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Medium term stochastic load model for transformer and feeder from AMI load data spectral analysis

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ABSTRACT

A medium term stochastic load model using the hourly AMI load data aggregated at transformers and feeders is introduced. Load model frequency domain statistical parameters are derived from spectral analysis of AMI data. The load model is driven by a weather index based on Heating-Cooling Day Degree. This index is incorporated into the model using local, hourly weather data. Advantages of the proposed load model are discussed. Performance comparisons between the proposed model and several time-domain methods are presented.

1. Introduction

In recent years Advanced Metering Infrastructure (AMI) has become an integral part of the smart grid initiative. AMI meters can provide detailed and accurate load profile data for each individual customer. Through various levels of AMI load data aggregation, a multi-level view of load behavior can be achieved. This information is valuable in analysis, such as power flow and transformer loading. It is also valuable to operations, including load forecasting and demand-side management [1].

In order to efficiently and reliably operate a smart grid an accurate and efficient load estimation model is needed. Load estimation models can generally be categorized into two groups: (1) Traditional time series and statistical methods, such as regression and ARMA models [2–10], and fuzzy approaches [11–13]. (2) Machine learning methods involving neural network and support vector machine [2–4,14–16].

The majority of load modeling literature focuses on short (from minutes to several days) and long term (from a year to a decade) load estimation at the system or substation level, where the load generally ranges from several MW to several GW [2–4]. These conventional load models are generally constructed using time-domain load data. In the time-domain it is difficult to describe and quantify the diverse and complicated load pattern characteristics that exists in AMI load data [17,18].

The load patterns for distribution transformers and feeders are diverse and strongly influenced by local weather conditions. For these load types there is limited research on developing medium term (from a day to a year) load estimation models using statistics from spectral analysis of hourly AMI load data and the corresponding weather data.

The proposed load model is constructed using frequency-domain statistics derived from AMI load data spectral analysis [17]. The statistics are used to estimate the hourly load profile for transformers and feeders under different weather conditions.

The paper is organized as follows. Section 2 introduces the frequency domain AMI daily load profile representation, the weather index, and the frequency domain daily 24-h statistical load model. Section 3 describes the input data for this study. In Section 4 the performance of the proposed load model is evaluated by comparing the estimated hourly load and the actual AMI load measurements. Section 4 also discusses the computational performance of the proposed load model. Conclusions are presented in Section 5.

2. Frequency domain stochastic load model

The proposed load model will be referred to as a Frequency Domain Weather Sensitive Stochastic Load Model (FDWSSM). The FDWSSM is derived from AMI load and weather data collected for a set of transformers and feeders. The model construction

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process consists of three major steps which are presented in the following three subsections.

2.1. AMI data partition by daily weather index

In the US, Heating-Cooling Degrees (HCD_D) [18] is a commonly used measure to evaluate a utility customer's energy usage dependency on the average daily temperature $\overline{Temp_D}$. HCD_D is defined in Eq. (2), where the temperature is in Fahrenheit degree (°F).

$$\overline{Temp_D} = \frac{Max(Temp_D(n)) + Min(Temp_D(n))}{2} \quad (1)$$

$$HCD_D = \overline{Temp_D} - 65^\circ\mathrm{F} \quad (2)$$

where subscript D is the day index, hour index n ϵ [0,23].

For the majority of customers, the largest portion of their electricity usage is from the heating, ventilating, and air conditioning (HVAC) equipment, whose operation is sensitive to the HCD_D value. In order to model the weather sensitivity of daily load profiles and calculate the frequency domain statistics of a set of loads under certain weather conditions, a HCD_D based Weather Index (WI in Eq. (3)) is used to partition the daily AMI load data into sets.

$$WI = Round(HCD_D/10.0) \times 10 \quad (3)$$

where $Round(x)$ rounds value x to the nearest integer, subscript D is the current day index.

WI represents a range of HCD_D values. In this paper each WI has a 10 HCD_D degree range. Using this degree range results in all AMI data sets used in the statistical analysis having at least 30 daily samples. In this paper, this minimal sample size is due to the limit of the current AMI data coverage. The WI is an integer number used as a data index in the load database to categorize a set of days whose daily heating-cooling degree values are within the WI's range.

Table 1 lists the values of WI used in this paper and the corresponding daily average temperature ($\overline{Temp_D}$) range in both °C and °F.

Table 1
Daily average temperature $\overline{Temp_D}$ range for WI.

WI	$\overline{Temp_D}$ range °F		°C	
−40	20	30	−7	−1
−30	30	40	−1	4
−20	40	50	4	10
−10	50	60	10	16
0	60	70	16	21
10	70	80	21	27
20	80	90	27	32

For different WI the daily load profiles of a particular transformer/feeder exhibit different load pattern characteristics. The AMI data used in this paper were collected in an area where the majority of the electrical load is from residential customers and small-to-medium sized commercial customers. The weather condition has a strong influence on the daily load profiles of the transformers and feeders that serve these customer types.

Fig. 1 presents a set of normalized daily load profile (by the daily peak) plots for a transformer supplying commercial customers (first, second plots), and a transformer supplying residential customers (third, fourth plots). Each line in the plot represents a daily profile with the same WI value. There are two WI values in the sample plots: the winter WI = −20 is between 40°F and 50°F, and summer WI = 10 is between 70°F and 80°F. The transformer that supplies the commercial customers has a more consistent single-peak, daily load pattern for both WI values. During winter the transformer's hourly load variation is smaller than the hourly load variation observed during the summer. The transformer that supplies residential customers has different load patterns for winter and summer. In the winter the transformer exhibits a double-peak pattern (one peak occurs in the morning and the other peak occurs in the evening). In the summer the transformer's daily peak region moves to a later hour of the day.

2.2. AMI load data frequency domain representation

Time domain AMI daily load profiles are expressed as a set of time-series load data points. These data points have an auto-correlated relationship [19] which lacks orthogonality. Because of the lack of orthogonality, the time domain hourly data is not suitable to be modeled and analyzed independently. Because of this it becomes more difficult to model stochastic load pattern characteristics using time domain load profile representations [20].

Using the technique introduced in [17], the original AMI load profile can be transformed to a set of independent, orthogonal, frequency domain components (defined by a magnitude value and a phase value) that can be modeled and analyzed independently. Once the daily AMI load data is partitioned by WI, the frequency domain statistics can be extracted and the stochastic models can be constructed for each of the AMI daily load profile frequency domain components.

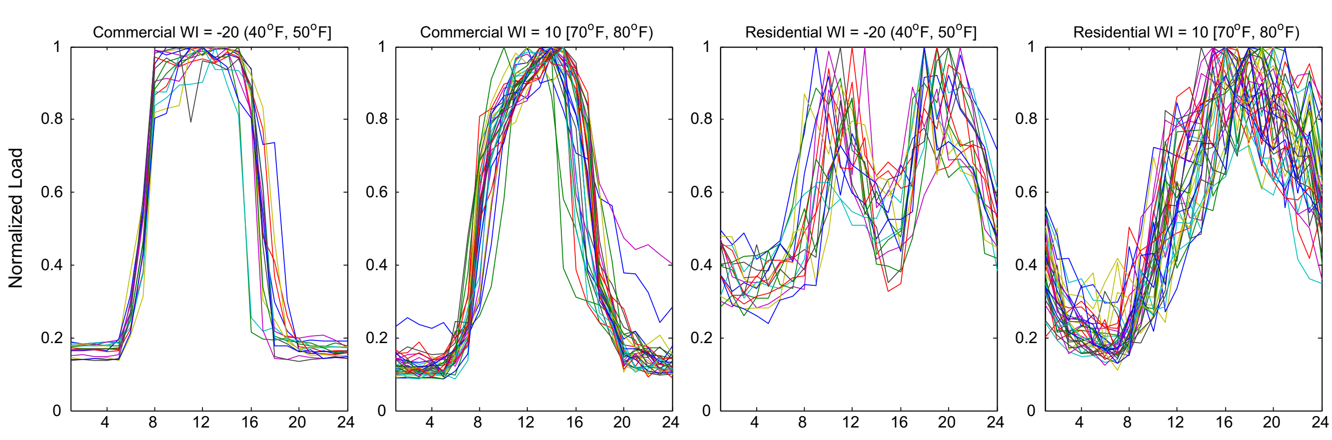

Fig. 1. Sample commercial and residential transformer normalized daily load profiles under different WI.