Analyzing the Impact of the 5CP Ontario Peak Reduction Program on Large Consumers

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ABSTRACT

Peak reduction is an important problem in the context of the electricity grid and has led to conservation programs in various jurisdictions. For example, in Ontario, Canada, residential customers are charged higher prices during peak times, while large industrial and commercial customers pay heavy surcharges that depend on their load during Ontario's five peak-demand days. Reducing these surcharges is a challenging problem for large consumers due to the difficulty of predicting peak days in advance.

We study the impact of this peak reduction program, called 5 Coincident Peaks (5CP), on consumers by analyzing the difficulty of predicting peak-demand days and peak hours on those days. We find that even the state-of-the art peak-prediction algorithms require consumers to curtail load ten or more times, and even then, they may not identify all five peak-demand days. We also analyze alternative policies that cold help reduce peak demand in Ontario.

KEYWORDS

Peak reduction; peak prediction; demand response; 5CP

1. INTRODUCTION

Peak reduction is an important problem in many contexts, including the electricity grid. Since the grid must be provisioned for peak consumption, reducing peak demand can eliminate the need for costly infrastructure expansion. Furthermore, the additional supply required to meet peak demand often involves activating dirty and inefficient power sources, or purchasing electricity from other jurisdictions at high prices. As a result, various peak reduction programs are employed in many jurisdictions. For example, in Ontario, Canada, residential customers are subject to Time-of-Use (TOU) pricing with higher rates during peak times, whereas large industrial and commercial customers incur additional charges based on their load during peak times.

Let Class-A customers be those whose monthly peak exceeds 5 Megawatts (Independent Electricity System Operator, 2015a), and let the Global Adjustment (GA) be the difference between the expenses and revenues of Ontario's power system (Independent Electricity System Operator, 2015b). To balance the budget, in any given year, every customer pays a share of the GA deficit accumulated in the previous year[1]. Class-A customers have two choices: their GA share may be calculated based on their total annual load, or based on its contribution to Ontario's load in the previous year during Ontario's five peak hours (on different days) of the year (Independent Electricity System Operator, 2015d). The latter option is called the 5-Coincident-Peaks (5CP) program. The rest of the GA is covered by the remaining customers in various ways, not based on the 5CP program.

Table 1 lists the top five hours of peak demand (on different days) between May 1, 2013 and April 30, 2014, along with Ontario's total load at that hour, and the load of a hypothetical Class-A customer at that hour. To calculate the GA share of this customer, we divide the customer's demand by Ontario's total demand during the five peak hours. This gives 38.8/120571 = 0.00032. The total GA in 2013/2014 was $8.45 billion, meaning that this customer's GA charges are 0.00032x8.45 billion = $2.7 million. Larger customers may pay even higher GA surcharges: for example, Western University, located in London, Ontario, reports that $7 million of its $17 million electricity bill consists of GA charges (Western, 2015). Thus, Western University can reduce their GA charges by $700,000 with a ten-percent load reduction on the (peak hour of the) five peak days. As the GA costs continue to rise (DiRuscio and Hilbig, 2014), these potential savings will become even higher.

To benefit from the 5CP program, class-A customers must predict when each of the five days with Ontario's highest peak hourly load will occur, so they know when to reduce load and therefore

[1] More precisely, the GA share based on May 1 of year i-1 till April 30 of year i is paid between July 1 of year i and June 30 of year i + 1.

reduce their GA charges. We refer to these five peak days as 5CP days. However, while various short-term and long-term demand forecasts are provided by the Ontario electricity system operator (IESO), without the benefit of hindsight it is not obvious which five days will be the actual 5CP days in a given year until the end of the year. In this paper, we analyze how the issue of peak load prediction impacts consumers in the context of the 5CP program. Our objective is twofold:

- To show that the 5CP program may be impacting large consumers more than intended due to the difficultly of predicting peak-demand days;
- To explore related policies for reducing peak demand.

Table 1: Ontario's 5CP days in 2013/2014 (Independent Electricity System Operator, 2015a)

Top 5 Peak Hours	**Ontario Demand**	**Customer's Demand**
July 17, 2013, 5pm	24689 MW	7.1 MW
July 16, 2013, 5pm	24207 MW	8.4 MW
July 18, 2013, 5pm	24070 MW	7.9 MW
July 19, 2013, 2pm	24009 MW	8.1 MW
July 15, 2013, 5pm	23596 MW	7.3 MW
Total during top 5 peak hours	120571 MW	38.8 MW

The 5CP program is different to Critical Peak Pricing (CPP) programs employed by various utilities in California (Bode et al., 2013; Newsham and Bowker, 2010). Both programs are designed to reduce peaks by targeting large customers. However, in CPP programs, utilities choose which days will be peak-pricing days according to some criteria, and notify the participating customers one day in advance. Furthermore, the number of called CPP days can range from 9 to 14. While we focus on the 5CP program, studying the difficulty of predicting peak-demand days is also relevant in the context of CPP.

We do not address the related question of evaluating the effectiveness of the 5CP program in terms of peak reduction. Ontario's peak demand has been declining since 2011, but it is difficult to determine the root cause of this reduction, especially since the IESO does not publish load data for Class-A consumers, only aggregated demand data for the entire province.

2. RELATED WORK

In practice, various ad-hoc methods are used to predict 5CP days and reduce load on those days. For instance, Western University, which is a Class-A customer, turns down the air conditioning during July and August afternoons, which is when 5CP days often occur (De Adder, 2012). We also discussed the 5CP program with several industrial customers in Ontario and found that they use very simple heuristics, e.g., plan to reduce demand whenever tomorrow's peak demand forecast exceeds 23,000 megawatts.

In the context of California's CPP, Gallagher (2008) describes the following methodology for calling peak-pricing days. Based on past history, the first step is to compute the fraction of peak days that have occurred in each half-month. During the current year, the idea is to adjust the demand threshold for peak-pricing days by comparing how many peak-pricing days have been called up to now with how many peak-pricing days have occurred up to this time of the year in the past. If more peak days have been called so far in the new year than in past years, the threshold is lowered, and vice versa. There is also work on optimal scheduling of peak-pricing days under various objectives (Chen et al. 2013; Park et al. 2015; Tyagi et al. 2011; Zhang, 2014).

Predicting peak days is related to *optimal stopping* problems. In these problems, we are given a sequence of values drawn from some distribution, one value at a time. Immediately after seeing each value, we need to decide whether we should stop and declare it to be the largest value in the sequence or whether we should keep going. There are also extensions of this basic approach to choosing k largest values for some integer k; see, e.g., (Babaioff et al. 2007; Kleinberg, 2005; Preater, 1994; Stockbridge and Zhu, 2012).

In previous work, we proposed an algorithm for day-ahead prediction of peak days that uses the short-term load and weather forecasts as input (Jiang et al., 2014; Jiang et al., 2014b). We found that our algorithm makes more accurate predictions than the above-mentioned CPP method (Gallagher 2008), the scheduling algorithm proposed by Tyagi et al. (2011) and the optimal stopping algorithm given by Babaioff et al. (2007). The insight behind our algorithm is to only use the 14-day short-term load forecast rather than long-term forecast, which we found to be much less accurate. In the remainder of this paper, we use our peak-prediction algorithm to illustrate the policy implications of the 5CP program.

3. METHODOLOGY

To analyze the impact of the 5CP programs on consumers, we play-back our peak-prediction algorithm on Ontario's load and weather data from 2007 till 2014. We input the 14-day short-term IESO load forecast (Independent Electricity System Operator, 2015c) and the day-ahead weather forecast for the City of Toronto (Government of Canada, 2015) to the algorithm, day by day. For each day, the algorithm predicts whether tomorrow will be a peak day. Then, for each year, we determine the actual five 5CP days from Ontario's historical demand data (Independent Electricity System Operator, 2015e), and we compare them with the peak days identified by the algorithm. To enable others to reproduce our analysis, we have made the algorithm source code freely available at https://github.com/y29jiang/Probabilistic-Algorithm-for-5CP.

While our algorithm identifies peak days, it is only necessary for Class-A customers to reduce load during the peak hour of each 5CP day, not for the entire day. Thus, we also need to solve the problem of predicting the peak hour on a given day. We do this using the day-ahead hourly load forecast published in the IESO System Status Reports (Independent Electricity System Operator, 2015e), and will evaluate the accuracy of this approach in Section 4.

The algorithm uses the following variables. L(i) is the actual peak hourly load on day i and E(i,d) is the peak hourly load forecast for day i as of day i-d, i.e., d days in advance. Let k be the number of peak days we want to identify, i.e., for 5CP, k=5. Let T be a load threshold that serves as a lower bound for the load on a peak day, i.e., any day i whose peak demand forecast E(i,d) is below T will never be called a peak day. For each year that we test, the initial value of this threshold T is the peak demand of the kth highest day of the previous year minus one percent.

Since Ontario has been summer-peaking, we only run the algorithm from May 1 till September 30 of each year and assume that 5CP days outside this range never happen. We also skip over holidays and weekends, which have lower peak demand, and only test weekdays. We also need a definition of extreme weather, which we set to be 30 degrees Celcius or higher.

Our algorithm proceeds as follows. For each upcoming day i (between May 1 and September 30), we predict that day i will be a peak day if the following three conditions are true: the day-ahead peak forecast, E(i,1), must be at least T, the weather forecast for i must be extreme, and the probability that E(i,1) ranks among the k highest values out of all the days (of the current year) we have seen so far plus all 14 days for which we have a short-term load forecast must exceed a threshold R. We refer to this probability as P(rank(i) <=k), and will explain how to derive it and the threshold R shortly. Next, we decide whether we should raise or lower the threshold T. We raise it to be equal to E(i,1) if E(i,1)>T and the weather forecast for i is not extreme. This may happen if the current year's demand is higher than last year's demand due to some external factors, and even normal-weather days have high demand. In this case, we need to use a higher T for the remainder of the current year. On the other hand, we lower T to be equal to E(i,1) if E(i,1)<T and the weather forecast for i is extreme. This may happen if the current year's demand drops due to some external factors and even an extreme-weather day has a lower expected demand than T. We summarize the algorithm below.

```
1.  FOR each upcoming day i
2.     IF E(i,1) > T AND extreme weather AND P(rank(i) <= k) > R
3.        PREDICT tomorrow will be a peak day
4.     IF (E(i,1) > T AND not extreme weather) OR (E(i,1) < T AND extreme weather)
5.        T = E(i,1)
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We remark that raising or lowering the threshold T in lines 4-5 is done with the assumption that there has been a permanent change in electricity demand from the previous to the current year, e.g., a weakening or strengthening of the economy. If we have reasons to believe that the change is temporary, we can choose not to adjust the threshold (e.g., it has been observed that electricity consumption drops when popular sporting events are being televised (Fischer, 2013)).

We now discuss how to compute P(rank(i) <= k). We need to know if tomorrow's peak is likely to be one of the k largest values from all the days we have seen so far plus the short-term peak forecast for the next 14 days. We performed the Chi-square goodness of fit test on the residuals of the short-term forecasts, i.e., L(i)-E(i,d), and verified that they are normally distributed with a mean of zero and some standard deviation that depends on d. For example, the residuals of the day-ahead forecasts (d=1) are smaller than those of, say, ten-days-ahead forecasts (d=10). Thus, as we will illustrate shortly, we can use the probability density function for the normal distribution to determine the probability that tomorrow's forecasted demand, E(i,1), exceeds an actual peak load L(p) from some day p from the past, or the probability that E(i,1) exceeds E(n,d) for some day n in the next 14 days for which we have a short-term load forecast.

We define P(rank_past(i)=j) as the probability of E(i,1) ranking j^{th} compared to the actual peak demand values we have seen so far, i.e., L(1) through L(i-1). Similarly, we define P(rank_future(i)=j) as the probability of E(i,1) ranking jth among the 14 days in our short-term forecast, i.e., E(i,1) through E(i+13,14). Assuming that the short-term forecasts for different days are independent, we can compute, for example, P(rank_future(i)=1) as P(E(i,1) > E(i+1,2)) * P(E(i,1) > E(i+2,3)) * … * P(E(i,1) > E(i+13,14)).

Next, we define θ(x,y)= P(rank_future(i)=x) * P(rank_past(i) = y). With that, P(rank(i) = j) can be computed as shown below in Table 2. Finally, we compute P(rank(i) <=5) as P(rank(i)=1) + P(rank(i)=2) + P(rank(i)=3) + P(rank(i)=4) + P(rank(i)=5.

Table 2: Computing P(rank(i) = j)

P(rank(i)=1) = θ(1,1)
P(rank(i)=2) = θ(1,2) + θ(2,1)
P(rank(i)=3) = θ(1,3) + θ(2,2) + θ(3,1)
P(rank(i)=4) = θ(1,4) + θ(2,3) + θ(3,2) + θ(4,1)
P(rank(i)=5) = θ(1,5) + θ(2,4) + θ(3,3) + θ(4,2) + θ(5,1)

We now discuss how to obtain the threshold R, which must be exceeded by P(rank(i) <= k) in order for day i to be called a peak day. The idea is to examine the actual 5CP days from the previous year and see what their P(rank(i) <= 5) was; we then take the minimum of these five probabilities. For example, in 2012, each actual 5CP day had P(rank(i) <= 5) of at least 0.1, so we use R=0.1 in 2013.

Worked Example: Suppose T=23,275 megawatts, R=0.1, and assume that tomorrow's weather is expected to be extreme. For brevity, assume we only have a short-term forecast for six days, not 14. These are shown in Table 3, along with their standard deviations, σ, computed from historical data. To compute P(E(i,1) > P(E(i+n,1+n)), we use the probability density function for a normal distribution with mean μ and standard deviation σ:

$$f(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

For example, P(E(i,1) > E(i+1,2)) = *f*(23665-23932, 0, 210+584) = 0.368; the other probabilities are computed similarly and are shown in the right-most column of Table 3.

Table 3: Peak demand forecast for the next six days

	forecast	σ	**P(E(i,1) > E(i+n,1+n))**
E(i,1)	23665	210	-
E(i+1,2)	23932	584	0.368
E(i+2,3)	16630	666	1
E(i+3,4)	17635	716	1
E(i+4,5)	16172	804	1
E(i+5,6)	18158	954	1

Furthermore, assume that the five days with the highest peak demand we have seen so far are as shown in Table 4. To compute the probability that tomorrow's peak forecast of 23,665 exceeds the actual demand on some previous day p, L(p), we again use f(23665-L(p), 0, 210). Note that the standard deviation term is simply the standard deviation of the day-ahead forecast since actual demand does not have a standard deviation. The right-most column of Table 4 lists the P(E(i,1) <L(p)) for each day p in the current list of top-5 days.

Tables 3 and 4 have all the information we need to compute P(rank(i) =1) through P(rank(i) = 5), as per Table 2. These probabilities are shown in Table 5. Finally, we compute P(rank(i) <= 5) = P(rank(i)=1) + P(rank(i)=2 + P(rank(i)=3) + P(rank(i)=4) + P(rank(i)=5) = 0 + 0.007 + 0.038 + 0.05 + 0.034 = 0.129. Given that R=0.1, we would predict that tomorrow will be a 5CP day.

Table 4: Five days with the highest actual peak demand so far

Rank so far	L(p)	P(E(i,1) <L(p))
1	24636	1
2	24107	0.9823
3	23910	0.8783
4	23801	0.7413
5	23745	0.6484

Table 5: Computing P(rank(i)=j)

j	P(rank_future(i) = j)	P(rank_past(i) = j)	P(rank(i) = j)
1	0.368	0	0
2	0.632	0.017	0.007
3	0	0.104	0.038
4	0	0.136	0.05
5	0	0.093	0.034

4. RESULTS AND DISCUSSION

There are two types of errors a peak-prediction algorithm can make: false positives and false negatives. If a peak day is identified, but it does not end up being one of the actual 5CP days, it is a false positive. If an actual 5CP day is not identified as such by the algorithm, it is a false negative. Thus, false positives may lead to unnecessary load curtailment, while false negatives mean lost opportunities for reducing the GA charges.

We begin by analyzing the number of peak days called by our algorithm, the number of false positives and the number of false negatives. Results are shown in Table 6. For example, in 2007, the algorithm identified ten peak days in a day-ahead manner, but only four of these ended up being actual 5CP days (hence the one false negative). In other words, six of the ten peak days were false positives. Thus, it is difficult to correctly guess all five or even four out of five actual 5CP days in a day-ahead fashion without incurring any false positives. This means that Class-A customers who want to reduce load on all five actual 5CP days, and therefore reduce their GA charges, have to reduce load on many other days as well.

Table 6: Number of called peak days, false positives and false negatives returned by the tested peak-prediction algorithm from 2007 to 2014

Year	Number of called peak days	Number of false positives	Number of false negatives
2007	10	6	1
2008	9	4	0
2009	7	3	1
2010	7	2	0
2011	8	3	0
2012	10	5	0
2013	11	6	0
2014	9	4	0

False negatives result in missed opportunities for GA savings. False positives also have a cost, ranging from minor discomfort due to turning down the air conditioning to loss of revenue due to a stopped production line. In the worst case, the operational losses due to load reduction may exceed the GA savings. Our results suggest that a customer should consider enrolling in the 5CP program if its expected GA savings exceed the operational cost of curtailing load on at least *ten* days.

Next, we move to the problem of identifying the peak hour on a given day. In this experiment, we compared the actual peak hour (Independent Electricity System Operator, 2015e) with the predicted peak hour from the IESO hourly day-ahead load forecast (Independent Electricity System Operator, 2015f) between May 1 and September 30, 2015. Out of 104 non-holiday weekdays in this time range, the peak hour was predicted correctly on 65 days, i.e., 63 percent of the time. On 22 days, the prediction was off by one hour, with the load on the predicted peak hour being only slightly lower than the load on the actual peak hour; e.g., (hour ending) 6pm instead of 5pm or 8pm instead of 7pm. On the remaining 17 days, there were two daily peaks several hours apart, one slightly higher than the other, and the predicted peak hour corresponded to the lower peak; e.g., 5pm instead of 8pm or vice versa. In general, we found that peak hours happened most often between 12 and 2pm, and 5 and 8pm. Thus, not only do class-A customers have to curtail load on more than five days to satisfy the 5CP program, on each day they may have to curtail load on several hours.

One may ask whether the 5CP program can be made more customer-friendly while still achieving its goal of reducing Ontario's peak demand. We now investigate the effect of "downgrading" to a 2CP or 1CP program, in which it suffices to curtail load on (the peak hour of) one or two days rather than five. For each year from 2007 to 2014, we calculate the number of peak days our algorithm would have had to call to ensure that there were zero false negatives that year, i.e., that all of the top-five peak days were identified. We then repeat this analysis assuming a 4CP program, i.e., the GA surcharge is calculated based on consumption (in the peak hour) on the top four peak-days, a 3CP program, a 2CP program and a 1CP program. Table 7 presents the results, with the first row of numbers corresponding to 5CP, the second row to 4CP and so on.

Table 7: Number of peak days that would have to be called to ensure no false negatives

K-CP	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
5	10	9	11	7	8	10	11	9
4	8	7	9	6	7	8	7	7
3	7	6	6	5	5	4	6	4
2	5	4	6	5	4	3	4	4
1	2	2	4	3	2	3	3	2

Our results suggest that in a 2CP program, Class-A customers could use our algorithm to identify roughly 5-6 days on which to curtail load. However, even then, there may be occasional false negatives, which are more serious than in the 5CP program. In 2CP, missing one of the two 2CP days cuts the potential GA savings in a half; in 5CP, missing one of the five peak days only reduces the potential GA savings by one fifth.

Another downside of a 2CP program is that it may not reduce Ontario's annual peak as much as the 5CP program could. To see this, consider Table 8, which lists the peak demand from 2007 to 2014, along with the difference between the top-1 and top-2 demand day, the difference between the top-2 and top-3 demand, and so on. These differences are relatively small, meaning that the fifth-highest peak is not much lower than the highest peak.

Table 8: Differences between top peak-days from 2007 to 2014 (in MW)

Difference	2007	2008	2009	2010	2011	2012	2013	2014
1st	25628	24001	24005	24566	25285	24470	24708	24140
1st-2nd	210	379	1175	59	982	669	628	433
2nd-3rd	141	398	427	18	645	18	17	144
3rd-4th	81	30	381	78	546	249	369	469
4th-5th	533	58	23	26	138	4	9	81

5. CONCLUSIONS AND POLICY IMPLICATIONS

In this paper, we examined the impact of the 5CP peak reduction program on large electricity consumers in the province of Ontario, Canada. This program effectively requires consumers to predict when Ontario's five peak days will occur in a day-ahead manner and to curtail load on the peak hour of those days. In exchange, customers can reduce their electricity surcharges, which depend on their contribution to Ontario's load on the five peak days.

The main policy implication of our results is that the 5CP program may be impacting the business operations of large consumers---and therefore also Ontario's economic prosperity and growth---more than intended. As illustrated in Table 6, even a state-of-the-art peak prediction algorithm may call more than ten peak days per year, and even then, these potential peak days may not include all five actual peak days for that year. Thus, consumers may have to reduce operations on ten or more days in order to reduce their electricity surcharges under the 5CP program. Moreover, it is not always possible to predict the peak hour from the day-ahead hourly load forecast, meaning that consumers may have to shed load on more than one hour (up to four or five hours according to our analysis) of each peak day.

Our results from Table 6 can also answer the question of what might happen if a CPP-like program replaced the 5CP program in Ontario. We argue that the province could use our algorithm to identify roughly 10 to 15 peak-pricing days in a day-ahead fashion and be reasonably certain that these would include five (or at least four) days with the highest actual demand.

Another important policy implication of our findings is that changing from a 5CP to a 2CP program, in which it suffices to curtail loads on the top two peak-demand days of the year to reduce the electricity surcharges, is less effective for peak reduction. The number of days on which consumers have to curtail load drops to five or six, but, as we showed in Table 8, even the fifth-highest peak day may have nearly as much demand as the highest and second-highest peak days. Thus, reducing demand only on the top-2 days still leaves us with a high annual peak.

Finally, an interesting direction for future work is to evaluate the difficulty of predicting peak-demand days in other jurisdictions and characterize what makes a jurisdiction a good candidate for a 5CP or CPP like program. Locations with a moderate climate may have more difficulties with peak prediction, whereas peak-demand days in those with a more extreme climate (hot summers and/or cold winters) may be easier to predict since peak demand tends to be correlated with heating and/or air conditioning usage due to extreme weather.

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