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. It creates a matrix of inputs from real historical data to learn trends, and has inherent advantages of handling nonlinear functions faster.

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.

* For any kind of machine learning, the dataset must be first cleaned by removing irrelevant, missing or unfinished values that could misdirect the program. For this we designed a pipeline to delete rows with missing values, which focuses the dataset to only relevant time, regional load or weather data.
* 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

Our business model comprises of 9 focal segments:

The first segment of the business model is the **value proposition**. SMART Power will accurately provide consistent forecasts of regional electrical load demand using advanced Machine Learning algorithms. The current methodology of load testing uses historical data such as temperature which does not provide an accurate analysis when dealing estimating for fluctuations resulting from different contributing factors such as holidays, extreme weather and in a more recent example, a global pandemic. With accurate forecasting, crown corporations such as the Independent Electricity System Operator (IESO) is able to minimize loss when they are selling a surplus of generated electricity.

Our second segment focuses on our **customers**. SMART Power’s Machine Learning algorithms will benefit many private companies or crown corporations in the Electricity generation industry. These potential customers include: Ontario Power Generation, Hydro One, Ontario Hydro, Ontario Energy Board, the IESO and many different Licensed Electricity Retailers such as Canada Energy Wholesalers Etc.

Next, we move on to the **channels.** Our customers will be able to access SMART Power’s reports using a webservice that will allow them to filter the program to their own settings. Furthermore, online data storage can hold customer forecasts where accessibility can be provided upon request.

The fourth segment to our business model is **customer relationships.** IESO is both a customer and supplier; it is in their best interests to support SMART Power with accurate data. Many corporations are interested and are looking for solutions to improve their short-term forecasting. In regard to the current methodology of load testing, it would make more monetary sense to become a customer of SMART Power.

The fifth segment comprises of the **revenue stream.** SMART Power will have two options regarding the service: The first is a subscription-based service. We will charge customer a monthly fee to access the forecasting platform. $1,000/month as a basic subscription for weekly load forecasting for a single region and $2,000 per month for a premium hourly load forecasting for a single region. The second option is the purchase the forecasting model outright: Crown corporations and industry titans will most likely be will to purchase the forecasting model outright, however the price would have to be negotiated.

The sixth segment of the business model comprises of **resources.** In order for SMART Power to be successful, there is a few resources that will be required. Regular data will need to be gathered for regional load and weather, price to train the model with new information and a healthy amount of bandwidth for the online webservice.

The next segment is our **partners.** SMART Power plans to partner with London Hydro Inc. as they provide insight on local distribution. Furthermore, the IESO will provide historical data on local electrical demand and prices whilst Statistics Canada will be able to provide historical weather data.

The penultimate segment is SMART Power’s **key activities.** In order to operate as efficiently as possible, we will have to regularly collect data for the regional load, weather, and price to improve model accuracy.

The final segment of our business model is our **cost model**. The primary costs that will be incurred is data storage relevant to the model. Our secondary costs will be from Microsoft Azure subscriptions and regional data collection.