Smart Power Video Script

# Intro

Welcome to our video presentation for the Discover AI challenge for smarter and sustainable economies. Introducing the team, we have:

- Adam Dunn, an electrical engineering graduate from Western University

- Dheeraj Ghangas, an Honour’s Bachelor of Business Administration graduate from Wilfrid Laurier University

- Nathen Gay, an Honour’s Bachelor of Technology student at Seneca College

For our project we wanted to be able to leverage AI and analytics with reliable data as well as incorporate the Microsoft Azure Cloud platform to do so. With that in mind, the Smart Cities pillar seemed like the perfect fit to start our project.

# Need for Product

From the smart cities topic we wanted to investigate new methods of short-term energy demand forecasting on a regional basis. The current methodology used by the Independent Electricity System Operator has difficulty estimating for fluctuations resulting from holidays, extreme weather or other force majeures. These inaccuracies in forecasts can cause a surplus in electrical generation, asset investment risk and additional fees to the downstream customer.

The way a power system works is that all load must be consumed at some point and a surplus eventually becomes a liability. To eliminate a surplus, the System Operators sell it as a loss leader which leads to a reduced or negligible profit margin. In some cases when it is difficult to sell the surplus, the IESO must pay a neighboring operator to accept the load.

In the past, reducing surplus by at least 1% in the Ontario energy market has generated $100-200k in initial savings and can have a cascading effect on improved asset investment in the $2-4 million range.

# Idea and Solution

Our team idea seeks to improve the prediction accuracy and reliability by using a machine learning time series model. This means accounting for seasonality in data and using its repetitive nature to predict the patterns again; which has had success in the finance, retail and transportation sectors.

To develop this type of solution, we used the Azure Machine Learning Workspace to train a model using existing datasets from Toronto, Ottawa and the Bruce Peninsula; giving various population sizes.

* These datasets tried to encapsulate things that directly affect electrical demand such as weather, cost, and seasonality. The reliability and accessibility was also a factor, as everything must be obtainable on a regional and hourly basis for a time series model to perform. All of our collected data was publicly sourced through StatsCanada and the IESO for free.

**Record HERE**

* To find the best fit model, we used an Automated Machine Learning tool in Azure that optimized the normalized root mean squared error result from our dataset and had incredible performance for Toronto and Ottawa regions
* The next stage is being able to use the time series model to forecast future power demand and the best way to offer this as a product is as a web service which is made easy on the Azure platform.
* Using the Azure Kubernetes Service, we can deploy and manage a containerized web service application with CI/CD to continue to retrain the model with new data. The platform is completely scalable by adding additional AKS production clusters. For our prototype, we successfully deployed our model to an AKS cluster to build our web service however the costs associated made it unfeasible to keep it sustainably running during the development and testing phase.
* For testing our models as a proof of concept, a basic webservice was built using the machine learning pipelines.

# Example Walkthrough

One of the main advantages of using a machine learning model to forecast load is that it is a better estimator for force majeures. It does this by placing a weight factor on more recent data rather than loads on the same date in previous years. To prove this, we investigated the Ontario electrical demand from 2016-2019 and compared the trend to the same 7-day time period in 2020. The expectation during an event such as the COVID19-outbreak, with reduced business activity, is that electrical load would decrease by a fixed amount. What we found is that the shape profile of the curve changes during these events, signifying that a simple fixed rate reduction to peaks would not be sufficient. The normal electrical load follows a similar daily cycle with a signature “M” shape, with a morning and evening peak caused by fluctuations in people’s workdays. Under random events such as the COVID19 lockdown, some of the key differences include:

* A delayed or negligent morning peak
* Incorporation of a midday peak
* Reduction in overall energy demand across all hours of the day

This type robustness in a model is valuable because it allows system operators to quickly account for the loss of electrical demand from local businesses.

# Business Model and Cost Estimates