FORECASTING CUSTOMER'S ENERGY DEMAND USING MACHINE LEARNING

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Chapter 1

Smart Grid and PowerTAC Competition

In this chapter, I will describe Smart Grid and PowerTAC competition.

1.1 Traditional Energy Distribution and Consumption System

In traditional electricity generation system there are three subsystems [3]. In electricity generation subsystem, the generator rotates a turbine in magnetic field which generates electricity. The turbine rotates through the power of kinetic energy of water falling from a water fall or a river with strong current, or from the energy of nuclear powerplan or energy received from burning coal or oil. Traditional energy generation system then transmits the electricity through transmission grid and electricity gets distributed in the distribution grid. This generation system is one way meaning a single power generation source serves several consumption source.

1.2 Smart Grid

In contrast to the traditional electricity generation system, Smart Grid (SG) are two way [3]. So, any node in the distribution grid can produce electricity and push it to the distribuiton grid if necessary. The NIST report [3] states that the SG would make the electricity generation and supply robust against generator or distribution node failure, use renewable energy widely and efficiently, reduce green house gas emission, reduce oil consumption by encouraging usage of electric vehicles, it will give customers more freedom to choose among energy sources. Smart grids will encourage usage of electric vehicle as these vehicles have the ability to store power in a battery and transmit the power to the distribution grid if there is a necessity. The major challenge with the usage of renewable energy is it is uncertain. This uncertainity causes the ability to predict how much energy the SG can produce in a future time slot hard. Success of SG will need efficient methods to predict energy production [9].

1.3 Smart Grid and Renewable Energy

One of the major focus of Smart Grid(SG) will be using renewable energy. There are challenges involved with using this abundant source of energy [10]. People are already showing strong motivation to use renewable energy as indicated by the statistics that 20% of total energy is from the renewable sources which is second after coal 24%. People are using renewable energy due to economic reward and environmental concern. Major challenge with Renewable energy is amount of the energy produced is greatly varying. Since the energy produced is volatile there must be a storage mechanism that balances out the surplus energy. The usage of rechargeable electric vehicles might serve the purpose of storage. Accurate prediction of the renewable energy might enable the electric car users to absorb surplus energy and push it back to the grid in peak hours if necessary.

1.4 Importance of accurate load forecasting

. Accurate load forecasting is important to ensure efficient fuel usage, reduce wastage of energy and planning proper operation of power generators [7].

Chapter 2

Related Works

In this chapter I will describe what other works has so far been done to predict customer's future energy demand.

Predicting customer's energy demand is important becasue failure to predict the demand accurately can cause monetary and environmental loss. Customer's with shifting load can use the energy produced by the renewable energy. Those customers can shift their load to a time where there is a high probablity of renewable energy production.

Acting directly on the real environment can be risky. The powerTAC simulation system gives a low risk platform where the researcher's can build and test their works before deploying to real world.

There are different types of load forecasting namely short term load forecasting and long term load forecasting. Short term load forecasting deals with forecasting the customer's demand has the range of time couple of weeks. Long term load forecasting may forecast customer's demand over month or year [2].

TACTEX'13 won the PowerTAC competition in 2013. In a week a customer have 24 * 7 = 168 slots. TACTEX'13 the winner of PowerTAC competition 2013 kept track of average usage of 168 weekly slot for each customer. To predict a future time slot, their agent would look at at which weekly slot the future time slot would fall in. Then the agen uses that weekly slot's average usage as the prediciton of the future slot.

The ARIMA model uses both moving average and auto regression to forecast the demand. To make a forecast about a future time slot, the auto regression model uses some previously observed time slots values based on its degree. Moving average scheme would use the average of all the known time series data points to make a prediciton about a future time slot .Problem with univariate ARIMA model is that they don't take into account other variables that my affect the demand such as temperature. [2] attempted to forecast the energy demand for a region of Taiwan. They found temperature has effect on the energy usage of customers. To make prediction about the demand they used a transfer function that relates the daily temperature with energy usage along with the ARIMA model. This scheme resulted better than the univariate ARIMA model. They manually clustered the population in four categories such as commercial, office, residendial and industrial customers.

Intuitively weather variables such as temperature seem to have some effect on how much energy people use. Researchers have found that weather effect relies on the time duration the training data has. [1] trained a SVM energy demand predictor that would predict energy demand of customers for the month January. The training data consited of every half hour's electricity demand from 1997 to 1998, average temperature from 1995 to 1998. They trained the predictor with only the portion of data that are related to the month

January. They have found that within the month of January the temperature does not vary much and excluding the temperature from the feature set actually gives better prediction. Again, if energy demand is long term which means the window of prediciton is about a year, the temperature seems to have effect on the energy demand of the customers. [4] collected data of 18 months from households of a region of Australia. They collected the weather data from weather office and from self transplanted devices. They observed how the household customers use appliances based on the temperature. They came into conclusion that for that region, equilibrium point for energy is usage at temperature 0.25 degree celcius. If the temperature increases or decreases from this temperature, the electricity usage increases. They explained the behavior by stating as the temperature decreases, houses customers tend to use heaters and if the temperature rises they tend to use coolers more.

Regional load forecasting will enable us to know which regions need more energy. If we know which regions need more energy, we will know most suitable places to place electricity generator plants. [5] worked on load forecasting based on region. They diivided electricity usage of Taiwan in 4 areas. For each region, they collected GDP, population, highest temperature and aggregated load. After that, they trained Artificial Neural Network model for each region. For baseline, they trained linear regression model for each region. The result showed that, the ANN based load forecasting methods performed better than the linear regression methods.

[8] have used clustering method to forecast customer's future electricity demand. They collected data from more than 4000 household customers in Ireland for about 6 months. Collected data included electrecticity usage at 30 minutes interval, appliances used in the home and different socio-economic information about the people living in a particular house. They clustered each days usage which they call load profiles. A customer's daily usage then can be assigned to one of those load profiles. The customer is then charactersized by the the mostly used load profile. The authors then train a linear regression classifier that was built upon the socio-economic information of a the customers, types of appliances used in the house and the description of the house to figure out the common load profile of the given household. The predicted load profile of the customer received from the linear regression model will be used to predict the demand of the customer for a given day.

[6] the authors proposed a methodology to model electric car user cusotmer's demand. They uses data of electric car users of Netherlands from 2000 to 2007. The data included purpose and starting time of each drive, duration of the drive and the time the driver spent at the purpose destination and when the time when the driver returned home. From this data, the authors found usually the drivers would recharge their car at around hours 17:00 to 19:00. So the electricity generators may find this time a peak demand time due to the added energy demand of the electric vehicle customers.

[7] the authors observed load of certain hour of a certain day is highly correlated with load of some certain days before that day. On the basis of the observation, they would take ten most similar looking days electricity usage and feed it to an ANN to make forecast of the day. The authors found the other variables that may affect the load such as temperature, humidity may change so swiftly that inclusion of them may reduce the accuracy of the predictor. So they excluded all the social, environmental variables from their model of prediction.

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