Improving Time-of-Use Electricity Pricing in Ontario

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Abstract

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 and supplying electricity, and to make consumers defer appliance usage; this would reduce the daily electricity consumption peak that can both reduce the cost of generation and carbon footprints. We first critique the current ToU scheme in Ontario and make recommendations to improve it. Subsequently, we create an Agent-Based Model (ABM) to study ToU pricing and its effectiveness in reducing peak loads, which allows us to evaluate the benefit of our recommendations. We find that while ToU is effective in incentivizing load deferral, improvements can be made in the Ontario ToU scheme.

Keywords: Demand Response, Agent-Based Model, Electricity pricing

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 as a result, the generation systems are not used at 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.

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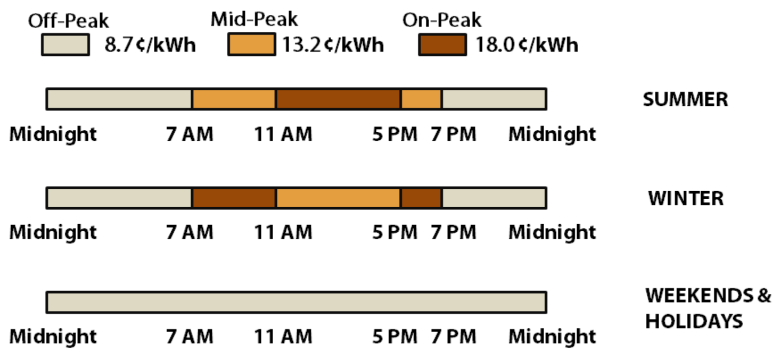

Figure 1: Ontario ToU Pricing Scheme [1]

Figure 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 perfectly matches generation.

In prior work [2] (which is also partly presented in Section 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 2013, 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 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 Figure 5.
2. The ToU scheme should comprise four seasons. The recommended start dates and daily period divisions are shown in Figure 2.

We note that in a study by Navigant [3] using electrical load data from households in Ontario, it was found that there has been a 3.3% reduction in household electrical peak load between 2009 and 2013[1]. However, this does

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

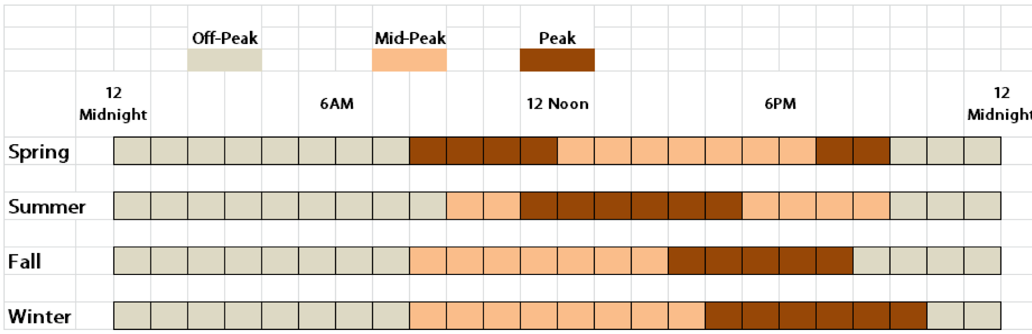

Figure 2: Daily Periods of the 4-Season TOU Scheme

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.

In this study, we aim to improve the effectiveness of ToU pricing in Ontario. We create an Agent-Based Model (ABM) that models the residents of Ontario, and how they use deferrable loads such as washing machine, clothes dryer, and dishwasher. Agent-based modeling is a system modeling method that comprises actors existing within a certain environment [4]. These agents are autonomous actors that have certain properties, interact with one another, and carry out certain actions based on these properties and the environment. For example, to study ToU pricing, agents are homeowners that have household appliances and use these appliances based on their needs and possibly, in response to the electricity prices. Here the environment comprises of variables such as the ToU electricity pricing scheme and typical electrical appliance loads.

We conduct a survey with respondents from Ontario and execute different scenario analysis using the ABM. The results show that improvements could be made to the existing ToU pricing scheme in Ontario. The rest of this paper is structured as follows: In Section 2, we critique the ToU electricity pricing scheme in Ontario and make recommendations; in Section 3, we describe the ABM for simulating the response of electricity consumers to different electricity pricing schemes and policies; in Section 4, we detail the Ontario case study and discuss the results; in Section 5, we discuss the implications of each studied policy; Section 6 comprises related work while Section 7 highlights limitations and areas of future research; we conclude the paper in Section 8.

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.

2.1. Data

Our study is based on the publicly available Ontario hourly aggregate load demand between 2003 and 2005 [5]; 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[2]. 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.

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 [6].

2.2.1. 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.

[2]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.

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 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 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 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.

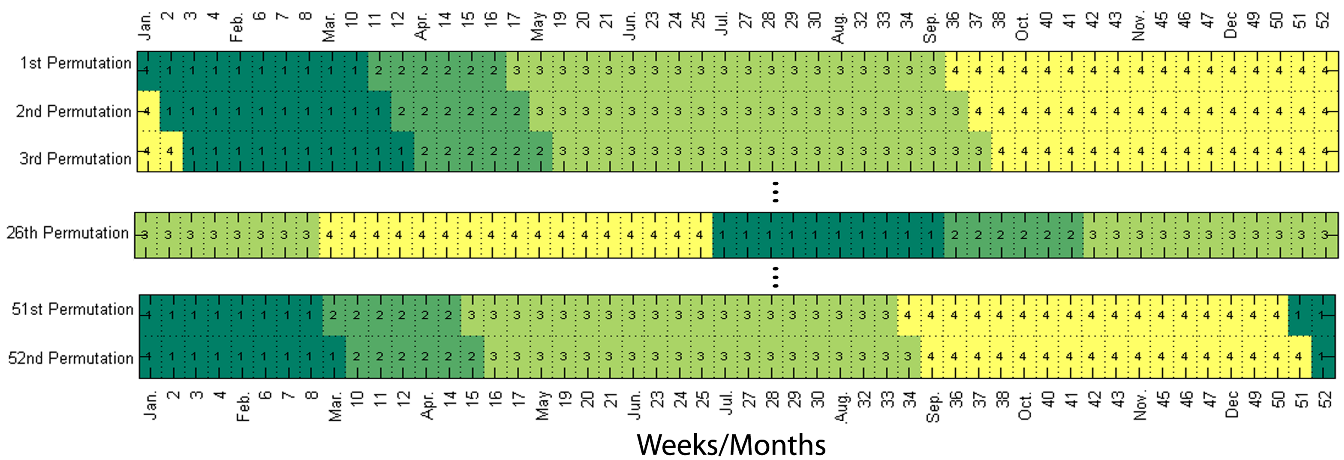

Figure 3: Cyclic Permutations for Seasonal Sequence $S = [10, 6, 19, 17]$

Table 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

2.2.2. 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:

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

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 $\phi^W(j)$.

2.2.3. Seasonal Sequence Score

We measure the validity of a seasonal sequence based on the R^2 cluster validity index [7, 8]. Higher R^2 values indicate better clusters. The R^2 value of a seasonal sequence, for a sequence with K seasons, is given by:

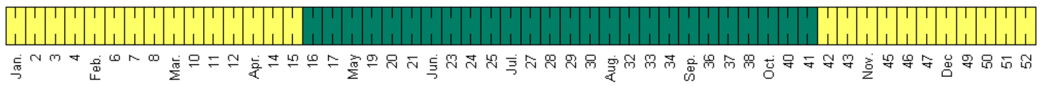

Figure 4: Clustering for Two 26-Week Seasons

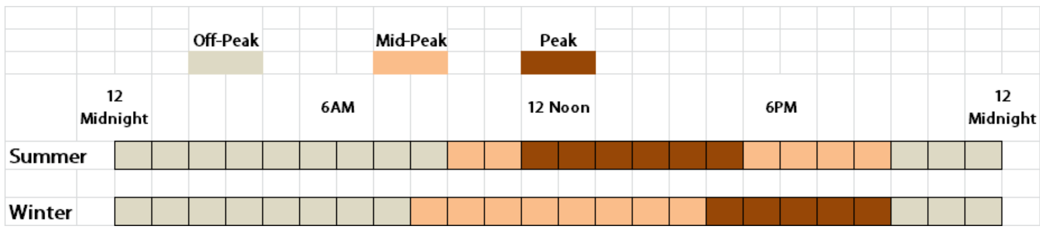

Figure 5: Daily Periods of the 2-Season TOU Scheme

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

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.

2.3. Clustering Results

We now discuss the clustering results.

2.3.1. 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 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 Figure 5. 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 1.

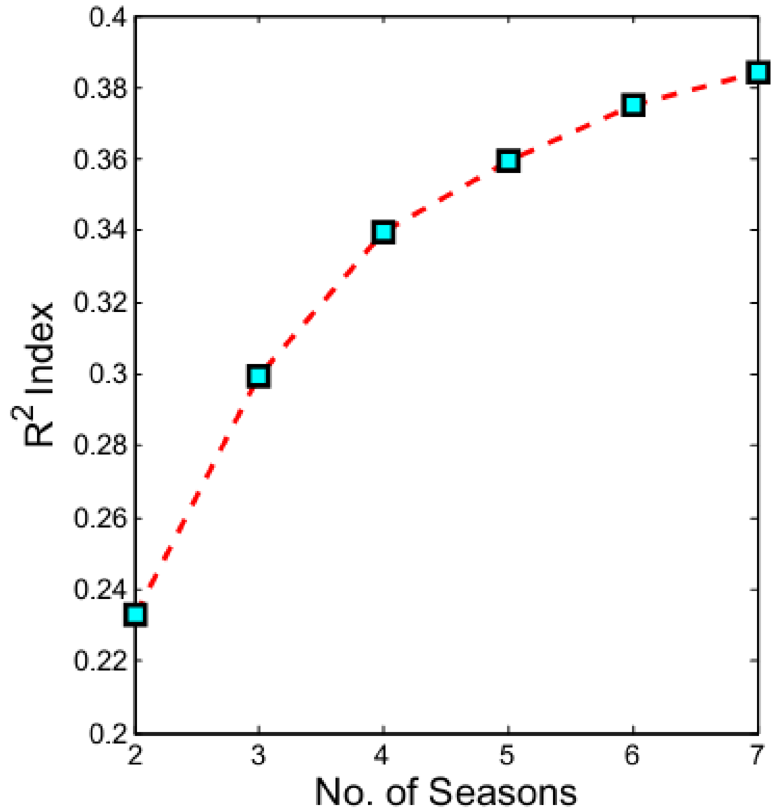

Figure 6: R^2 Index for Different Numbers of Seasons

2.3.2. 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 6 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 7 shows the duration of each season given different number of seasons per year.

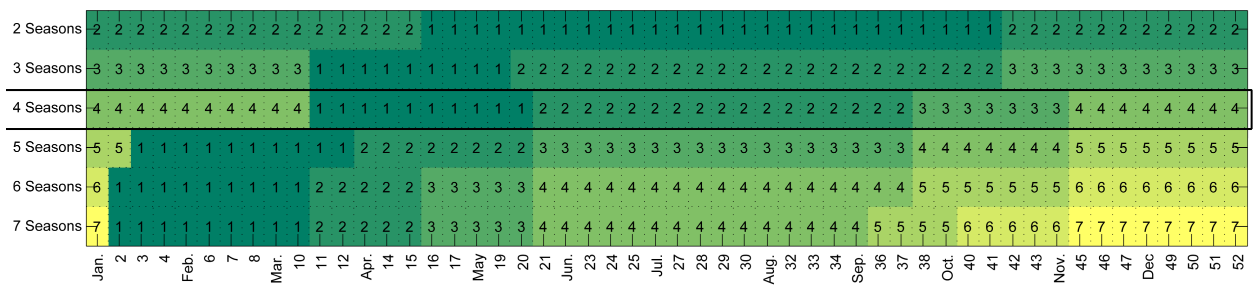

Figure 7: Optimal Seasonal Sequences for 2-7 Seasons

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.

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 2 [9, 10]. 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 2, 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 in technology adoption 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

Table 2: Typical Household Appliances [10, 9]

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

on ToU pricing and have identified different reasons for agents' response to ToU pricing. These include the following household and system variables:

- Level of education [11]: This corresponds to the highest level of formal education achieved by the resident, ranging from primary school to graduate level.
- Income [12, 11]: 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 [12, 13]: 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 [11, 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 [12]: 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 [15]: 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.

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 [9, 10, 16].

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 [17], 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 3 and 4.

3.3. Feature Selection and Logistic Regression

To predict the usage of appliances, we attempt to fit responses to the two survey questions presented Tables 3 and 4 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

Table 3: 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?* (WM: Washing Machine, CD: Clothes Dryer, DW: Dishwasher)

Peak-to-Off-Peak Price Ratio	**WM**	**CD**	**DW**
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: Survey Question on Monthly Savings: *How much monthly savings from your appliance would urge you to use it at night or during weekends?* (WM: Washing Machine, CD: Clothes Dryer, DW: Dishwasher)

Monthly Savings	**WM**	**CD**	**DW**
None			
$5 per month			
$10 per month			
$15 per month			
$20 per month			
More than $20 per month			
Cannot say			

Table 5: Logistic Regression Result for Dishwasher Usage with the Peak-Off-Peak Price Ratio as a ToU Variable

Variable	**Coefficient**	**Standard Error**	z	$P > \|z\|$
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

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. If the consumers can estimate monthly savings, we believe they would make decisions based on the monthly savings. We take this approach in the agent decision model.

From our analysis, 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 8 to 11 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 8 shows the feature selection result for dishwasher usage with peak-off-peak price ratio as the determinant ToU variable; Table 5 shows the corresponding logistic regression results. The *education* variable and the intercept do not fall within the 95% confidence interval.

In Figures 9 to 11 there are variables that are correlated with the decision to defer appliance usage. However, the logistic regression results show that these variables cannot be fitted with a 95% confidence interval. Tables 6 to 8 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 3 and 4. We discuss this next.

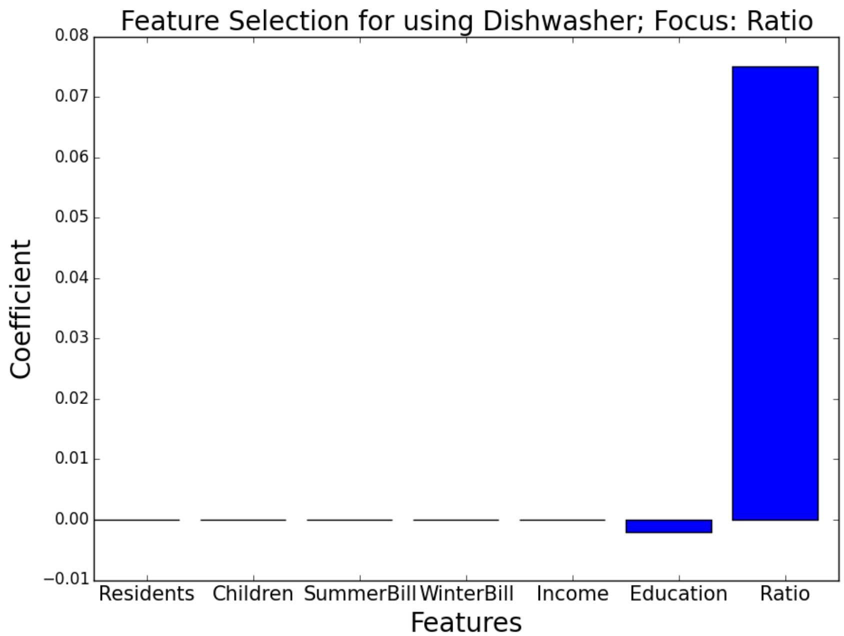

Figure 8: Feature Selection for Dishwasher Usage with the Peak-Off-Peak Price Ratio as a ToU Variable

Table 6: 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

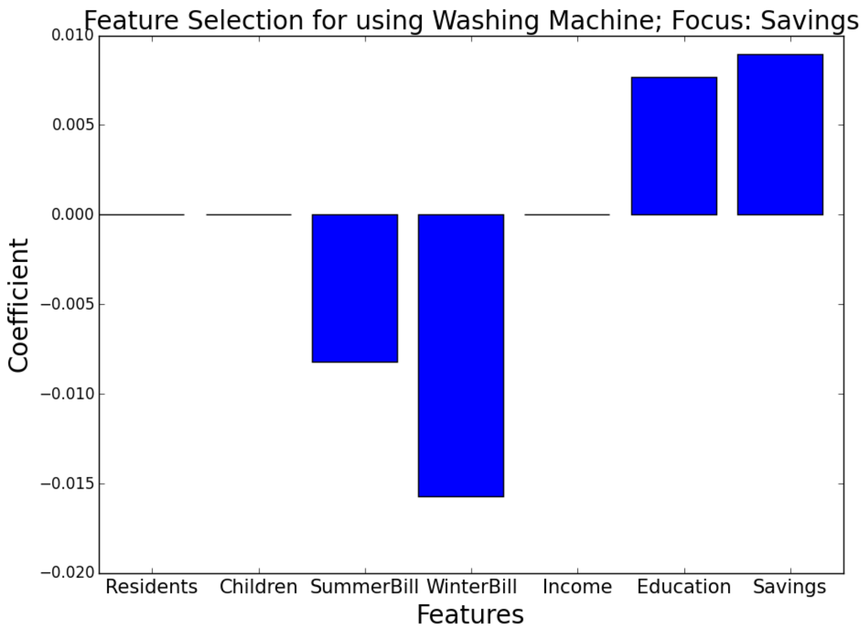

Figure 9: Feature Selection for Washing Machine Usage with the Monthly Savings as a ToU Variable

Table 7: 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

Table 8: 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

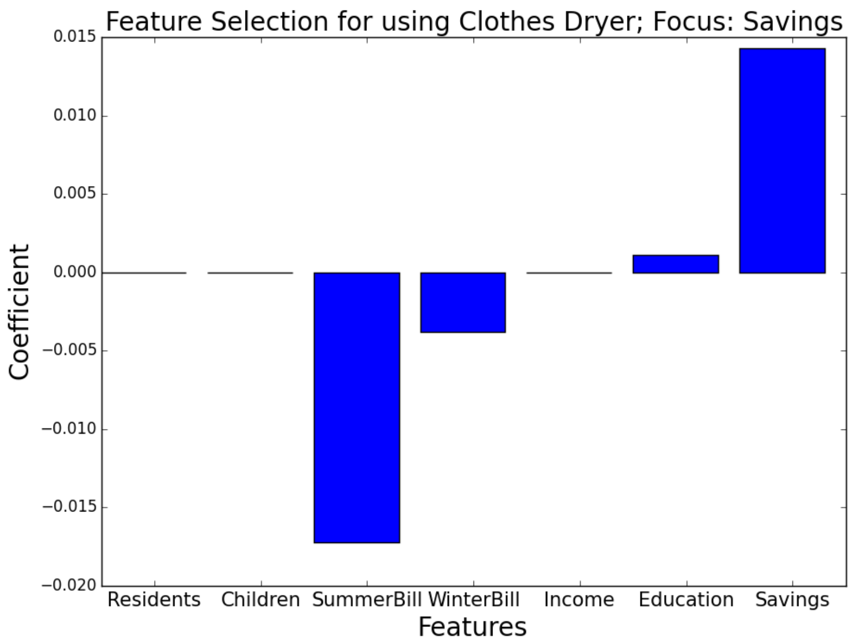

Figure 10: Feature Selection for Clothes Dryer Usage with the Monthly Savings as a ToU Variable

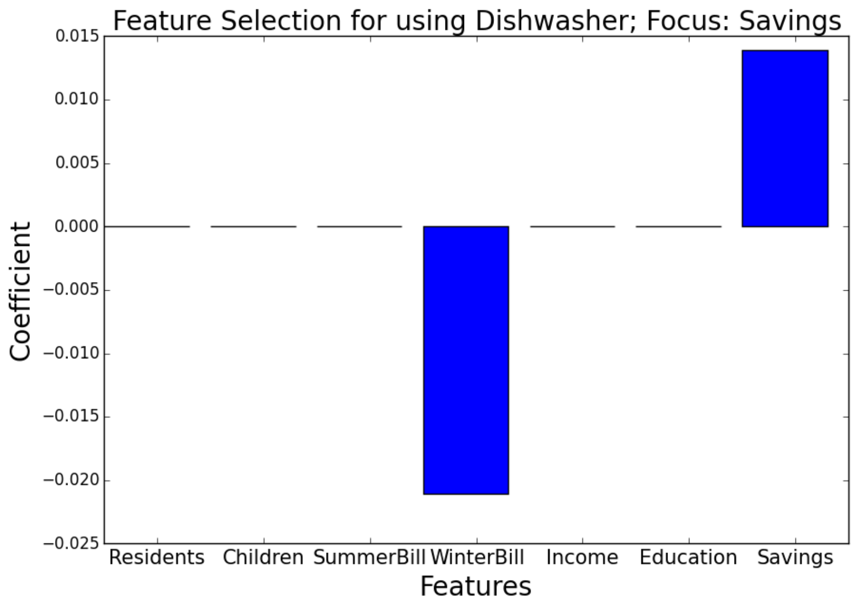

Figure 11: Feature Selection for Dishwasher Usage with the Monthly Savings as a ToU Variable

3.4. Agent Parameters and Behaviours

Table 9 shows the agent parameters and Table 10 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.

Table 9: 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.	Survey[3].
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.

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.
- Otherwise, if the agent can estimate monthly savings, the decision is based on the stated monthly savings 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 1 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.
- 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.

[3]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.

Algorithm 1 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.WeeklyUsage[appliance] do
                    UsageTime ← random(agent.UsagePeriod[appliance])

                    if UsageTime ∈ Peak ∪ MidPeak then
                        if agent.WillShiftLoad then
                            UsageTime ← random(OffPeak)
                        end if

                    end if

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

            end for
        end if
    end for
end function
```

Table 10: 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 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 [16].

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. 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. [15] 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 Figure 5.
- *Opt4*: A ToU scheme with four seasons. We set the ToU scheme as shown in Figure 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 5. 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. This may seem counterfactual as a higher ratio would be expected to increase customer participation in ToU. However, given that ToU pricing has already been introduced with a peak-off-peak ratio of 2:1, and the current level of participation in appliance usage deferral due to ToU pricing is high – 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.

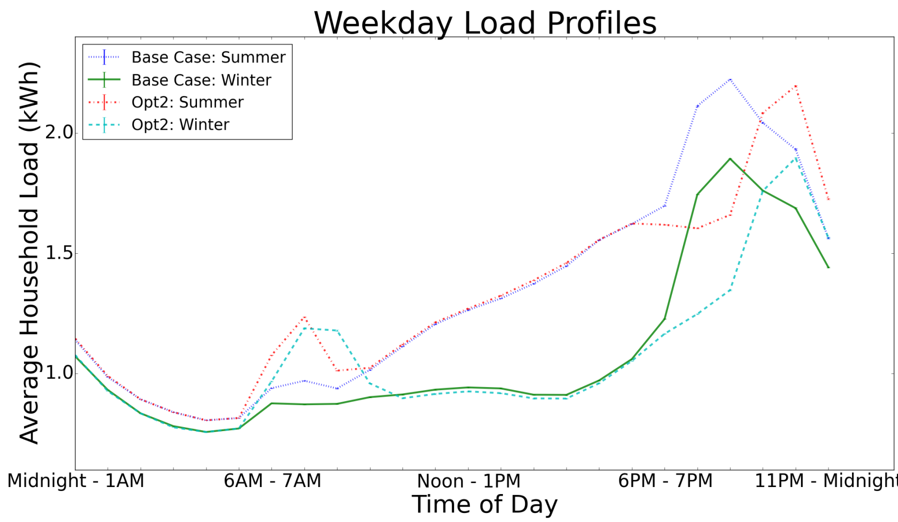

Figure 12: Average Weekday Load Profiles: *Opt2* Scenario

Figure 12 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.

As seen in Figure 13 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 be any clear benefit of a four-season ToU scheme over the optimal two-season scheme. 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

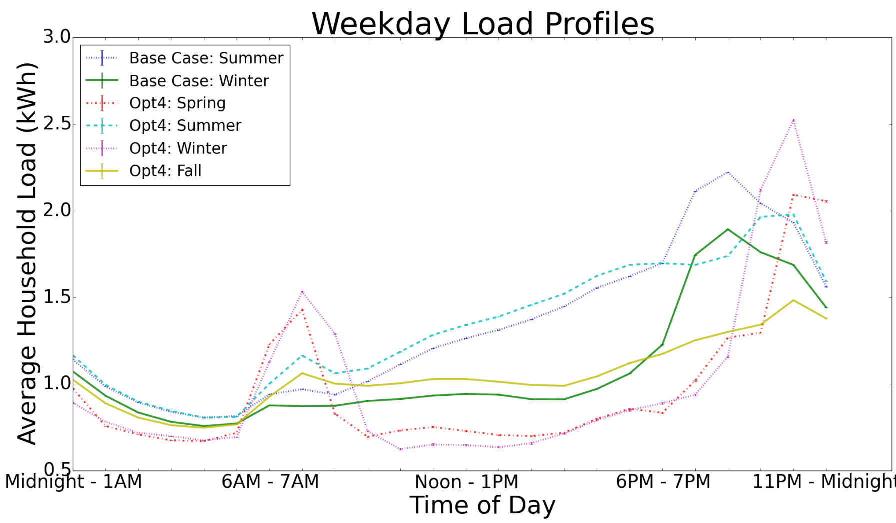

Figure 13: Average Weekday Load Profiles: *Opt4* Scenario

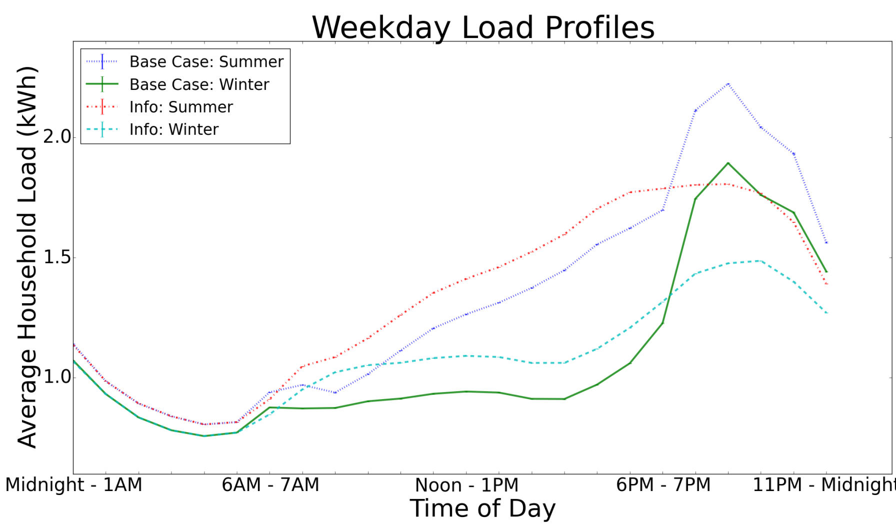

Figure 14: Average Weekday Load Profiles: *Info* Scenario

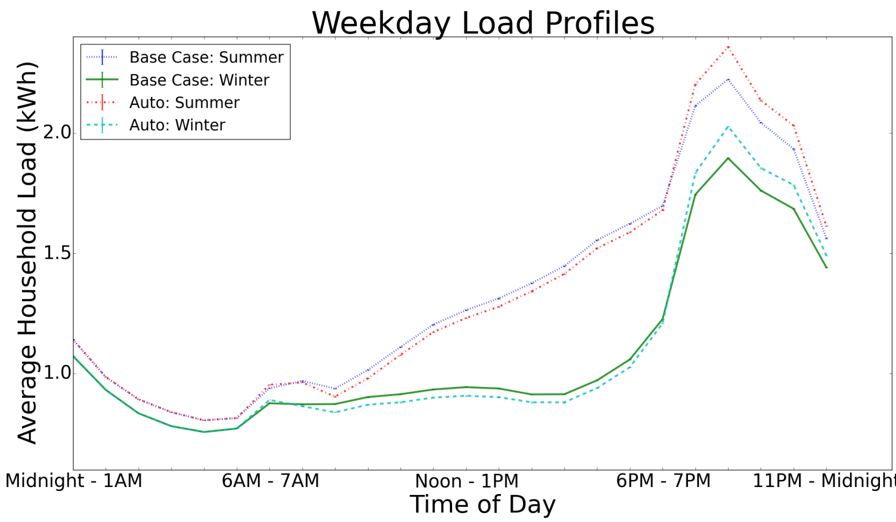

Figure 15: Average Weekday Load Profiles: *Auto* Scenario

scheme could be challenging for electricity consumers.

In Figure 14, 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 15; 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 16), 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 is beneficial given that electricity is much cheaper during these periods than the load profile peak period in the base case.

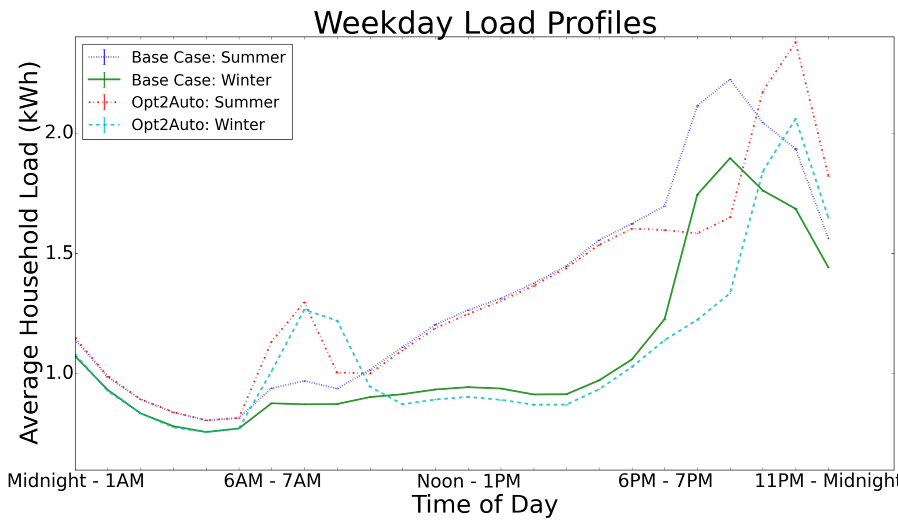

Figure 16: Average Weekday Load Profiles: *Opt2Auto* Scenario

5. 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.

6. Related Work

There have been studies that review the effectiveness of ToU pricing and other DR programs [15, 18]. Faruqui et al. [15] 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 [3] 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 [19] 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 [13] 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. [20] 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 [21] 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.

7. 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 study.

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.

8. Summary

In this study, 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 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. However, a two-season ToU scheme with a later peak period as seen in Figure 5 could be more effective in deferring loads to cheaper periods than the current ToU scheme, therefore effectively reducing the PAR of the Ontario regional load profile. 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.

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