Final Summary GridEd

Introduction and Background

In the State of New York, the New York Independent System Operator (NYISO) is tasked with controlling and monitoring the operation of the electrical power grid within the state. With the emergence of more and more behind-the-meter photovoltaic (PV) systems, NYISO is faced with the challenge of being able to accurately predict the power production from these systems, in order to achieve a balance between the load and required generation. Behind-the-meter PV refers to a system that is designed to power a single building or facility, with the generation occurring on the consumer side of the meter. Without the knowledge of how much power is generated from these systems, NYISO is unable to precisely estimate power generation, and whether they need to ramp up or ramp down the energy production for the next day. If NYISO under commits the amount of electricity produced, then system stability, frequency, and voltage may be affected. Overcommitting the amount of electricity needed in system, however, unnecessarily increases cost. By having a model that shows how much power a behind-the-meter PV system will generate the next day based on the weather forecast, NYISO will have a much clearer picture of how much electricity needs to be produced.

This is the first semester of a multi-semester project to create a mathematical model that will be able to accurately predict how much energy the PV system array on top of the East Campus Athletic Village (ECAV) at Rensselaer Polytechnic Institute will produce on a given day. The model takes as inputs the weather, time of year, and many other factors and outputs predictions of the solar energy output of the panel. The end goal of the model is to be able to use it with any given behind-the-meter PV system. The team has created both a statistical model, using regression analysis, and an artificial neural network that is trained to accurately predict the output from learning parameters specified by the operator. These models are compared and analyzed in the report to put forth a recommendation for future teams.

Project Execution

For the statistical model, the team began by researching time series analysis and regression modeling. This research, coupled with discussions amongst faculty who had expertise in the area of statistical modeling, led the team to develop a three step process of creating the model. Step one is to create a regression model to find the relationship between input and output variables. Step two is to perform time series analysis on each individual input variable to predict future input variables. Step three is to take these predicted input variables and put them back into the regression equation to produce the predicted future output variable. In this semester, the team sought to accomplish step one of this process, creating a regression model.

For the artificial neural network, a large learning curve presented itself to the team, as no member had any formal experience with learning techniques or neural networks of any sort. A lot of time went into researching different types of neural networks, how to implement one effectively, and deciding the approach. The team decided to take two different software approaches, using both MATLAB and C++. For the C++ model, one input layer, one hidden layer, and one output layer were created, and propagation and training then occurred on the network. For the MATLAB model, the Neural Network Toolbox functionality was used, which is a graphical user interface provided as part of MATLAB that allows the user to select the problem that fits the one the user wishes to solve, and then provide the data necessary to train the network.

In order to train all of the models, acquisition of suitable data was a necessity, and remained a focus of the team throughout the entire semester. Weather data was obtained from the National Oceanic and Atmospheric Administration as well as OpenWeatherMap, to obtain information such as temperature, precipitation, cloud coverage, UV index, solar irradiance, etc. One issue that was faced by the team was the difficulty of obtaining accurate and reliable historical data to train the network. In order to solve this issue for future teams, software was developed to automatically collect current weather data on 15 minute intervals, so that, by the time the next team goes to work on this project, they will have 5 months of historical data at no cost. This process will create a good database of weather data to train any models developed in the future.

Conclusions and Recommendations

Comparison

To compare the models that have been created, the team began by brainstorming any possible criteria that could be used. The most relevant criteria were brought out and consisted of accuracy, interval sensitivity, and potential for further improvements. These three were chosen because the accuracy that has been achieved by the model is the main goal of the project. However, it is also important what potential is for the model in further semesters. The Interval Sensitivity is the ability of a model to predict at the levels desired by NYISO. These would be from six seconds to entire days. The comparison in shown in Table 1.

Table 1: Model Comparison

	Statistical Model	Artificial Neural Network Model	Winner
Accuracy (rMSE)	4.5	N/A	**Statistical**
Interval Sensitivity	Both are as good as the prediction data provided		**Tie**
Potential	Can be made slightly better but not much space for flexibility.	Can be made very accurate and flexible.	**Neural**

Recommendations

Based on the comparison analysis of both the statistical model and neural network model, the team recommends that both models continue to be worked on in the future. Even though the neural network is not currently functioning, there is a chance that it could be even more accurate than the statistical model is right now once it is completed. Also, because the neural network has a lot more potential in terms of accuracy and flexibility, it should still be worked on in the future. For the statistical model, the only improvement it can make will be done through adding in new input variables, which will have to be completed through extensive data collection in the future.

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