a survey is used to populate the ABM. Our framework is a tool that can be used to simulate different policy scenarios, elucidating the potential impact of each policy and informing important policy decisions.

Our framework leverages the capability of ABMs to capture emergent properties in a system; a system is a sum of its parts, therefore, the collective impact of agent actions at the lower level of a system result in systemic changes at the top level. We have instantiated the framework by studying energy policies in the context of three different case studies. With these case studies, we show that our approach can be applied to solve real-world energy problems. We summarize our contributions below.

5.1.1 Summary of Contributions

In Chapter 1, we introduce and discuss the ABM framework for studying and evaluating energy policies. This framework improves on similar frameworks by employing a data-driven approach, therefore creating the concept of a data-driven energy agent.

In Chapter 2, we create an ABM to study PV-battery system adoption. While most studies focus on only PV adoption, we include battery adoption due to the potential combined impact of distributed generation and storage on the electric grid. The contributions in Chapter 2 are summarized as follows:

- A data-driven ABM that models PV-battery system adoption.
- A case study on PV-battery system adoption in Ontario.
- Policy recommendations on improving PV-battery system adoption in Ontario. We found that an increase in the rate of adoption of PV systems in Ontario is unlikely. As a result, we propose that the best way to improve PV-battery system adoption is to offer incentives that reduce system prices. Also, the FiT should not be reduced significantly to keep electricity consumers interested in purchasing PV panels.

This ABM for PV-battery system adoption is currently being used to study PV and battery adoption in Germany.

In Chapter 3, we study EV adoption and usage with an agent-based EV ecosystem model. We take the ecosystem approach since it goes beyond just EV adoption, incorporating both EV driving and charging. With a more complete ecosystem model, the impact of policies that aid EV adoption on the EV ecosystem can be captured. We deviate from our framework in Chapter 3; we do not create a survey for this study but use a survey conducted by the California Department of Transportation [23]. The contributions in Chapter 3 are summarized as follows:

- An agent-based EV ecosystem model that can be used to study EV adoption and usage. This model can be of use to policymakers, utilities, battery manufacturers, and charging station planners.
- A case study on EV adoption and usage in San Francisco.
- A case study on EV adoption and usage in Los Angeles.
- Policy recommendation: In the Los Angeles case study, we found that reduced EV prices are more effective in improving EV adoption than increased EV range.
- Policy recommendation: In the San Francisco case study, we found that EV rebates are still required to make EVs cost competitive with ICEVs. We also found that educating consumers on TCO is not necessarily effective in improving EV adoption in San Francisco. In addition, additional driving range does not have a significant impact on EV adoption.

In Chapter 4, we study the impact of ToU pricing on electricity consumption patterns. With a focus on how consumers in Ontario use three appliances with flexible usage – washing machine, cloth dryer, dishwasher – we compare different ToU schemes. The contributions in Chapter 4 are summarized as follows:

- A critique of the correctness of the ToU scheme in Ontario, with respect to the selection of seasons and daily peak, mid-peak, and off-peak periods.
- A data-driven ABM that models consumer appliance usage in response to ToU prices.
- A case study on Ontario.
- Policy recommendations on improving ToU pricing: We propose that a different 2-season scheme should be used, with different peak, mid-peak, and off-peak periods. In addition, the use of home control devices is likely to be widely accepted in Ontario, therefore, making the distribution of such devices a viable policy.

5.2 Future Work

In addition to the areas of future work identified in Section 3.7 and 4.6, we discuss avenues for future work in this section.

5.2.1 Grid Defection Case Studies

Grid defection is a scenario where consumers depend on other sources of electricity other than the electric grid. In partial grid defection, consumers are still connected to the grid but also consume electricity from other sources such as PV panels. Full grid defection is a situation where a consumer disconnects completely from the grid. While full grid defection may seem benign, it could result in a significant problem for the electric grid. As more consumers disconnect from the grid, the price each consumer pays for operating and maintaining the grid increases; as the price of electricity increases, more consumers are likely to defect from the grid resulting in a *death spiral*.

Particularly, this is a problem where the price of electricity from the grid is more expensive than or close to electricity from solar panels, i.e., PV solar systems have attained *grid parity*. This is the case in Honolulu, Hawaii [19]. A case study on policies to avert grid defection and to capitalize on the benefits of having customers with PV-battery systems could yield interesting results that would be useful for other regions in the future.

5.2.2 Impact of Electric Bicycle Proliferation in Developing Countries

In developing countries, particularly in rural areas, energy is often a challenge. This energy challenge often affects people's quality of life and daily activities. The electric bike can be considered as part of the solution, as it is a technology that can transport people and goods while providing a source of energy with a rechargable battery. With a significant penetration of electric bikes, a central solar charging station could be used to charge these batteries. Given that the typical electric bike might be too expensive for rural dwellers, it would be important to consider policies that would provide charging infrastructure and subsidized electric bikes. This can be studied using our ABM framework, and the impact of such a policy on economic activity and social well being can be evaluated.

5.3 Concluding Remarks

The energy industry is continuously changing, with the introduction of new technology, improvement of existing technology, and changing energy demands. Therefore, existing energy policies have to be revised and new policies have to be created, to cater to the needs of the changing energy industry and to guide the transition of energy systems to a desired state. In this thesis, we have introduced and exemplified our framework in the evaluation and comparison of energy policies. We have also introduced the concept of an energy agent, and how that could be beneficial in modeling energy systems in ABMs.

Despite the effectiveness of ABMs in studying energy policies, there are limitations such as the availability of data and the representative collection of surveys. However, the ABM framework approach for energy policies could still be used to evaluate energy policies, as we have shown in this thesis. We have published the findings from this thesis at conferences and journals, and we look forward to discussing with respective stakeholders about the real-world adoption of the policy recommendations made in this thesis.

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APPENDICES

Appendix A

Ontario Survey on Solar PV and Battery Adoption

A.1 Introduction

You are invited to participate in a research study conducted by Adedamola Adepetu, under the supervision of Professor Srinivasan Keshav, at the Cheriton School of Computer Science, University of Waterloo, Canada. The objectives of the research study are to forecast and evaluate how solar panels and batteries may affect the future state of Ontario's electric grid. The study is for Adedamola Adepetu's PhD thesis.

This survey would take about 10 minutes. Survey questions focus on how much you would pay for solar panels and batteries, and your attitude towards solar panels and batteries. You may decline to answer any questions that you do not wish to answer by leaving them blank. You can withdraw your participation at any time by not submitting your responses, without penalty or loss of remuneration. To receive remuneration please proceed to the end of the questionnaire, obtain the unique code for this HIT, and submit it. You will receive $1.00 deposited into your CrowdFlower account. Participation is voluntary and there are no known or anticipated risks from participating in this study.

It is important for you to know that any information that you provide will be confidential. All of the data will be summarized and no individual could be identified from these summarized results. Furthermore, the web site is programmed to collect responses alone and will not collect any information that could potentially identify you (such as machine identifiers).

This survey uses Survey MonkeyTM which is a United States of America company. Consequently, USA authorities under provisions of the PATRIOT Act may access this survey data. If you prefer not to submit your data through Survey MonkeyTM, do not accept this HIT.

The data, with no personal identifiers, collected from this study will be maintained on a password-protected computer database in a restricted access area of the university. As well, the data will be electronically archived after completion of the study and maintained for two years and then erased.

Should you have any questions about the study, please contact Adedamola Adepetu at a2adepet@uwaterloo.ca or (519) 888 4567, Ext. 37869, or contact Prof. Keshav at keshav@uwaterloo.ca or (519) 888 4567, Ext.34456. Further, if you would like to receive a copy of the results of this study or have questions about the survey, please contact either investigator.

Be assured that this study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee. However, the final decision about participation is yours. If you have any comments or concerns resulting from your participation in this study, please feel free to contact Dr. Maureen Nummelin in the Office of Research Ethics at 1-519-888-4567, Ext. 36005 or maureen.nummelin@uwaterloo.ca.

Thank you for considering participation in this study.

1. Consent to Participant: I agree, of my own free will, to participate in this study.

    - I agree to participate.
    - I do not wish to participate.

2. How much do you know about solar panels?

    - know nothing about them
    - I have heard about them
    - I have read some articles about them
    - I am quite knowledgeable
    - I have expert knowledge

3. Do you currently have solar panels installed at your home/business?

    - Yes
    - No

A.2 PV and Battery Purchase

We will now ask you some questions about how comfortable you are with purchasing a solar panel system for your home or business. In order to answer these questions, you need to know a little bit about them. In Ontario, you have the option of installing solar panel systems to sell electricity to your electric utility and for your own use.

In addition, you can buy batteries to store electricity and use them when electricity is at its most expensive or during outages. In Ontario, you can get a contract to sell electricity from your solar panel system to your electric utility for 20 years. Solar panels have a lifetime of about 25 years and batteries have to be replaced every 3-5 years.

Things you should know in order to aid your choices:

Payback period (years): This is the time it takes for the solar panel system to pay for itself. In other words, this is the time it takes for your solar panel electricity sales (from selling electricity back to the electric utility) to add up to the total amount of money you'd spend on purchasing and maintaining (if at all) the solar panel system. After this period, you start making a profit!

Annual Return on Investment (ROI): This is a comparison of the benefit and cost of investing in a solar panel system. For example, an annual ROI of 5% on a $10,000 investment implies a profit of $500 every year. However, you would actually start making money on the investment only at the end of the payback period.

4. Below (Figure A.1) are the costs, returns on investment, and payback periods associated with purchasing different capacities of solar panel systems (labeled A - D) with and without an associated battery storage system.

   Note that these are not competing options, so feel free to pick more than one system that you're comfortable paying for. Also, note that you have the option of obtaining a bank loan to pay for the system.

   Please select which of the systems (Table A.1) you would be comfortable buying (select one or more systems, or none).

5. Consider a different cost and price scenario, would you purchase the following solar panel systems (Figure A.2) given the costs, returns on investment, and payback periods? Feel free to choose more than one option (Table A.2).

6. One last time, consider ANOTHER cost and price scenario, would you purchase the following solar panel systems (Figure A.3) given the costs, returns on investment, and payback periods? Feel free to choose more than one option (Table A.2).

Figure A.1: System Options for Question No. 4

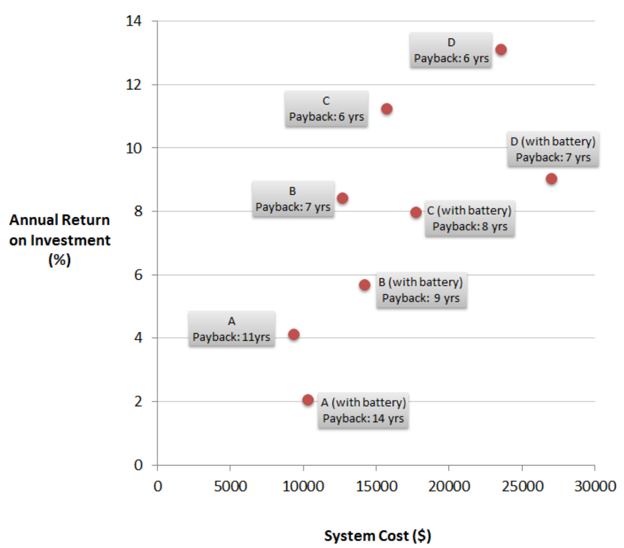

Figure A.2: System Options for Question No. 5

Table A.1: Survey Question No. 4

	Yes	**No**
A		
B		
C		
C (with battery)		
D		
D (with battery)		

Table A.2: Survey Question No. 5 and 6

	Yes	**No**
A		
A (with battery)		
B		
B (with battery)		
C		
C (with battery)		
D		
D (with battery)		

7. Which one of these classes do you belong to? If both, choose home owner.
   - Home owner
   - Business owner
   - None

A.3 Social Effect and Environmental Concerns

8. If you observe your family, friends, neighbours or businesses similar to yours (if you own a business) using solar panels, would this make you consider solar panels if you

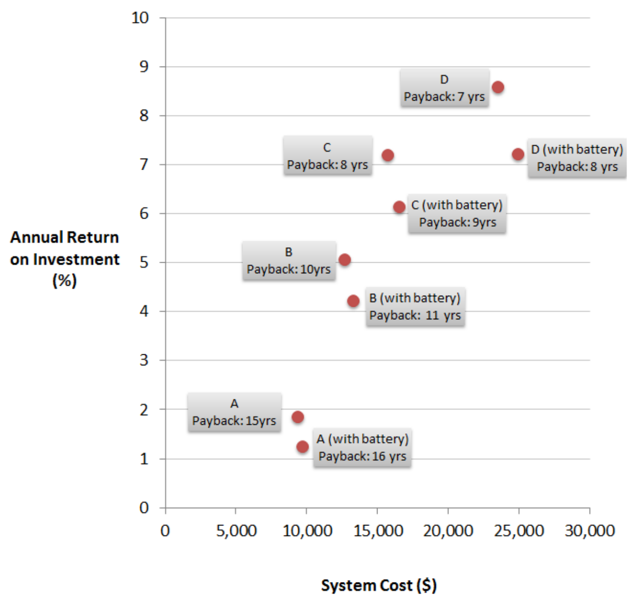

Figure A.3: System Options for Question No. 6

haven't?

- Extremely Unlikely
- Very Unlikely
- Neutral
- Very Likely
- Extremely Likely

9. To what extent do you agree that using solar panels makes a contribution to preserving the environment?

   - Strongly Disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly Agree

10. How much does preserving the environment play a role in your decision to buy or not to buy solar panels?
    - 1: No effect
    - 2
    - 3
    - 4
    - 5: Very significant
11. Do you agree with the statement "Four dollars plus ten dollars is equal to three dollars."
    - Agree
    - Neither agree nor disagree
    - Disagree
12. Choose a range for the maximum amount you're willing to spend on a solar panel system
    - $0-$4,999
    - $5,000-$9,999
    - $10,000-$14,999
    - $15,000-$19,999
    - $20,000-$24,999
    - $25,000-$29,999
    - $30,000-$34,999
    - $35,000-$39,999
    - More than $40,000

A.4 ACT Ratings

You're almost done, this is the last set of questions!

We would like to know your immediate emotional reactions to certain roles, actions, and objects, with respect to using solar systems and disconnecting from the grid. This part of the study will help us understand your decisions better.

Research has shown that emotions have three different components:

i. How good or nice versus bad or awful are things?

ii. How weak and powerless versus strong and powerful are things?

iii. How calm and quiet versus arousing and active are things?

Please answer as quickly as possible, NO ANSWER is WRONG or RIGHT. We are simply interested in your intuitions.

13. Please rate the badness vs. goodness of the following (Table A.3)

14. Please rate the weakness vs. strength of the following (Table A.3)

15. Please rate the passivity vs. activity of the following (Table A.3)

Table A.3: Survey Question No. 13, 14, and 15

	Extremely powerless: -4	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**Extremely powerful: 4**
Home owner									
Business owner									
Buying									
Solar panel									
Battery									

A.5 Survey Conclusion

Thanks for your participating in our Ontario Solar Panel and Battery Adoption survey. Your feedback is extremely valuable!

Please keep the payment code you get after closing this page. You'll use it for payment validation.

Please note that the question "Do you agree with the statement *'Four dollars plus ten dollars is equal to three dollars?'* " was added in order to ensure that questions are answered attentively.

If you are interested in the results of this survey, or have any general comments or questions related to this study, please contact Adedamola Adepetu at a2adepet@uwaterloo.ca or (519) 888 4567, Ext. 37869, or contact Prof. Keshav at keshav@uwaterloo.ca or (519) 888 4567, Ext.34456.

We would like to assure you that this study has been reviewed by, and received ethics clearance through a University of Waterloo Research Ethics Committee. If you have any concerns regarding your participation in this study, please contact Dr. Maureen Nummelin, the Director, Office of Research Ethics, at 1-519-888-4567, Ext. 36005 or maureen.nummelin@uwaterloo.ca.

Appendix B

Research Survey On Estimating The Effectiveness Of Time Of Use Electricity Pricing In Ontario

B.1 Introduction

You are invited to participate in a research study conducted by Adedamola Adepetu, under the supervision of Professor Srinivasan Keshav, at the Cheriton School of Computer Science, University of Waterloo, Canada. This pilot study involves a survey targeted at residents of Ontario, Canada. The objectives of this study are to evaluate the impact of Time-of-Use (ToU) electricity pricing in Ontario, and estimate what alternative ToU pricing schemes might be more effective in reducing peak electric loads. The study is for Adedamola Adepetu's PhD thesis.

This survey would take about 15 minutes. Survey questions focus on what appliances you use in your household, your pattern of using these appliances, and electricity prices that might make you change this pattern. Some questions ask for demographic information such as income, size of household, number of school age children, etc. This information would help us to gain a better understanding of the factors that affect the pattern of electricity consumption. You may decline to answer any questions that you do not wish to answer by leaving them blank. You can withdraw your participation at any time by not submitting your responses, without penalty or loss of remuneration. To receive remuneration please proceed to the end of the questionnaire and submit it. You will receive $1 deposited into your Crowdflower account. The amount received is taxable. It is your responsibility to report this amount for income tax purposes. Participation is voluntary and there are no known or anticipated risks from participating in this study.

When information is transmitted over the internet privacy cannot be guaranteed. University of Waterloo practices are to turn off functions that collect machine identifiers such as IP addresses. However, Crowdflower collects IP addresses and makes it available to us but we will not use or save your IP addresses. Also, we will be verifying that you reside in Ontario through the report provided by Crowdflower. If you prefer not to submit your survey responses through Crowdflower, please do not sign up for this study. The data collected from this study will be maintained on a password-protected computer database in a restricted access area of the university. Also, the data will be electronically archived after completion of the study and maintained for seven years and then erased.

Should you have any questions about the study, please contact Adedamola Adepetu at a2adepet@uwaterloo.ca or (519) 888 4567, Ext. 37869, or contact Prof. Keshav at keshav@uwaterloo.ca or (519) 888 4567, Ext.34456. Further, if you would like to receive a copy of the results of this study or have questions about the survey, please contact either investigator. Be assured that this study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee. However, the final decision about participation is yours. If you have any comments or concerns resulting from your participation in this study, please feel free to contact Dr. Maureen Nummelin in the Ofce of Research Ethics at 1-519-888-4567, Ext. 36005 or maureen.nummelin@uwaterloo.ca. Thank you for considering participation in this study.

1. Consent to participant: I agree, of my own free will, to participate in this study.
   - I agree to participate
   - I do not wish to participate
2. How many people live in your household?
   - 1
   - 2
   - 3
   - More than 3
   - Cannot say
3. Do you have any school age (6 - 12 years) children living in your household?

- Yes
- No
- Cannot say

4. Do you, or anyone in your household, spend some time at home during the day (7AM - 7PM) on weekdays (Monday - Friday)?

   - Yes
   - No
   - Cannot say

5. On average, how much is your MONTHLY electricity bill in SUMMER (May - October)?

   - Less than $50
   - $50 - $99
   - $100 - $149
   - $150 - $199
   - $200 upwards
   - Cannot say

6. On average, how much is your MONTHLY electricity bill in WINTER (November - April)?

   - Less than $50
   - $50 - $99
   - $100 - $149
   - $150 - $199
   - $200 upwards
   - Cannot say

7. What is your annual income?

   - $0-$24,999
   - $25,000-$49,999

- $50,000-$74,999
- $75,000-$99,999
- $100,000-$124,999

8. Select your family income if you live with your family.
   - $125,000-$149,999
   - $150,000-$174,999
   - $175,000-$199,999
   - $200,000 and up
   - Cannot say

9. What is the highest level of school that you have completed?
   - No schooling completed
   - Primary school
   - Some high school, but no diploma
   - High school diploma (or GED)
   - Some college, but no degree
   - 2-year college degree
   - 4-year college degree
   - Graduate-level degree
   - Cannot say

10. Which of the following electric appliances do you have in your household? (Check all that apply)
    - Washing machine (laundry)
    - Cloth dryer (electric)
    - Cloth dryer (gas)
    - Dishwasher
    - TV
    - Electric cooker

- Air conditioner
- Electric heater
- Central cooling/heating system (electricity)
- Central heating system (gas/ hot water)

11. How do you pay for your electricity usage?

    - I pay to the local electricity utility
    - I pay my landlord based on the electricity bill
    - I pay a xed monthly fee to my landlord
    - Cannot say

12. Did you know that, in Ontario, weekday electricity prices (Monday - Friday, 7AM - 7PM) are more expensive than both weekend prices and weekday nightly prices?

    - No
    - Yes

13. Do you know by how much the weekday price (Monday - Friday, 7AM - 7PM) is more expensive than the night/weekend price?

    - No
    - Yes, day price is 1.5 times as expensive as night price
    - Yes, day price is 2 times as expensive as night price
    - Yes, day price is 3 times as expensive as night price
    - Yes, day price is more than 3 times as expensive as night price

14. How much money do you think you could save (or are already saving) each month by operating appliances during periods when the electricity is cheaper?

    - Less than $10 per month
    - $10 per month
    - $20 per month
    - $30 per month
    - $40 per month

- More than $40 per month
- Cannot say

15. Which of the following appliances do you try to use during the cheaper periods, i.e., in order to reduce your bill? If electricity pricing does not affect your appliance usage, choose 'None'. Choose multiple appliances if this is the case.
    - None
    - Washing machine
    - Cloth dryer
    - Dishwasher

16. Do you agree with the following statement: Three dollars plus Ten dollars is equal to Five dollars?
    - Agree
    - Neither agree nor disagree
    - Disagree

17. How much monthly savings from your WASHING MACHINE would urge you to use it at night or during weekends? Choose None if you are not willing to change your appliance usage.
    - None
    - $5 per month
    - $10 per month
    - $15 per month
    - $20 per month
    - $More than $20 per month
    - Cannot say

18. How much monthly savings from your CLOTH DRYER would urge you to use it at night or during weekends? Choose None if you are not willing to change your appliance usage.
    - None

- $5 per month
- $10 per month
- $15 per month
- $20 per month
- $More than $20 per month
- Cannot say

19. How much monthly savings from your DISHWASHER would urge you to use it at night or during weekends? Choose None if you are not willing to change your appliance usage.
    - None
    - $5 per month
    - $10 per month
    - $15 per month
    - $20 per month
    - More than $20 per month
    - Cannot say

20. What difference between the day price and night price would urge you to change how you use your WASHING MACHINE? Choose None if you are not willing to change your appliance usage.
    - None
    - Day price is 1.5 times as expensive as night price
    - Day price is 2 times as expensive as night price
    - Day price is 3 times as expensive as night price
    - Day price is more than 3 times as expensive as night price
    - Cannot say

21. What difference between the day price and night price would urge you to change how you use your CLOTH DRYER? Choose None if you are not willing to change your appliance usage.
    - None

- Day price is 1.5 times as expensive as night price
- Day price is 2 times as expensive as night price
- Day price is 3 times as expensive as night price
- Day price is more than 3 times as expensive as night price
- Cannot say

22. What difference between the day price and night price would urge you to change how you use your DISHWASHER?

    - None
    - Choose None if you are not willing to change your appliance usage.
    - Day price is 1.5 times as expensive as night price
    - Day price is 2 times as expensive as night price
    - Day price is 3 times as expensive as night price
    - Day price is more than 3 times as expensive as night price
    - Cannot say

23. During which of the following time periods of weekdays (Monday - Friday) do you typically use your WASHING MACHINE? Choose multiple time periods if that is the case.

    - 6 AM - 9 AM
    - 9 AM - 12 Noon
    - 12 Noon - 3 PM
    - 3 PM - 6 PM
    - 6 PM - 9 PM
    - 9 PM - 6 AM

24. During which of the following time periods of weekdays (Monday - Friday) do you typically use your CLOTH DRYER? Choose multiple time periods if that is the case.

    - 6 AM - 9 AM
    - 9 AM - 12 Noon
    - 12 Noon - 3 PM

- 3 PM - 6 PM
- 6 PM - 9 PM
- 9 PM - 6 AM

25. During which of the following time periods of weekdays (Monday - Friday) do you typically use your DISHWASHER? Choose multiple time periods if that is the case.

    - 6 AM - 9 AM
    - 9 AM - 12 Noon
    - 12 Noon - 3 PM
    - 3 PM - 6 PM
    - 6 PM - 9 PM
    - 9 PM - 6 AM

26. How many times on weekdays (Monday - Friday) do you typically use your WASHING MACHINE?

    - Once per week
    - 2 times per week
    - 3 times per week
    - 4 times per week
    - 5 times per week
    - More than 5 times per week

27. How many times on weekdays (Monday - Friday) do you typically use your CLOTH DRYER?

    - Once per week
    - 2 times per week
    - 3 times per week
    - 4 times per week
    - 5 times per week
    - More than 5 times per week

28. How many times on weekdays (Monday - Friday) do you typically use your DISHWASHER?
    - Once per week
    - 2 times per week
    - 3 times per week
    - 4 times per week
    - 5 times per week
    - More than 5 times per week
29. If your friends or close relatives tell you that they have saved some money by changing how they use appliances, how likely is this to change your appliance usage?
    - Very likely
    - Somewhat likely
    - Neutral
    - Somewhat unlikely
    - Very unlikely
30. If you're given a smart device to automatically schedule your appliances (dishwasher, washing machine, cloth dryer) to lower your bill, would you use it?
    - Yes
    - No
    - Maybe
31. If you're given a smart device to automatically control your home temperature, would you use it?
    - Yes
    - No
    - Maybe
32. At what temperature do you set your air conditioner at home during the day?
    - I don't have air conditioning.

- Below 20°C (68F)
- 20°C (68F)
- 21°C (70F)
- 22°C (72F)
- 23°C (73F)
- 24°C (75F)
- More than 24°C (75F)
- Cannot say

33. How much monthly savings in summer would make you set your home temperature at 25°C (77F) during the day? Choose None if you are not willing to change your temperature setting.

    - None
    - $5 per month
    - $10 per month
    - $15 per month
    - $20 per month
    - More than $20 per month
    - Cannot say

Thanks for your participating in our 'Estimating the Effectiveness of Time-of- Use Electricity Pricing in Ontario' survey. Your feedback is extremely valuable! Please note that the question "Do you agree with the following statement: 'Three dollars plus Ten dollars is equal to Five dollars?' " was added in order to ensure that questions are answered attentively. If you are interested in the results of this survey, or have any general comments or questions related to this study, please contact Adedamola Adepetu at a2adepet@uwaterloo.ca or (519) 888 4567, Ext. 37869, or contact Prof. Keshav at keshav@uwaterloo.ca or (519) 888 4567, Ext. 34456. We would like to assure you this study has been reviewed by, and received ethics clearance through a University of Waterloo Research Ethics Committee. If you have any concerns regarding your participation in this study, please contact Dr. Maureen Nummelin, the Director, Office of Research Ethics, at 1-519-888-4567, Ext. 36005 or maureen.nummelin@uwaterloo.ca.