

# Critiquing Time-of-Use Pricing in Ontario

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**Abstract**—Since 2006, with the progressive deployment of Advanced Metering Infrastructure, jurisdictions in the Canadian province of Ontario have been increasingly using Time-Of-Use (TOU) pricing with the objective of reducing the mean peak-to-average load ratio and thus excess generation capacity. We analyse the hourly aggregate load data to study whether the choice of TOU parameters (i.e., number of seasons, season start and end times, and choice of peak and off-peak-times) adequately reflects the aggregate load, and to study whether TOU pricing has actually resulted in a decrease in the mean peak-to-average ratio. We find that since the introduction of TOU pricing not only has the mean peak-to-average load ratio actually *increased* but also that the currently implemented TOU parameters are far from optimal. Based on our findings, we make concrete recommendations to improve the TOU pricing scheme in Ontario.

## I. INTRODUCTION

The progressive introduction of Advanced Metering Infrastructure (AMI), also known as “smart meters,” has made it possible for utilities to charge different prices during different times of the day. This is known as Time-Of-Use or TOU pricing. Given that electricity generation capacity is sized for rare peaks, this allows utilities to charge more during load peak periods, so that price-sensitive consumers shift the elastic component of their load to off-peak periods, reducing the peak, and thus the need for excess generation capacity. Ideally, a TOU pricing scheme would completely even out the daily load, so that the peak-to-average (PTA) ratio would be 1.0.

AMI has been rolled out in the Canadian province of Ontario since 2006—at great expense—with the stated goal of introducing TOU pricing and thus flattening the daily load curve [1]. Current AMI penetration is over 92% and nearly all jurisdictions in Ontario use TOU pricing. The current TOU scheme has two *seasons*, summer and winter, with different electricity prices for each part of each day for each season (Figure 1) [1]. The summer season occurs from May 1 to October 31 and the winter season occurs from November 1 to April 30. In addition, all weekends and statutory holidays are classified as Off-Peak periods.

Given that TOU pricing has been in place for more than six years, it is interesting to evaluate its performance. We do so using publicly available aggregate hourly load data and answer the following broad questions:

- 1) **Effectiveness:** Has the daily PTA ratio in Ontario decreased since the introduction of TOU pricing?

- 2) **Optimality:** Does the current TOU scheme use the best possible parameters, i.e., number of seasons, season start and end times, and choice of Peak and Off-Peak times?

Our analysis indicates that since the introduction of TOU pricing not only has the mean peak-to-average load ratio actually *increased* but also that the currently implemented TOU parameters are far from optimal.

Our work, therefore, makes the following contributions:

- A careful analysis of aggregate Ontario load data to study the effectiveness and optimality of the current TOU scheme
- The finding that the existing TOU scheme is neither effective nor optimal
- Concrete recommendations to better align the TOU scheme to actual load variations

The paper is laid out as follows. In Section II we describe the background to our work. In Sections III and IV we describe the underlying data set and the data analysis techniques used in our study. Section V details our results, Section VI details our recommendations, and we conclude with Section VII.

## II. BACKGROUND AND RELATED WORK

Lacking storage, most electricity grids are sized to handle relatively rare peak loads. Reducing peak loads can partially eliminate the need for expensive peaking generators, making it a very desirable goal. One widely used approach to reduce load peaks is dynamic pricing, where a unit of electrical energy costs more during peak times. This encourages consumers to shift their loads to off-peak (cheaper) times. Utilities use many time-varying pricing approaches such as TOU, Critical Peak Pricing (CPP), Real Time Pricing (RTP), and Peak Time Rebates (PTR) [2].

Newsham and Bowker [2] reviewed and compared results from recent studies on pilot peak load reduction schemes in North America. They found that the most effective approach

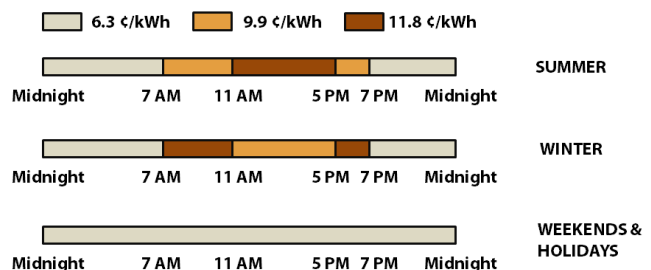


Fig. 1: Ontario's TOU Pricing Scheme in 2013

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is CPP, where a higher peak price is charged only on a few days called event days, whereas flat pricing is used during all other days. Event days are defined based on demand prediction and are advertised one day ahead. The CPP is capable of 30% peak load reduction while a simple TOU scheme is expected to achieve only a 5% peak load reduction.

Faruqui *et al.* [3] compares Ontario's TOU pricing with 50 other deployments. They find that winter months in Ontario have a daily dual peak pattern and summer months in Ontario have a single peak, which makes TOU pricing appropriate. They propose four alternative TOU designs:

- Adding and reallocating the wind/solar generation costs to the peak period
- Reducing the length of on-peak and off-peak periods to four hours
- A TOU pricing scheme exercised only in the summer season
- A TOU scheme with each day split into two periods

These different designs were simulated and it was concluded that the Ontario Electricity Board should consider implementation costs, price ratio improvements, rate-setting process simplification, and customer responsiveness. Although the effect of price ratio on TOU has been investigated in subsequent work from the same team in Reference [3], load seasonality and its effect have not been studied.

One focus of our work is load *seasonality*, that is, the variation in daily aggregate load during different seasons of the year. Seasonality in electrical loads has not been studied in great detail in the research literature. Some recent studies have however taken seasonality into consideration for short-term load prediction. For instance, [4] uses a time series modeling method, Seasonal AutoRegressive Integrated Moving Average (SARIMA), to predict the peak load within a one-day interval. In addition, [5] clusters days based on load similarity in order to forecast anomalous days 24 hours ahead of time.

### III. DATASET

We now discuss the dataset used in our work. We used the publicly available Ontario hourly aggregate load demand between 2003 and 2012 [6]. These hourly values aggregate residential, commercial, and industrial loads. This dataset is ideally suited for our TOU pricing study because of its fine granularity, completeness, and the fact that TOU pricing is aimed at reducing the PTA at the regional utility level [1]. The dataset is ideal also because it allows us to evaluate aggregate load characteristics before and after the implementation of the TOU scheme in 2006.<sup>1</sup>

It is well known that aggregate load varies on weekdays and weekends. To allow us to compare data across years, we aligned data from each week of the year by discarding data from the last day of each year (and from last two days in each leap year). This reduced each year to 364 days, which is exactly 52 weeks.

<sup>1</sup>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.

### IV. DATA ANALYSIS TECHNIQUES

To evaluate the change in peak-to-average ratio across years, we use a standard statistical technique called *bootstrapping*, which we discuss in Section IV-A. To determine the optimal TOU parameters, we first divide the calendar year into *seasons*, which are intervals containing days with similar load profiles. We discuss our approach to finding seasons in Section IV-B.

#### A. Bootstrapping

In order to investigate the effectiveness of TOU pricing, we examine the mean difference in load behaviour before and after the TOU scheme was implemented using bootstrap confidence intervals. The bootstrap is a non-parametric statistical method [7] that can be used to construct confidence intervals for distribution parameters, such as mean and variance, even when the sample size is not adequate to assume that point estimates are normally distributed.

Suppose we wish to construct a confidence interval for the mean  $\mu$  of a distribution  $F$  from which we have a random sample  $X = X_1, \dots, X_n$ . The sample mean  $\bar{X}_n = n^{-1} \sum_i X_i$  is an unbiased point estimate of  $\mu$ . By assessing the variability of  $\bar{X}_n$ , we will construct an interval that contains  $\mu$  with specified probability  $1 - \alpha$ . A *bootstrap sample*  $X^* = X_1^*, \dots, X_n^*$  is a random sample of size  $n$  drawn uniformly with replacement from  $X$ . In a bootstrap sample, members of the original sample  $X$  occur zero or more times. To construct a confidence interval, we draw  $B$  bootstrap samples, and we compute their sample means  $\bar{X}_{n,1}^*, \dots, \bar{X}_{n,B}^*$ . Let  $\bar{x}_\beta^*$  be the  $\beta$  sample quantile of  $\bar{X}_{n,1}^*, \dots, \bar{X}_{n,B}^*$ . The  $1 - \alpha$  *pivotal confidence interval* for  $\mu$  is given by  $(2\bar{X}_n - \bar{x}_{1-\alpha/2}^*, 2\bar{X}_n - \bar{x}_{\alpha/2}^*)$  [7].

#### B. Time Series Clustering

We determine the seasons in a set of load profiles using clustering by exhaustive search. We now discuss the details of this approach, first discussing the exhaustive enumeration of all possible seasons, then the feature representation used for clustering. Our approach is similar to that of Inniss [8].

1) *Enumerating all Possible Seasons*: We first discuss how to enumerate all possible seasons in a year. We define a *seasonal sequence* as a set of contiguous seasons that sum up to 52 weeks (one year), with the proviso that seasons are no shorter than 4 weeks, no longer than 40 weeks, and that seasons can 'wrap around' the year. For example, a seasonal sequence  $S = [a, b, c, d]$  would refer to 4 ordered seasons with lengths of  $a, b, c$ , and  $d$  weeks, but where the start date of the first season is undefined. It is therefore possible to enumerate *all* possible seasons (that meet our constraints) by cyclically permuting all possible seasonal sequences for all possible start points  $k = (1, 2, \dots, 52)$  in a year. For example, Figure 2 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 I 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

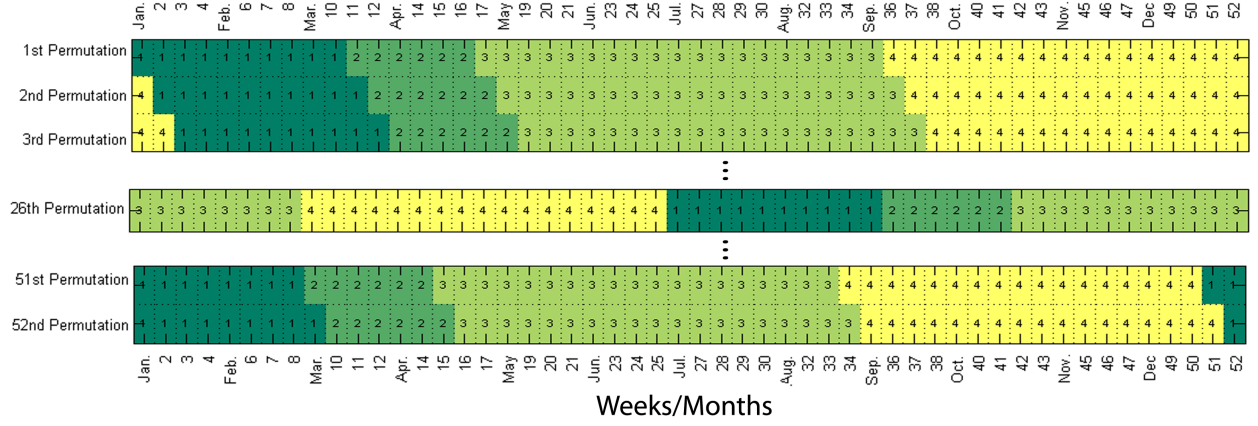


Fig. 2: Cyclic Permutations for Seasonal Sequence  $S = [10, 6, 19, 17]$

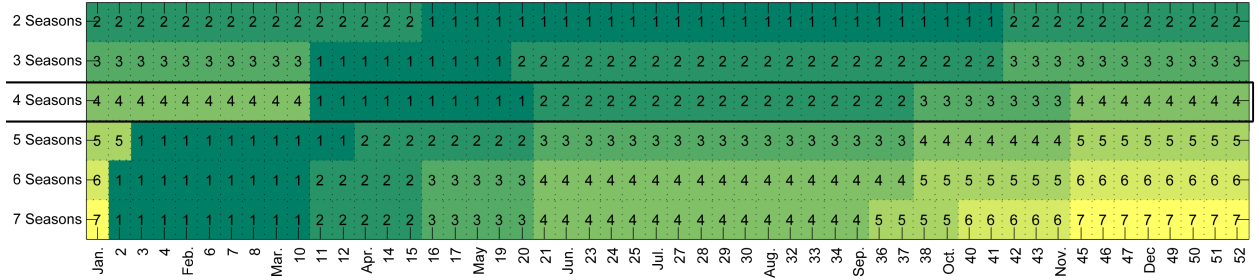


Fig. 3: Optimal Seasonal Sequences for 2-7 Seasons

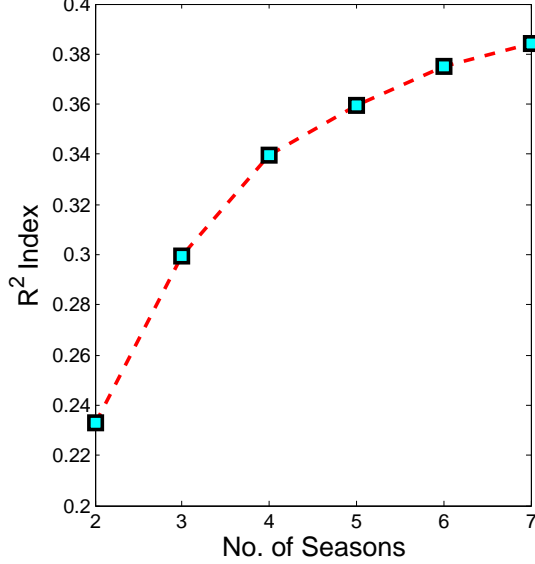


Fig. 4:  $R^2$  Index for Different Numbers of Seasons

of seasons. Note that, 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.

TABLE I: 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) *Feature Representation*: Recall that a TOU scheme tries to reduce load during peak times. We first formally define peak times based on the hourly load profile for a day, and then we cluster days of the year such that days with similar allocations of peak times are clustered together. Let the daily load at hour  $h$  be denoted  $L(h)$ ,  $h = 1 \dots 24$ . We define a 24-element daily feature vector  $\phi^D$  whose  $h$ th element  $\phi_h^D$  is given by

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

where  $P_{50}$  and  $P_{75}$  are the 50th and 75th percentiles respectively of the load for that day. The basic unit of time for defining a season is one week, a natural time unit in this context. Concatenating the feature vectors of the days in the  $j$ th week of the year results in a 168-element feature vector  $\phi^W(j)$  for week  $j$ . We cluster weeks based on these  $\phi^W(j)$ .

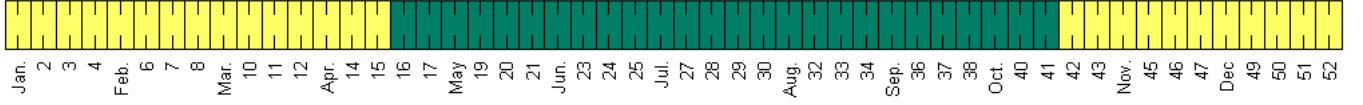


Fig. 5: Clustering for Two 26-Week Seasons

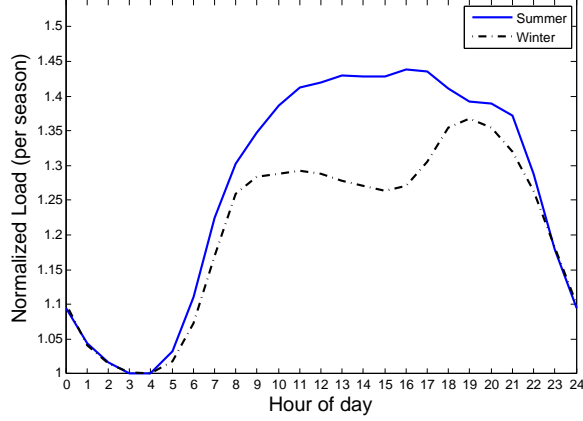


Fig. 6: Normalized Aggregate Weekday Load Curves for Current TOU Scheme

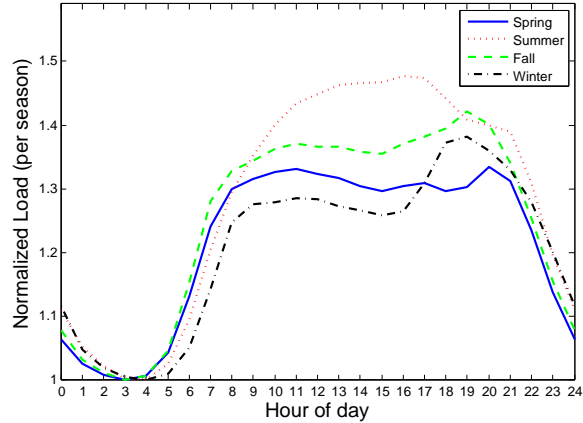


Fig. 7: Normalized Aggregate Weekday Load Curves for Optimal Seasonal Sequence

3) *The Score of a Seasonal Sequence*: Given a particular seasonal sequence and the underlying set of weekly feature vectors  $\phi^W(j)$  for  $j = 1 \dots 52$ , we assign the sequence a score based on the  $R^2$  cluster validity index [9], [10]. Higher  $R^2$  values indicate better clusters. The  $R^2$  value of a seasonal sequence, for a sequence with  $K$  seasons, is given by:

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

where  $C_i$  is the set of weeks in the  $i$ th season and  $\bar{\phi}_i$  is the centroid of the  $i$ th 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  $i$ th season in

multiple years.) Note that the difference between  $\phi^W$  vectors is calculated using the Euclidean distance.

After evaluating the  $R^2$  value over all possible seasonal sequence enumerations, we show the best  $R^2$  value for a particular value of  $K$  as a function of  $K$  in Figure 4. We select the best number of clusters (seasons) based on the point where there is an elbow in the  $R^2$  graph.

## V. RESULTS

We now address the effectiveness and optimality of the TOU scheme currently implemented in Ontario using the methods described in Section IV.

### A. Effectiveness of the TOU Scheme

To evaluate the effectiveness of TOU pricing, we use bootstrapping to compare the change in the PTA ratio of the aggregate Ontario load data between 2005 and 2012. We chose these years because TOU was introduced in 2006, and because 92% of residential and small scale customers were participating in the TOU scheme as of September 2012 [11].

Let  $P = P_1, \dots, P_n$  and  $Q = Q_1, \dots, Q_n$  be the  $n = 365$  observed daily PTA values from 2005 and 2012 respectively. We define  $D = D_1, \dots, D_n$  such that  $D_i = Q_i - P_i$ ; thus  $D_i$  is the difference between the respective PTAs observed on day  $i$  in 2012 and day  $i$  in 2005. We construct a confidence interval for the true mean of the  $D_i$ . Analyzing the paired differences allows us to produce a narrower confidence interval by accounting for the intrinsic variability in PTA over a year.

We used  $B = 1000$  bootstrap samples of the paired differences in daily PTA to construct a 95% bootstrap pivotal confidence interval for the mean difference, giving  $(0.006, 0.012)$ . Therefore, the mean of the PTA in 2012 is slightly *higher* than that in 2005. The mean of the PTA in 2012 was also found to be higher than in 2003 and 2004. While it may be argued that TOU has been effective by keeping the PTA fairly constant, the TOU scheme has clearly not reduced the PTA ratio, which was the rationale for its introduction.

To gain more insight into this result, we also compared the mean daily peak load and the mean daily average load in 2003, 2004, 2005 with corresponding values in 2012. We find in all cases that the mean daily average load and the mean daily peak load distributions in 2012 are lower than in the prior years, indicating an overall reduction in the load. Therefore, although the PTA ratio has indeed increased, there has not been an additional need for peaking generation capacity.

### B. Optimality of the TOU Scheme

In this section, we investigate the optimality of the current TOU scheme and find the optimal TOU scheme in Ontario.

1) *Given two 26-Week seasons, when should they start and end?*: We answered this question in two ways. First, we computed the best seasonal sequence, with the constraint that there be two fixed 26-week seasons, using aggregated load data from 2003 to 2005. The results show that the boundaries, when implemented in 2006, should ideally have been shifted backwards by 3 weeks. For an updated 26-week season scenario at the present time, we cluster using data from 2003 to 2012. The optimal 26-week seasons are presented in Figure 5, showing that the boundaries in the current TOU scheme should ideally be shifted back by 2 weeks.

2) *What is the optimal number of seasons?*: Figure 3 shows the optimal seasonal sequence for scenarios with different number of seasons, ranging from 2 to 7. Figure 4 also shows their corresponding best  $R^2$  values. We choose the optimal number of seasons by finding an elbow in the  $R^2$  curve. Slight elbows can be seen at 3 and 4 seasons. Moreover, the  $R^2$  index increases significantly from 2 to 3 seasons, and from 3 to 4 seasons. However, additional improvements in  $R^2$  are sharply diminished after 4 seasons; therefore, the optimal number of seasons appears to be 4.

*C. Are the Peak, Mid-Peak, and Off-Peak times appropriately chosen?*

Figure 6 shows the normalized<sup>2</sup> aggregate load curves (with load data from 2003 - 2005) for each season in the current TOU scheme (Figure 1). Although the current TOU scheme prices electricity as if there were two equal load peaks in winter, Figure 6 shows that two such peaks do not exist in the winter season! Rather, there is one very slight Mid-Peak in mid-morning and one much more prominent Peak in the evening. The distribution of the peak periods in the current TOU scheme therefore does not appear to properly represent load behaviour.

Figure 7 shows the normalized aggregate load curves for each of the four seasons obtained based on the optimal seasonal sequence deduced from our clustering analysis. The dates for each season are shown in Table III, and our recommended daily pricing periods for each of the seasons are indicated by the red boxes in Figures 8 to 11.

Figures 8 to 11 also convey information about our certainty in the Peak status of each hour. Our clustering analysis placed 500 weekdays of data into the Spring season, 850 into Summer, 350 into Fall, and 900 into winter. The numbers in the hourly boxes in Figures 8 to 11 show for how many of these days the hour was Off-Peak, Mid-Peak, or Peak, according to Equation 1. For example, in all 500 of the Spring days in our dataset, 2 AM–3 AM was considered Off-Peak (i.e.,  $\phi_3^D = 0$ ). On the other hand, of the 900 Winter days, approximately one third considered 9 PM–10 PM to be Off-Peak, one third considered it to be Mid-Peak, and one third considered it to be On-Peak.

<sup>2</sup>The daily load curves were summed up and divided by the minimum load value. Prior to that, the annual loads had been divided by the minimum load of the year in order to remove the effect of generally higher load values in some years.

TABLE II: 2-Season 26-Week TOU Scheme

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

TABLE III: Recommended 4-Season TOU Scheme. Periods are given in Figures 8 through 11.

	Period
Spring	March 11 - May 19
Summer	May 20 - September 15
Fall	September 16 - November 3
Winter	November 4 - March 10

By acknowledging our uncertainty in the Peak status of different hours, we may choose TOU period allocations more flexibly. For example, 10am-11am in Fall is most likely to be a Peak period, but since it is just one hour surrounded by Mid-Peak hours and because it is labeled a Mid-Peak hour in 48% of Fall days, it is labeled as a Mid-Peak period for ease of use. The normalized aggregate load curves shown in Figure 7 were also used to inform our recommendation; for example, the Spring season was not assigned any Peak period since the actual load difference between Mid-Peak and Peak times was not practically significant.

## VI. RECOMMENDATIONS

We have evaluated and discussed the effectiveness and optimality of the TOU scheme, as well as the appropriateness of the TOU scheme's distribution of Peak, Mid-Peak, and Off-Peak periods. Based on the results obtained, we make the following recommendations:

- 1) If the 2-season TOU scheme is to be maintained (for reasons such as simplicity and acceptability by the public), the season boundaries should be shifted backwards by 2 weeks with the Summer season starting on April 15 and the Winter season starting on October 14. This is based on the two-season 26-week clustering result shown in Figure 5.
- 2) In addition to the first recommendation, the 2-season TOU scheme should also reflect the actual distribution of Peak, Mid-Peak, and Off-Peak times in the load during each season. This results in a new TOU scheme shown in Table II.
- 3) The number of seasons in the TOU scheme should be changed from 2 to 4. The recommended 4-season TOU scheme is shown in Table III and Figures 8 to 11. This TOU scheme is primarily based on the distribution of Peak, Mid-Peak, and Off-Peak periods (Equation 1) in the representative weekday load curves for each season, as seen in Figure 7.
- 4) Since the PTA is increasing, other metrics could be used to estimate the effectiveness of TOU pricing instead of the PTA.

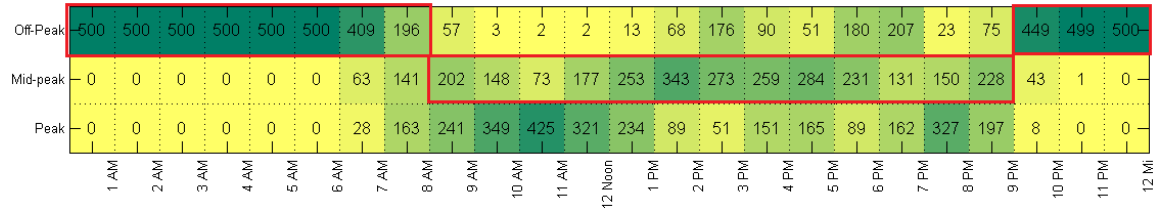


Fig. 8: TOU Periods for Spring

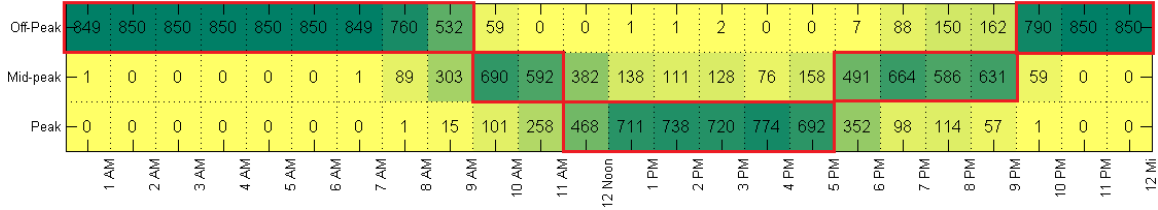


Fig. 9: TOU Periods for Summer

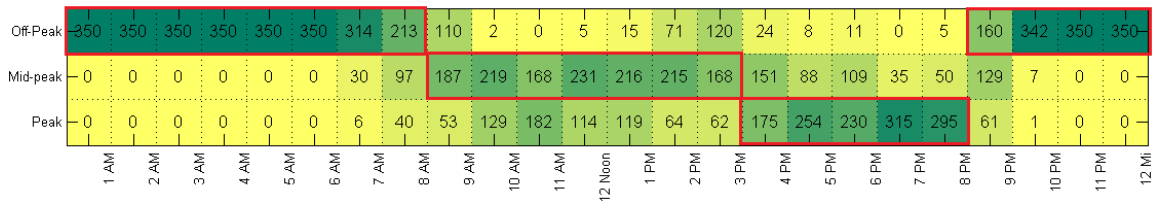


Fig. 10: TOU Periods for Fall

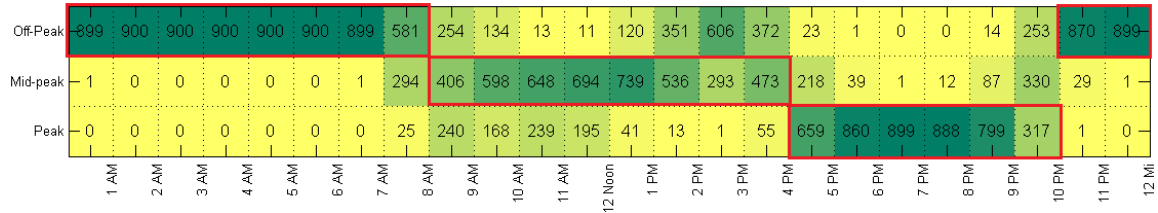


Fig. 11: TOU Periods for Winter

## VII. CONCLUSION

In order to evaluate the impact of TOU pricing in Ontario, we have studied Ontario's TOU pricing scheme and analyzed the Ontario load history. However, the impact of the current TOU scheme is not as expected. Although TOU pricing was implemented in order to reduce the PTA, we find that no reduction has occurred. As a result, we have made recommendations which can be used to improve the effectiveness, optimality, and appropriateness of the TOU pricing scheme in Ontario.

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