Energy Efficiency and Flow in the Smart Grid

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Energy Efficiency, Flow Analysis and Power Management - Smart Grid

February 2020

Abstract

Data analytics plays a prominent role in modern industrial systems such as electricity transmission. Smart meter data is irregular and unpredictable from traditional system-level data. Probabilistic forecasting of energy loads provides a clearer interpretation of uncertainty and volatility in future energy demand. Renewable energy exhibits volatility and intermittent and random behavior. Our approach for forecasting future energy demand is a hybrid combination of different methods from machine learning, representation learning, and deep learning.

1 Background

The smart grid is the next-generation power system which is innovative in grid infrastructure in its connectivity. The connectivity, such as the constant communication required in the system, is which is provided by the internet of things, a system of interrelated computing devices, mechanical and digital machines, or objects that are provided with unique identifiers (UIDs) and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction. This results in a large volume of data which demands methods more powerful than conventional methods to perform good analysis and decision-making.

The goal of our project is renewable energy and electrical load forecasting.

Renewable energy exhibits strong volatility and randomness, which leads to the increase of the reserve capacity of electric energy systems, and increasing the cost of power generation. The intermittent characteristics of wind and photovoltaic energies bring challenges to safe and stable operations in a low inertia power system [12].

The accuracy of renewable energy forecasting is necessary for the tasks of power system planning, management, and operations. Deterministic forecasting models are not sufficient to characterize the inherent uncertainty of renewable energy data, so probabilistic forecasts can give quantified uncertainty information and aids in planning, management, and operation of energy systems.

Accurate load forecasting is essential for energy management, system operation, market analysis and saving investments.

The methods in the existing literature include physical methods, statistical models, machine learning models, deep learning models, and hybrid methods. Physical

Existing Grid	Smart Grid
one-way communication	two-way communication
centralized generation	distributed generation
few sensors	sensors throughout
manual monitoring + restoration	self-monitoring + self-healing
failures and blackouts	adaptive, islanding
few customer choices	many customer choices

Table 1: Comparison of Existing Grid and Smart Grid

methods involve numerical weather prediction models that simulate atmospheric dynamics based on physical principles and boundary conditions [14]. Physical methods effectively forecast atmosphere dynamics but require great computational resources for calibration, and are not fit for short-term forecasting horizons.

Statistical methods try to determine the mathematical relationship between online time series data, and include autoregressive moving average [1], Kalman filters [16], Markov chain models [18], gray theory [13], support vector machines[3], feedback neural networks[11], artificial neural networks [4], and ARIMA [6].

Machine learning models include deep neural networks that forecast energy demand given climate, date, and building usage rate information[2], support vector machines [8], fuzzy support vector machines[15], and linear regression[10].

Deep learning models that have been proposed include recurrent neural networks that measure the environmental consumption level for each country [7] and autoencoders that extract the building energy demand and predict future energy consumption [9].

2 Introduction to the Project

We investigate new research directions as outlined in [5]. One direction is to develop probabilistic forecasting models. There has been a large amount of work regarding deterministic prediction of renewable energy but not as much regarding probabilistic forecasting models. Probabilistic forecasting models are able to numerically quantify uncertainties that exist within renewable energy times-series data.

Probabilistic forecasting assigns a probability to each prediction result. The existing methods for probabilistic renewable energy prediction are categorized into parametric and nonparametric methods. In methods that are parametric, the time series data of renewable energy are assumed to follow prior distributions; i.e., Gaussian, beta, and Gamma distributions.

Another direction is to extract features from renewable energy data with representation learning and deep learning. Existing deep learning prediction models only consider a single deep learning algorithm for feature extraction. Therefore, it is desirable to integrate multiple deep learning algorithms to extract deep prediction features.

2.1 Data Preprocessing

This step consists of cleaning the data, feature selection, and normalization.

Cleaning the data involves removing nan values, removing unreasonable or abnormal characteristics; i.e, values of wind speed and power that is negative. These values can be filled by the mean value. Data entity identification and data redundancy identification are performed [17].

In practice, excessive variables may cause problems. Feature selection involves the selection of a set of input variables from the raw data that the forecast performance has a greater dependence on. A feature weighting algorithm is applied. It involves assigning weights to features according to their correlation and discarding features whose weights are less than the threshold [12].

Data normalization and transformation: Normalization transforms the raw data to the same orders of magnitude in order to improve the convergence rate and the forecasting accuracy (c5). Skewness processing, data standardization, data discretization, and attribute construction are performed (c3).

2.2 Clustering

Because of the large amount of data, we can reduce the complexity by clustering the training samples based on similarities. This will reduce inconsistencies and random behavior of training samples and improve the forecasting accuracy. The historical meteorological information is used to form a k-means clustering approach where the days are classified into different categories based on factors such as similarities in temperature [12].

2.3 Learning

Supervised or unsupervised learning algorithms are applied, depending on whether there is a label attached to each item in the dataset or not. The format of the dataset is time series data consisting of an ordered list of tuples. The tuples consist of a timestamp and a feature vector, with features such as wind speed, air pression, temperature, humidity, solar irradiance, and more.

Representation learning (RL) is a research area with the goal of determining suitable features. It overcomes feature learning difficulties by exploiting automatic data-driven feature engineering and feature selection approach. Latent or hidden features which describe the data with sufficient accuracy are learned during feature learning, which is the main procedure in representation learning(c13). The extraction and selection of features help the machine learning algorithm reach improved results for a particular task, alternative to directly using the raw data.

Feature engineering is the process of creating features in a way so they help the ML algorithm to improve its performance. When this is done automatically by an algorithm, it is called feature extraction and it is part of the representation learning process.

Deep architectures promote the re-use of features and can potentially lead to progressively more abstract features at higher levels of representations. We use methods with deep architectures such as deep belief networks.

Deep belief networks make up a generative graphical model that is made up of simple, unsupervised networks (such as restricted Boltzmann machines). It consists of bidirectional and symmetrical connections between different layers.

A RBM functions as a stochastic neural network, and it has one layer of Boolean visible neurons and one layer of binary-hidden units. The main objective of an RBM is to learn a probability distribution over its input data space, in order for its configuration to exhibit desirable properties. The probability distribution is learned via minimization of an energy model. This model is designed as a function of network parameters that is based on thermodynamics laws.

The activation probability of hidden layers given the visible layers as well as the probability of visible layers given the hidden layers can be estimated iteratively to find the network parameters.

When training a deep network, the goal is to find optimal values on each of the filter matrices so that given data it can find the class where it belongs. The filters on different layers learn different features.

Another method is transfer learning. It works well because one utilizes a network which is pretrained on a dataset and this network has already learned to recognize little details in its initial layers. Therefore we are simply adding a few dense layers at the end of the pretrained network, and learning which combination of the learnt features help to recognize the objects.

2.4 Forecasting

The model is used to perform prediction. The probabilistic results for each household are predicted in succession.

2.5 Model evaluation

The datasets are split into training, validation, and test sets. This makes it possible to select the best model based on the validation set and the test set can evaluate the task on unseen data. The forecast error helps us determine if the latent feature representation performs well in a forecasting task. Additionally, the mean absolute error, root mean square error, and mean relative error can be used to evaluate the accuracy of the prediction given predicted values $\hat{y}_i$. The performance of forecasting is evaluated.

3 Introduction to the Dataset

Data sources can be sorted into three categories: measurement data, business data, and external data (c3 Teng et al., 2014). Measurement data make up most of the operation parameters in power systems; through the installed sensors and smart meters. The system's current and historical status is able to be retrieved from this measurement data. External data cannot be measured by smart meters but impacts the operation and planning in the power system. It includes data such as social events or weather conditions. The business data includes marketing strategies and rivals' behaviors.

We work with measurement data. We describe the electrical load data that we will use.

One group of datasets is from Pecan Street Institute, including 6 years of historic one-minute interval data on circuit level electricity use for 750 homes, dynamic (constantly updating) datasets on one-second to one-minute interval electricity use for power for 350 homes in Texas, and times-series datasets. To obtain this dataset, I emailed a professor and signed up for a student account at the Pecan Street Institute.

A second dataset is data from the Australian Smart Grid Smart City (SGSC) project that was collected from 10,000 customers in New South Wales from 2010 to 2014, where the electricity consumption in kWh was recorded every half hour for each meter.

We describe the renewable energy data we will use. We use a wave energy dataset provided by the Marine Institute that consists of several years of hourly wave forecasts on a grid of points off the Irish coast that is used to predict the potential accessible wave energy resources.

4 Plan

4.1 Milestone 1

For the first milestone, we review the literature and organize the plan for our project. We create the project proposal.

4.2 Milestone 2

For the second milestone, we perform data preprocessing. We also perform clustering based on similarities in specified features. We design the representation learning model architecture.

4.3 Milestone 3

In this milestone, we improve our model. We test various methods to see which model delivers the most accurate results. We combine the methods that are most effective into our final algorithm.

We create simulations of real-time energy data as time series data. We also create a real-time application to process the real-time data.

4.4 Milestone 4

In the final milestone, we create visualizations of the electrical networks that have been optimized, and create time series visualizations of our prediction results.

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