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Polynomial-Fourier series model for analyzing and predicting electricity consumption in buildings

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ABSTRACT

Electricity consumption in various types of buildings can be viewed in terms of periodic and irregular activity, or in terms of long-term trends, periodic activity and irregular activity. These different viewpoints vary in terms of time frame, from hourly to seasonal, making it difficult for construction models to accurately predict electricity consumption. A polynomial-Fourier series (P-FS) model is developed to analyze period activity and long-term consumption trends for use by middle management and engineers. Case studies show that the P-FS model provides accurate predictions of electricity consumption, which is very useful for evaluating energy policy and determining forward-looking electricity budgets based on limited data inputs and mathematical iterations.

1. Introduction

Energy consumption is a key issue in the management of buildings, with electricity usage varying hourly and seasonally in response to a wide range of factors including user activity and weather. It is fundamentally important but conventionally complicated to have an accurate model for predicting electricity demand in buildings [1]. The key factors in determining a building's electricity consumption is the activities of its users, which can be periodical (e.g., seasonally-determined heating or cooling or low usage during weekends or holidays) or irregular (e.g., installation of new electrical fixtures or power failures). The trend of electricity consumption may be affected by chronic factors like ageing of equipment or global climate change. Accurately predict building energy consumption using very limited building energy data is a significant challenge for the energy end-user.

1.1. Energy performance and consumption

1.1.1. Energy performance

Various methods have been proposed for estimating electricity consumption and performance in various types of buildings. Lam and Hui [2] developed the DOE-2-based building energy simulation program to assess office building energy performance in Hong Kong. The program was built by using data from a generic office building model. Important input design parameters were analyzed and identified in terms of annual energy consumption, peak design loads and building load profiles. The study concluded that sensitivity techniques are useful for assessing a building's thermal response in energy simulations. However, the results should be interpreted in context with a clear understanding of the technique's implications and limitations. Korjenic and Bednar [3] used dynamic simulations to analyze and validate the total energy performance of office buildings and their HVAC systems. Comprehensive energy consumption data were collected from each HVAC component and appliance in actual office buildings and compared with the simulation results. They found that good agreement can be achieved using available input data, especially building occupancy patterns and activities. The intent was to use simulations to establish performance criteria by which one could predict energy consumption during the planning phase, analyze actual energy consumption, and validate building performance.

Yan et al. [4] proposed a simplified energy performance assessment method for existing buildings in space cooling based on energy bill disaggregation and energy performance analysis. This method requests very limited building energy data and can effectively assess energy performance at both building and system levels, and disaggregate whole-building consumption into that of three groups of end-users. The method was validated in two actual buildings, and found that disaggregated energy consumption and key HVAC system energy performance indicators agreed well with the "measured" data in mechanical cooling months. Edwards et al.

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[5] reported on the evaluation of seven different machine learning algorithms applied to a data set for a new residential building containing sensor measurements collected every 15 min, to determine which techniques are most successful for predicting consumption over the next hour. The research concluded that Neural Network-based methods perform best on commercial buildings but Least Square Support Vector Machines perform best on residential data.

Maile et al. [6] proposed the Energy Performance Comparison Methodology (EPCM), which enables the identification of performance problems based on a comparison of measured data and simulated data representing design goals. The EPCM is based on an interlinked building object hierarchy that structures detailed performance data from a spatial and mechanical perspective. This research was developed and tested using multiple case studies. Graeme et al. [7] proposed a methodology to identify potential electricity saving opportunities in school buildings based on electricity consumption data sampled half-hourly. Monthly gas data was measured for 37 secondary schools at half-hourly increments. The technique monitors consumption over time, identifying any changes in usage patterns and quantifying their effects. The analysis produces results allow energy professionals to rapidly detect changes in electricity consumption.

1.1.2. Regional energy consumption prediction

Wang and Don [8] proposed a GA-based ANN model to predict energy consumption in China. The inputs to the ANN model are four variables including gross domestic product, industrial structure, total population and technology progress. Test results indicate the proposed model provide accurate forecasts. Ying et al. [9] applied the adaptive network based the fuzzy inference system (ANFIS) model to predict the regional electricity loads in Taiwan. The proposed ANFIS model was found to have better forecasting performance than the regression model, artificial neural network (ANN) model, support vector machines with genetic algorithms model, recurrent support vector machines with genetic algorithms model and hybrid ellipsoidal fuzzy systems for time series forecasting model.

1.1.3. Building energy consumption prediction

McLoughlin et al. [10] proposed a time series composed of building load models to determine four building load types (electricity, heating, hot water, and cooling energy). The relative building energy requirements for hotels, hospitals, and offices in Korea were then used to simulate building energy operations in which electricity demand is met by engines, refrigerators, and storage. Grubera et al. [11] combined a structure's architectural characteristics and usage modes to provide an accurate estimation of total energy consumption and supply costs. This approach also helps identify how variations in structural configuration and electricity rates impacts energy consumption and related costs, and to accurately identify specific structural parameters useful for enhancing energy efficiency and lowering operational costs. In addition, this approach emphasizes the importance of including occupant demand in estimating energy usage. Kwok et al. [12] proposed a multi-layer perception (MLP) model to estimate a building's cooling load. The training samples used included weather data obtained from the Hong Kong Observatory and building-related data acquired from an existing commercial building in Hong Kong that operates 24 h a day. The results demonstrate that the building occupancy rate plays a critical role in building cooling load prediction and significantly improves predictive accuracy.

Sandels et al. [13] proposed a data analysis approach to predict electricity consumption on load level in office buildings on a day-ahead basis. The analytical approach consists of three steps: (1) conduct exploratory data analysis, (2) produce linear models between the predictors (weather and occupancies) and the outcomes (appliances, ventilation, and cooling loads) in a step wise function, and (3) use the models from (2) to predict the consumption levels with day-ahead prognosis data on the predictors. Two major findings are accomplished. The occupancy is correlated with appliance load, and outdoor temperature and a temporal variable defining work hours are connected with ventilation and cooling load. Due to the inherent forecast errors in the day-ahead prognosis data, the error rate decreases if fewer predictors are included in the predictions. Basu et al. [14] proposed a general model using a knowledge as well as data driven approach to predict the appliance usage in housing. The proposed model is able to predict the appliance usage in housing which helps the system to organize energy production and consumption and to decide which appliance will be used at each hour (energy planning). The home automation system can advise the inhabitants to change the time of using a certain utility. The proposed model is tested over the IRISE data and using different machine learning algorithms.

Chae et al. [15] proposed a data-driven forecasting model for day-ahead electricity usage of buildings in 15-min resolution. Variable importance analysis is used to select key predictors for electricity consumption including day type indicator, time-of-day, HVAC set temperature schedule, outdoor air dry-bulb temperature, and outdoor humidity. The model is constructed using artificial neural networks (ANN) with a Bayesian regularization algorithm, and is found to provide reasonably good predictions of electricity consumption in 15-min time intervals along with daily peak electricity usage. Platon et al. [16] integrated artificial neural networks (ANN), case-based reasoning (CBR) and principal component analysis (PCA) to develop hourly electricity consumption predictive models of institutional buildings. Only using PCA-selected outputs is found to cause no loss of accuracy, and ANN models are found to provide more accurate predictions of electricity consumption than CBR models. The errors of both model types are acceptable according to ASHRAE recommendations.

1.2. Fourier series model

Fourier series (FS) [17] expressed a periodical function or a data set into a series contains a constant and series of sinusoids with different amplitude, frequency and phase angle, has been used to analyze structural vibration [18–20] and many other events such as sea levels [21,22]. FS also has been partially used to forecast electricity demand [23–25] and predict categories benchmark [26].

Gonzalez-Romera et al. [23] proposed a hybrid approach, integrating FS and neural networks to investigate the periodic behavior of monthly electric demand series in Spain. FS is used to forecast the periodic behavior while the neural network is used to predict the trend. The proposed approach has been shown to be quite satisfactory with a MAPE of less than 2%. Another FS-based method was proposed to calculate electrical outlets and power submeters in commercial buildings, and then to isolate HVAC terminal end-use hourly electricity consumption, and real world case studies showed that the approach produced accurate predictions of hourly consumption, with both mean relative error and coefficient of variability controllable within 10% [24]. McLoughlin et al. [25] found that Fourier transforms are better suited to predicting relatively uniform electricity consumption, and Gaussian processes are useful for characterizing less regular electricity demand.

1.3. Polynomial-Fourier series model

Several techniques have been used for electric energy demand forecasting. According to Sandels et al. [13], the prediction methods can be classified into three types: simple averaging, statistical models, and artificial intelligence models. These techniques have their own advantages and disadvantages. Statistical models, such as