Peak Power's Pre-Interview Assignment

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General Knowledge

1. **How does a "Dispatchable Load" participate in the Ontario Energy Market?**

To define Dispatchable Load, let's first define non-dispatchable load. Non-dispatchable Loads are conventional power users: they take power based on their needs regardless of the electricity time-of-use (Off-peak, Mid-peak, On-peak) at the time. They are limited in ways to manage their power demands as they can only avoid using power at Mid-peak or On-peak, when electricity costs are higher.

Dispatchable Loads (DL) are typically heavy power users, such as industrial companies, who are looking to actively save electricity costs. They can form an agreement with the regional Independent System Operator (ISO) in which the DLs can submit bids to purchase electricity. The IESO, Ontario's ISO, operates a real-time marketplace where the market clearing price (MCP), which is determined based on the settled bids, changes every 5 minutes. The DLs are to adjust their power consumptions according to instructions made by the IESO. For example, if, at any 5-minute interval, the MCP is higher than what the DL bids, they would have to reduce their consumption per the IESO's dispatch instructions.

2. **How does reducing a customer's non-coincident peak (NCP) in a month create value?**

Non-coincident Peak (NCP), or Non-coincident Demand, is a customer's maximum energy demand during any specified period which, in this case, is a month. Coincident Peak is the energy demand during the hour of the month where the grid peaks. They are not mutually exclusive, as a NCP can be a CP.

Since NCP represents the customer's overall peak demand, reducing its value is beneficial to both the customer and the power supplier. Lower peak demand reduces the sizing and load costs for the suppliers, which could, then, lower peak demand prices. For the province of Ontario, NCP/Peak Demand is the metric that is used to determine how much a customer would have to pay for Global Adjustment (GA) as part of their electricity bill. If customer is eligible to participate in the Industrial Conservation Initiative (ICI) as a Class A customer, then they would have to pay GA based on the percentage contribution to the top five peak Ontario demand hours over a 12-month period. Thus, if a customer's NCP/Peak Demand is reduced, their percentage contribution to the GA would also be reduced, thus lowering their overall power costs. Also, if their NCP/Peak Demand less than or equal to 5 MW, they would not be automatically qualified to be in Class A. This would mean that they are a B Class customer who pays their monthly electricity consumption through a flat $/kWh rate. This means that reducing their NCP will lower costs.

3. **How much value would be created by reducing the NCP of a Toronto Hydro Customer with an average NCP of 1,500 kW by 1 kW/1 kVA? (Use the attached Toronto Hydro Tariff - 2019 document)**

Goal:

- The monthly savings as the result of reducing the customer's monthly (per 30 days) average NCP by 1 kW / 1 kVA.

Relevant given information:

- Customer's average NCP is 1500 kW
- NCP reduction is by 1 kW and 1 kVA, with a power factor of 1.
- 2019 Toronto Hydro Tariff – Schedule A

Assumptions:

- Calculations:
    - For Tariff of Rates and Charges will be made within the timeframe from January 1, 2019 to December 31, 2019
    - Do not include charges not subject to Ontario Energy Board (OSB) approval, such as the Debt Retirement Charge, Global Adjustment, and HST
    - Are per month, or 30 days.
- The customer is:
    - Non-residential and in Class A

- Average NCP/Peak Demand of 1500 kW (1.5 MW) which is within the 1 – 5 MW range for Class A eligibility

- Not an embedded wholesale customer
- Not located in a rural or remote area
- An RPP customer

Calculations:

Based on the given information and assumptions above, the following modifications were made to the Tariff of Rates and Charges for customers for General Service from 1,000 to 4,999 kW of Toronto Hydro during 2019.

MONTHLY RATES AND CHARGES - Delivery Component	Units	Value
Service Charge	$	983.72 (per 30 days)
Rate Rider for Recovery of 2015 Foregone Revenue - effective until December 31, 2019	$	18.89 (per 30 days)
Rate Rider for Recovery of 2016 Foregone Revenue - effective until December 31, 2019	$	5.48 (per 30 days)
Distribution Volumetric Rate	$/kVA	6.3766 (per 30 days)
~~Rate Rider for Disposition of Global Adjustment Account (2019) - effective until December 31, 2019 (Applicable only for Non-RPP Customers) - Approved on an Interim Basis~~	~~$/kWh~~	~~0.00068~~
Rate Rider for Disposition of Lost Revenue Adjustment Mechanism Variance Account (LRAMVA) (2019) - effective until December 31, 2019	$/kVA	0.1251 (per 30 days)
Rate Rider for Disposition of Deferral/Variance Accounts (2019) - effective until December 31, 2019 - Approved on an Interim Basis	$/kVA	(0.2186) (per 30 days)
~~Rate Rider for Disposition of Capacity Based Recovery Account (2019) - effective until December 31, 2019 (Applicable only for Class B Customers) - Approved on an Interim Basis~~	~~$/kVA~~	~~0.0114 (per 30 days)~~
Rate Rider for Recovery of the Gain on the Sale of Named Properties - effective until December 31, 2019	$/kVA	0.0056 (per 30 days)
Rate Rider for Recovery of Hydro One Capital Contributions Variance - effective until December 31, 2019	$/kVA	0.0038 (per 30 days)
Rate Rider for Application of IFRS - 2014 Derecognition - effective until December 31, 2019	$/kVA	0.0627 (per 30 days)
Rate Rider for Recovery of 2015 Foregone Revenue - effective until December 31, 2019	$/kVA	0.1226 (per 30 days)
Rate Rider for Recovery of 2016 Foregone Revenue - effective until December 31, 2019	$/kVA	0.0356 (per 30 days)
Retail Transmission Rate - Network Service Rate	$/kW	2.5677 (per 30 days)
Retail Transmission Rate - Line and Transformation Connection Service Rate	$/kW	2.3030 (per 30 days)
MONTHLY RATES AND CHARGES - Regulatory Component		
Wholesale Market Service Rate (WMS) - not including CBR	$/kWh	0.0032
~~Capacity Based Recovery (CBR) - Applicable for Class B Customers~~	~~$/kWh~~	~~0.0004~~
~~Rural or Remote Electricity Rate Protection Charge (RRRP)~~	~~$/kWh~~	~~0.0003~~

Standard Supply Service - Administrative Charge (if applicable)	$	0.25 (per 30 days)

The following details the customer's total monthly (30-day) costs for an average NCP of 1500 kW before and after reductions were applied, and the savings from reduction.

Total Charge before reduction	$ 21540.49
Total Charge after reduction	$ 21526.80
Savings	**$ 13.69**

Therefore, the **savings/value created** by reducing the customer's average NCP by 1 kW / 1 kVA is **$13.69**.

The following are sample calculations. The full list of calculations can be found in attached Excel File "Q3."

$$NCP = 1500\ kW \times 1\frac{1\ kVA}{kW} = 1500\ kVA$$

$$LRAMVA_{after}(30\ days) = 0.1251\frac{\$}{kVA} \times 1499\ kW\ \frac{1\ kVA}{1\ kW} = \$187.52$$

$$WMS_{before} = 0.0032\frac{\$}{kWh} \times 1500\ kW \times \frac{24\ h}{day} \times 30\ day = \$21540.49\ for\ 30\ days$$

Case Question

This is a complex question. We are more interested in methodology and approach then the answer itself. Batteries located behind a customer's utility meter create value by dispatching at key times. This may include during high energy price hours or during the customer's highest monthly consumption hour. A Case Data file has been included which contains historic load, hourly energy prices, and battery schedules for one of Peak's sites in Ontario. Using this file, determine how much money the battery saved the customer during the October 2019 operational month based on the tariff summary below.

Tariff Summary

Value Stack Component	**Type**	**Explanation**
Energy	At the Hourly Energy Price (HOEP) included in the data file.	HOEP is settled by an organization called the Independent Electric System Operator (IESO) every five minutes using an auction. Large Customers pay for the energy they consume based on this ever-changing rate.
Non-Coincident Peak	\$11.25/kW-Month	Applies to the max hourly consumption of the facility during the month.

<u>Goal:</u>

- Determine the customer's savings as a result of having a battery dispatching energy at key times during the month of October.

<u>Relevant Given Information:</u>

- Tariff Summary table
- Case Data for October 2019 (Excel file)

<u>Assumptions:</u>

- The unit for the Hourly Ontario Energy Price (HOEP) is *cent / kWh*
- The Non-Coincident Peak (NCP) price *(\$11.25 / kW-Month*) is a one-off price that replaces the HOEP for the hourly consumption with the highest value during the month.

- Global Adjustment (GA) charges are not applicable to the analysis
- Each HOEP value (Price worksheet) represents the hourly average HOEP for 12 different instances (a different instance for every 5 minutes) of HOEP
- Each “15Min Load” value (Load worksheet) represents the total load, measured by the customer’s utility meter, from 3 instances occurring every 5 minutes
    - For example: for item with ID 201910010015 with the time stamp beginning from 10/1/2019 0:00 to 10/1/2019 0:15, the customer has used 317.76 kW
    - The same logic will be applied for every “15Min Inverter” value in the BatterySchedule worksheet

Analysis:

In order to determine the battery-driven savings, we need to calculate the customer’s total costs, during October, with and without utilizing the battery. This is done by multiplying the facility’s hourly load value with the corresponding HOEP while taking account of the NCP for the hour with the maximum hourly consumption.

All calculations are done in Python. The relevant “Assignment.ipynb” (Jupyter Notebook) and “.csv” files can be found in the assignment package.

The data in the “Price” worksheet suggests that the HOEP fluctuates around an average value every hour. A positive value indicates that the utility is charging the customer, and a negative value indicates the utility is paying the customer for consuming power.

The battery dispatches power to the customer’s utility meter in varying amounts during the day, influenced by the customer’s power demand and the HOEP set by the IESO. A positive value indicates the battery is supplying power directly to the customer to reduce the load drawn from the utility and minimizing costs during periods of high HOEP, or peak periods. Thus, a negative value means the battery is drawing power from the customer, likely to charge itself. Since this coincides with the period when the utility is paying the customer for consuming power, this further minimizes their costs and increases their savings.

Data Processing

After inspecting the three datasets, two observations were made:

1. The "Load" and "Inverter" data points were recorded every 15 minutes while the "HOEP" data points were recorded every hour.
2. There are 540 missing data values (null values) for the "Inverter" column in the "BatterySchedule" worksheet from 20:00 October 23, 2019 to 11:00 October 29, 2019. They are crucial in order to determine the accurate amount of the customer's savings during the month of October.

For #1, we can sum the four 15-Minute Load values for each hour to determine the customer's hourly load, known as "Load," in kW. The same can be done with the Inverter values, known as "Inverter," in kW. Calculations are done in Python, and they can be found in the "Assignment.ipynb" file. The following is a Pandas Dataframe, or table, showing the first five entries of the relevant hourly data. Note that "HOEP" values were converted from *cent / kWh* to *$ / kWh*.

	Hour	Load	HOEP	Inverter
0	1	1268.16	-0.0006	-600.0
1	2	1273.92	-0.0229	-600.0
2	3	1265.28	-0.0300	-10.0
3	4	661.44	-0.0293	0.0
4	5	837.12	-0.0081	0.0

For #2, the missing data cannot be resolved using traditional methods such as:

- Finding the original source of the data because it was not available online or in other sources.
- Dropping the data entries themselves because their 15Min Inverter values were needed to calculate the hourly Inverter dispatch.

Therefore, several Machine Learning techniques are considered to predict the null values. They were "Univariate Imputer," "Multivariate Imputer," "K-Nearest Neighbor (KNN) Imputer," and "Time-Series Forecasting." The missing data values are predicted on an **hourly** basis to reduce coding and computing time. The imputers are packages belonging to the Scikit-Learn public library.

Univariate Imputer

The Univariate Imputer imputes, or fills in, the missing data with:

- A prescribed constant value
- A statistic (mean, median, and mode)

Using a prescribed constant value would not work because there are no valid explanations for a single value to represent the hourly Inverter data across that long of a period (from 20:00 October 23, 2019 to 11:00 October 29, 2019), especially when considering that the battery must need to supply different amounts of power to the customer based on the customer's energy demand (Load) and the current price per kW (HOEP). With the same logic, using the mean, median and mode does not make sense either. So, we do not use the Univariate Imputer.

Multivariate Imputer

The Multivariate Imputer uses Multiple Linear Regression iteratively to predict the missing hourly Inverter values. It does this by modelling the target feature, "Inverter," as a function of other relevant features which in this case are the "Load" and "HOEP." The following DataFrame contains the predicted missing values at 2 AM (from days 23 to 28).

	Hour	Load	HOEP	Inverter Dispatch
20	2.0	682.56	-0.0078	0.000000
21	2.0	675.84	-0.0300	0.000000
22	2.0	646.08	-0.0300	0.000000
23	2.0	669.12	-0.0300	11.423217
24	2.0	676.80	0.0284	4.007815
25	2.0	633.60	-0.0385	45.722354
26	2.0	672.96	-0.0300	7.715192
27	2.0	674.88	0.0000	5.861513
28	2.0	667.20	-0.0300	13.277229
29	2.0	657.60	0.1094	0.000000
30	2.0	634.56	0.0409	0.000000

From the DataFrame above, the predicted values for "Inverter" are positive. However, when compared to the usual trend of the available data, the predicted values do not make sense.

At 2 AM, the HOEP is negative, which encourages the customer to consume more energy in order to further reduces their overall monthly utility costs. The battery, then, should be drawing power from the customer's facility to increase the total load value on the utility meter. This process was repeated for other hours such as 1 AM and 12 AM and with different numbers of iterations which yield similar results. Therefore, we cannot use the Multivariate Imputer method to predict our missing data.

KNN Imputer

The KNN Imputer uses the K-Nearest Neighbor classification approach to predict the missing values. It does this by calculating the Euclidean distance from a single data point to every other data point. It then predicts the missing value based on the k number of data points, or neighbors, around it. The following DataFrame contains the predicted missing values at 2 AM (from days 23 to 28).

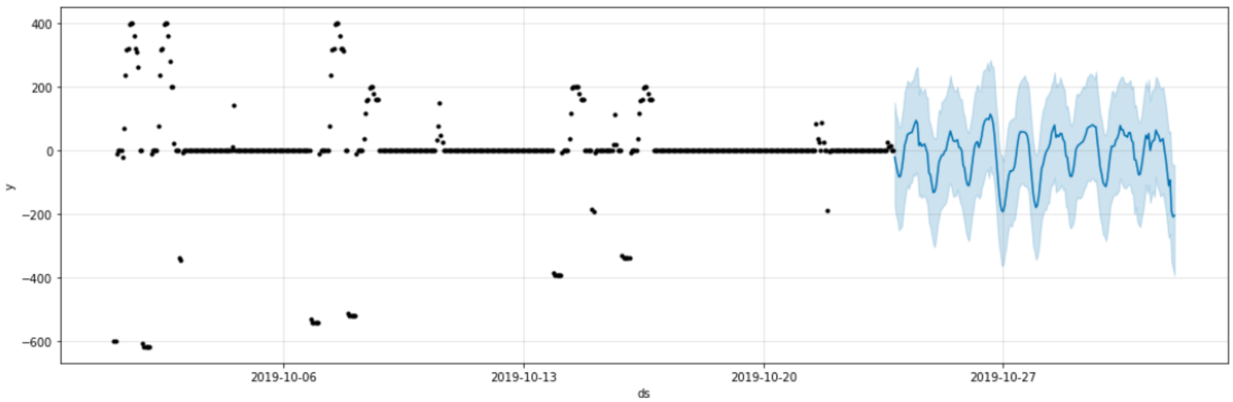
	Hour	Load	HOEP	Inverter Dispatch
15	2.0	1023.36	-0.0234	-336.0
16	2.0	669.12	-0.0013	0.0
17	2.0	674.88	0.0427	0.0
18	2.0	676.80	0.0564	0.0
19	2.0	684.48	-0.0021	0.0
20	2.0	682.56	-0.0078	0.0
21	2.0	675.84	-0.0300	0.0
22	2.0	646.08	-0.0300	0.0
23	2.0	669.12	-0.0300	0.0
24	2.0	676.80	0.0284	0.0
25	2.0	633.60	-0.0385	0.0
26	2.0	672.96	-0.0300	0.0
27	2.0	674.88	0.0000	0.0
28	2.0	667.20	-0.0300	0.0
29	2.0	657.60	0.1094	0.0
30	2.0	634.56	0.0409	0.0

From the DataFrame above, the predicted values for "Inverter" are all 0. This was due to the other data points around them all have the value of 0. This does not make sense as the values of "Inverter Dispatch" datapoints are not likely to influenced by the data points around them. Also, KNN classification is not very appropriate when dealing with time-sensitive data. Therefore, we cannot use the KNN Imputer method to predict our missing data.

Time-Series Forecasting

Time-Series Forecasting models and describes an observed time series in order to understand the series' underlying causes. It then uses the model to extrapolate / predict the future. It is, logically and intuitively, the most appropriate method to deal with the given dataset. The machine learning algorithm used in this assignment for Time-Series Forecasting will use the "Facebook Prophet" public library. It uses an additive model where non-linear trends (assumed in this dataset) are fit with chronological effects ranging from weekly to yearly as well as daily seasonality and holiday effects. It is also known to be robust to missing data and shifts to the trend, and it handles outliers well.

We will be fitting this model with daily seasonality effects and without holiday effects due to the limited available time to complete this assignment. The independent variables, or features, will be the hourly time-series itself, "Load," and "HOEP." The dependent variable, or target, will be the We will also forgo model evaluation for the same reason and cross-validation due to the limited amounts of datapoints. The available "Inverter" data will be used to train the model, and the missing data will be used to test the model. After training the model, values for the missing data were predicted and recorded in the "yhat" feature of the "df1_test_fcst" DataFrame, which can be found in the "Assignment.ipynb" file. Then, the data points were visualized on a plot, with the predicted missing data in **blue**.



According to the plot, the predicted values follow the observed trend in which the magnitudes of non-zero values decrease overtime. Also, the predicted values follow the trend in which the they are negative from midnight to early morning and positive during the day. However, there are noticeable areas in the available data where values are zero, but this observation is not the same for the predicted values. Even without evaluating the model, it is reasonable to say while it predicted values that makes sense logically and intuitively, the predicted values may not be very accurate.

Still, we will use these predicted values to fill in our missing data. For future improvements, we could consider other effects and parameters available in this algorithm, and we could also consider other time-series and regression algorithms as well.

Determining the total utility costs with and without using the battery

After filling in our missing values, we calculated the customer's month utility cost before and after using the battery and also the monthly savings. The "Inverter" values were subtracted from the "Load" values for the case where the battery is used. The NCP price was also used for the calculations. The costs and saving are displayed in the following table.

	Value ($)
Total monthly cost without battery	73237.27
Total monthly cost with battery	74262.93
Savings	**-1025.66**

According to the table, the customer's total monthly cost after using the battery is greater than the monthly cost before using the battery. This resulted in additional costs. Several explanations can be considered for this result.

Firstly, the predicted values to fill in the missing data are concluded to be inaccurate. This likely contributed to the higher value of the total month cost with battery than expected. Improvements to the existing predictive model would, most likely, yield a more accurate value for the customer's savings.

Secondly, the value of the NCP price (*$11.25 / kW-Month*) is much, much greater than every hourly HOEP which was never higher than *$1.00 / kWh*. This means if the maximum hourly load value for the case with battery is higher than the case without the battery, the former's resulting NCP-driven cost could drive its total month cost up and surpass the latter's total monthly cost.

Thirdly, for the case without the battery, the month's maximum hourly load is 1680.96 kW, resulting in an NCP-driven cost of $18910.10. However, for the case with the battery, the month's maximum hourly load is 1926.40 kW, resulting in an NCP-driven cost of $21672.00. The difference between these two cost values is $2761.90 which could have offset the savings calculated above, thus giving the customer a positive value of savings. Because these two loads were recorded at different time stamps, we can infer that the battery drained too much power at a certain instance which resulted in the load value of 1926.40 kW.

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