Understanding Solar PV and Battery Adoption in Ontario: An Agent-Based Approach

ABSTRACT

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. We find that PV-battery system adoption in Ontario is likely to be incremental rather than exponential. Moreover, we find that, of all the policies we evaluated, the most effective way to improve PV-battery system adoption is to significantly reduce its price.

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 Photovoltaic (PV) systems, particularly in a domestic setting, is their intermittency. Storage solutions, such as the Tesla Powerwall [30], 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 [30, 33]. Customer-owned batteries can also provide secondary services such as time-of-use price bill management, backup power, and reduction of peak power charges [7], 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 [15]. 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 Agent Based Model (ABM) [18] 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 [16, 21, 34, 35]. 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 [12, 19, 24, 27, 40, 41] 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 period1, 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 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.

The rest of this paper is structured as follows: Section 2 presents our ABM approach. We discuss the adoption of PV-battery systems in Ontario in Section 3 including the agent characteristics, agent behaviours, and environment conditions that are influenced in different scenarios. We present and discuss the results of different scenario simulations of our ABM in Section 4; Section 5 presents related work; Section 6 shows the perceived limitations of our work and areas of improvement and further consideration. We discuss the implications of different policies and identify advisable

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1The payback period is the time it takes for an investment to pay for itself.
policies for PV and battery adoption in Section 7; Finally, in Section 8 we summarize our work and highlight our contributions.

2. METHODOLOGY

In this section, we describe and discuss our ABM approach, with a focus on modeling energy systems and evaluating energy policies.

2.1 ABM Design

Agent-based modeling is an approach to modeling a complex, dynamic system where agents that have certain properties and behaviours interact with one another and with their environment [18]. ABMs are a bottom-up approach to system modeling, where changes in the system result from the aggregation of agent actions. ABMs are suitable for studying and evaluating energy policies because even complex policies can be easily modeled in terms of environment variables that affect how agents behave [21, 34, 35]. Agent properties in an ABM are typically determined by means of a survey, where each survey response corresponds to one or more agents.

Here we focus on an ABM for Ontario, 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 Data Sources

The results from an ABM are only as good as the data used to create the model. Typical data sources include surveys, official reports from public institutions and utilities, private industry reports, and vendor quotes.

A survey can provide basic data about homeowners such as their attitudes towards PV-battery systems and what systems they might purchase. Survey data can be used to create a purchase decision function, identify agent profiles, and create a general pattern of agent behaviour. In designing the survey, questions are asked to identify what parameters respondents consider in making decisions. As a result, the appropriate agent features can be systematically selected. Furthermore, the survey questions should cover the range of system options available to agents in the potential simulation scenarios; this way, we can interpolate between decision points not surveyed.

Official utility reports and documents, on the other hand, 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 [14] 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.

2.3 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), and whether the system includes a battery or not. We also consider the following irrational factors: prior knowledge of PV systems, perceived impact on the environment, 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 2.3.1. Social influence determines how knowledge of other agents’ actions influences when an agent enters the market to purchase a PV-battery system (Section 2.3.2) while other variables are fitted to a logistic regression equation that determines whether an agent purchases a particular system or not.

2.3.1 Modeling Irrationality using Affect Control Theory (ACT)

ACT is a theory to model the sentimental (or affective) aspects of actors, objects, and their behaviours [11], including human-technology interactions [31]. This theory is quite rich and we can only sketch it in what follows.

ACT models the degree of sentiment or affectiveness 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 from their self-identity due to their behaviours. 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 [28]. 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 is the homeowner, the Object is the solar panel, and the Behaviour 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 [28]. In this work, we use this deflection as a variable in the agent’s PV-battery purchase decision function.

2.3.2 Social Influence

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 [17]. According to Bass [2], 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 work, we represent this level of adoption with the social threshold T where 0 ≤ T ≤ 1 [9]. 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 [10] provide insight on the importance of social influence in PV adoption.

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

### 2.4 ABM Validation and Simulation Scenarios

To validate the model, we attempt to recreate the known past using our ABM. Specifically, we set environment parameters to past system prices and market conditions, and compare the degree of technology adoption predicted by the model with reality. In our case, we obtain data on past PV prices, Time-of-Use (ToU) electricity pricing schemes, and FiTs. Also, we obtain data on the adoption of PV systems under Ontario’s microFiT program [15]. By setting the environment parameters from the past, we can choose ABM model parameters, that is a particular pairing of \( \mu \) and \( \sigma \) for \( T \) in the agent population, so that it closely matches historical adoption. Each agent is randomly assigned a \( T_i \) from the selected distribution. This validation simulation is executed 80 times and the average adoption results are used. The selected \( \mu-\sigma \) pairing is then used for the agent population to simulate future scenarios.

In simulating future scenarios, we consider the base case, and alternative policy and price scenarios. The base case is the scenario where existing trends in system prices and market conditions are assumed to persist, and existing policies are applied without any intervention. This base case provides a reference for other scenarios. We then create alternative scenarios to test potential policy and market changes, and compare the results with the base case. This way, we are able to determine which energy policies have the most impact on PV-battery adoption, which policies are ineffective, and the necessity of any policy intervention.

### 3. PV-BATTERY SYSTEM ADOPTION IN ONTARIO

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.

#### 3.1 Data Description

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) [20] 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 1\(^2\)). 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 3.4. Other data such as electricity prices and PV-battery system prices are obtained from online sources [23,32] and vendor quotes\(^3\).

### 3.2 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 3\(^3\)). We assumed that the battery is charged during the Ontario ToU pricing mid-peak and off-peak hours (Figure 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 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 [6]:

\[
\text{Discounted Payback} = \frac{\ln\left(\frac{A_f}{A_i - \text{CapExed}}\right)}{\ln(1 + d)}
\]

\(^2\)All prices listed in this study are in Canadian Dollars, unless stated otherwise

\(^3\)We cannot provide the vendor names since they requested not to be cited.

\(^4\)We limit the PV component to 10 kW since this is the Ontario microFiT limit.
Table 1: Environment Parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>FiT ($/kWh)</td>
<td>This is the amount paid to a PV owner for each kWh generated from solar PV.</td>
<td>Ontario’s microFiT program pays $0.384/kWh for rooftop PV installations not more than 10 kW [13]. In our model, we assume solar PV systems are installed on the rooftop.</td>
</tr>
<tr>
<td>ToU Electricity Price</td>
<td>In the ToU pricing scheme, electricity consumers are charged at a rate based on the season and the time of day.</td>
<td>Figure 1 shows the ToU pricing scheme in Ontario (at the time of writing).</td>
</tr>
<tr>
<td>Installed Solar PV price ($/kW)</td>
<td>This is the cost of purchasing and installing a solar PV system of a certain capacity.</td>
<td>The rate per kW is dependent on the capacity. Figure 2 [32] shows the rate for each PV capacity range used in our work.</td>
</tr>
<tr>
<td>Installed Battery Price ($/kWh)</td>
<td>This is the cost of purchasing and installing a battery of a certain capacity.</td>
<td>With current market conditions [29], we set this at $1500/kWh.</td>
</tr>
<tr>
<td>Battery Depth of Discharge (DoD)</td>
<td>This is the maximum percentage of the listed battery capacity that can be used.</td>
<td>The current lithium ion (Li-ion) battery technologies have a DoD of about 80% [8, 37].</td>
</tr>
<tr>
<td>Battery Life (years)</td>
<td>This is the amount of time a battery can be used.</td>
<td>With Li-ion current technology, there is no particular fixed time as it depends on usage. As a result, we set it at 10 years.</td>
</tr>
<tr>
<td>Battery Charge Efficiency (years)</td>
<td>This is the ratio of the amount of energy stored on a battery while charging to the total energy dissipated in the charging process.</td>
<td>Li-ion batteries have a charge efficiency of 85% [37].</td>
</tr>
<tr>
<td>Battery Discharge Efficiency (years)</td>
<td>This is the ratio of the amount of energy obtained from a battery while discharging to the total energy dissipated in the discharging process.</td>
<td>Li-ion batteries have a discharge efficiency of nearly 100% [37].</td>
</tr>
</tbody>
</table>

Figure 2: Solar PV Prices in 2015

Figure 3: Sample Survey Question (1): Which system(s) would you buy?
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:

$$RoI = \frac{Total \ Inflow - System \ Cost \ - 100\%}{System \ Cost}$$ (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 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 4. As a result, we can interpolate and model agent decisions in scenarios with different electricity and system prices than those in our survey.

The survey was distributed using Crowdflower [3], 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 our attention test question correctly. Figures 3 and 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.

3.3 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. Using Lasso Least Angle Regression (Lasso LARS) [4], we identified the features that had the most impact on purchase decisions. To do so, we set the regularization parameter at $5.5 \times 10^{-7}$ in order to get a clear distinction of significant variables. Figure 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 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 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.

3.4 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 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.

3.4.1 Electricity Generation and Consumption
Table 3: Agent Parameters

<table>
<thead>
<tr>
<th>Agent Parameters</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electric Load (kWh)</td>
<td>This is the amount of electricity consumed by the agent during each hour in a year.</td>
<td>Electrical load data from some households in Ontario.</td>
</tr>
<tr>
<td>Maximum Solar PV Budget ($)</td>
<td>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.</td>
<td>Ontario survey.</td>
</tr>
<tr>
<td>PV-Battery System Ownership</td>
<td>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.</td>
<td>Ontario survey and simulation purchase decisions.</td>
</tr>
<tr>
<td>Social Network (S)</td>
<td>Each agent is assigned a social network from other agents. The size of each agent’s social network is obtained from a truncated normal distribution.</td>
<td>Agents are randomly selected from a uniform distribution to each agent’s social network, depending on the assigned size.</td>
</tr>
<tr>
<td>Adoption Threshold (T)</td>
<td>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 [2]. 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.</td>
<td>Randomly assigned from a normal distribution that has been validated using historical adoption of solar PV.</td>
</tr>
</tbody>
</table>

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 [20]. 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.

3.4.2 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

1: function PURCHASEPVBATTERY(Agents, Systems)
2:   for all agent ∈ Agents do
3:     SocialPV ← number of friends with PV
4:       total number of friends
5:     if agent.PVBatt is ∅ and agent.T ≤ SocialPV then
6:         ViableSys ← {}  
7:         for sys ∈ Systems do
8:           if agent.WillBuy(sys) then
9:             ViableSys ← ViableSys ∪ sys
10:         end if
11:       end for
12:      agent.PVBatt ← Random(ViableSys)
13:   end if
14: end for

Figure 6: Environment Variable Changes during the Validation Period
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 [15]. 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., 26,160 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 6). 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 [15].
- We apply a linear transition of ToU price, from January 2010 to January 2015 [23].
- According to NREL [5], 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 26,160 agents replicated from the survey. In addition, we ran simulations with different means $\mu$ and standard deviations $\sigma$ for $T$ in order to find the best match for historical adoption. For each $\mu$ and $\sigma$ of $T$, we executed 20 simulations and report the average adoption results. Figure 7 shows the errors associated with each $T$ distribution; the normal distribution with the lowest error and closest fit is that with $\mu = 0.42$ and $\sigma = 0.14$ (highlighted box in Figure 7). Figure 8 shows the scaled historical adoption compared to the simulated adoption. As a result, we use these values for ABM simulations of all other scenarios.

4. 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 9 and 10. 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, it is set at about 60%. Similarly, the ToU price in each period (as seen in Figure 1) is proportionally increased using the coefficients in Figure 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 [25]. We extrapolate this decay in price to 2025.

- We use the same ToU price trend from the past 5 years [23].
- 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 [38]. 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 [26, 36]. Assuming a price of 50% in 2020, we extrapolate this decay in price to 2025.

We make the following changes in alternate scenarios (Figures 9 and 10): reduced battery price, slowed FiT reduction, increased ToU price, reduced PV Price, reduced PV 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.

### 4.1 PV Adoption

Figure 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 12 and 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 13 where, in the base case, adoption due to net metering alone starts only after about 5 years.

Another insight from Figure 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 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 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 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.

### 4.2 Battery Adoption

Figure 14 shows the adoption of battery systems in scenarios where only one environment variable is changed from the base case while Figure 15 pertains to scenarios with multiple variable changes. In Figure 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 pur-
chase 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 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.

4.3 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 16 shows the total weekly PV electricity generation and Figure 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 high levels of PV penetration for the next decade.

5. RELATED WORK

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

Robinson et al. [27] 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. [24] 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 [19] 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. [12] 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. [39, 40] 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. [41] 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.

6. LIMITATIONS

The limitations of our work 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.

7. 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.

8. CONCLUSION

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.

9. REFERENCES


[34] Koen H van Dam, Igor Nikolic, and Zofia Lukszos.


