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Generation of synthetic benchmark electrical load profiles using publicly available load and weather data

Gobind G. Pillai, Ghanim A. Putrus *, Nicola M. Pearsall

Energy Systems Research Group, Engineering and Environment, Northumbria University, Ellison Building, Newcastle upon Tyne NE1 8ST, UK

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ABSTRACT

Electrical load profiles of a particular region are usually required in order to study the performance of renewable energy technologies and the impact of different operational strategies on the power grid. Load profiles are generally constructed based on measurements and load research surveys which are capital and labour-intensive. In the absence of true load profiles, synthetically generated load profiles can be a viable alternative to be used as benchmarks for research or renewable energy investment planning. In this paper, the feasibility of using publicly available load and weather data to generate synthetic load profiles is investigated. An artificial neural network (ANN) based method is proposed to synthesize load profiles for a target region using its typical meteorological year 2 (TMY2) weather data as the input. To achieve this, the proposed ANN models are first trained using TMY2 weather data and load profile data of neighbouring regions as the input and targeted output. The limited number of data points in the load profile dataset and the consequent averaging of TMY2 weather data to match its period resulted in limited data availability for training. This challenge was tackled by incorporating generalization using Bayesian regularization into training. The other major challenge was facilitating ANN extrapolation and this was accomplished by the incorporation of domain knowledge into the input weather data for training. The performance of the proposed technique has been evaluated by simulation studies and tested on three real datasets. Results indicate that the generated synthetic load profiles closely resemble the real ones and therefore can be used as benchmarks.

1. Introduction

Power utilities across the world are proceeding with deregulation in order to facilitate system expansion by attracting investment from the private sector. As a consequence, in several countries (e.g. UK, India) the electricity sector has been unbundled into generation, transmission, distribution and supply companies. An electric load profile gives the dynamic variability of the energy demand with respect to time for the consumer category considered. The use of load profiles simplifies the arrangement between distribution companies and electricity suppliers, as the total energy record available in conventional energy meters can be distributed through different interval periods [1]. Having load profile information will lower the uncertainty in network management decision making for distribution companies [2]. It will also aid them in pricing competitive electricity options and devising risk hedging strategies for electricity derivatives.

There has been an increase in the deployment of renewable energy systems in recent years for many reasons such as the national and the global carbon emissions targets for combating climate change, growing electricity demand, the need for national energy security and providing energy access to populations without electricity. It would be prudent for the decision makers of developing nations to devise efficient future-minded policies and carefully plan their investment in renewables within their financial constraints. Information passed onto decision makers without the proper inclusion of hourly load dynamics can lead to cost-ineffective suboptimal energy systems which might also prevent countries reaching their set target of renewable energy use [3]. Load profiles are also essential for system operators to plan conventional (dispatchable) generation, to account for the energy import from renewable energy systems and for paying customers.

The standard method of constructing an hourly load profile is by recording the energy consumption, at feeder or substation level, at regular intervals (usually one hour) and dividing this by the number of customers on that feeder to produce an average demand (after diversity demand). Hourly load profile measurements at state-wise (sub regional) customer category levels are undertaken

* Corresponding author. Tel.: +44 (0) 191 2273107.
E-mail addresses: gobind.pillai@northumbria.ac.uk (G.G. Pillai), ghanim.putrus@northumbria.ac.uk (G.A. Putrus), nicola.pearsall@northumbria.ac.uk (N.M. Pearsall).

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in developed nations, but are highly uncommon among developing nations like India owing to the capital requirement. Therefore, load profiling is accomplished by means of load research surveys whenever they are required. Surveying is a labour intensive process and it can take a long time to complete surveying for all states of a country. In many cases the results of these kinds of measurements or surveys when undertaken are archived in internal reports that are not easily accessible [4].

In the absence of true load profiles based on measurement or load research surveys, synthetically generated load profiles, which can be used as benchmarks, can be a viable alternative for research applications or renewable energy investment planning. In the past, predictive modeling of energy demand has been applied in a number of instances. Several studies have used ANN models for predicting energy consumption of individual and complex buildings [5,6]. Aydinalp et al. describe the modeling of the energy consumption in the Canadian residential sector using ANN models with weather and socio economic factors as inputs [5]. Magnano and Boland describe the synthetic generation of sequences of electricity demand for application in South Australia [7]. However, both these works have based their approaches on large datasets. The large data requirement makes them less easy to implement when the availability of data is limited, which is a typical characteristic of developing nations.

The load demand of a country or region depends on two major factors, the complexity of the economy and the weather of the area [8]. Studies have revealed that a large proportion of the variability in electricity demand is dependent on weather variables such as air temperature, humidity, wind speed, cloud cover and luminosity [9,10]. The sensitivity of electricity demand in the commercial and residential sectors to meteorological variables is higher than in the industrial sector [11]. Both the weather and illumination components are very dependent on the hour of the day so they will have an impact on the daily load profile.

In the past, several artificial intelligence methods like ANNs, genetic algorithms, fuzzy logic, fuzzy expert systems, self-organizing maps, wavelet transform, principal component analysis, grey system theory and support vector regression have been developed for forecasting electricity demand [8,9,12–14] Most of these methods are based on large datasets of historical time series of load data. In some cases, in addition to historical load data, both weather variables (temperature, relative humidity, wind velocity and cloudiness) and socio-economic factors have been used as inputs to the forecasting model [11]. Only recently, the synthetic generation of energy production or consumption using public data is starting to be recognized as a viable alternative to measurement and recording. Vladislavleva et al. used genetic programming to demonstrate the feasibility of wind energy prediction by using publicly available weather and energy data for a wind farm in Australia [15].

In this paper, the feasibility of using publicly available datasets of load profile and weather data to synthetically generate load profiles using ANNs is investigated. A method is proposed to synthetically generate load profiles for the states of a developing nation like India, where measured or surveyed load profiles are not available, using only publicly available weather data of that state and the surveyed or measured load profiles of other neighbouring states. This is based on the assumption that the socio-economic tendencies of all states in that nation are similar. Bilgili et al. employed a similar method for predicting a target station's wind speed using reference stations' data [16].

A general sketch of the proposed model is given in Fig. 1. The developed ANN model is able to synthesize load profiles for a region using only TMY2 weather data. For achieving this, the model is first trained using load profile data of a region neighbouring the target region, with the targeted output and TMY2 weather data of this region as the input. The limited number of data points in the load profile dataset and the consequent averaging of TMY2 weather data to match its period resulted in limited data availability for training. This challenge was tackled by incorporating generalization using Bayesian regularization into training. The other major challenge was facilitating ANN extrapolation and was accomplished by the incorporation of domain knowledge into input weather data for training. It is to be noted that the validity of the benchmark load profiles generated synthetically are conditional and they are meant only to be used as a substitute for load profiling when the necessary load profile data is not available.

This synthetic load profile generation also shares a common base with load forecasting in terms of the use of weather and economic factors; however, it does not make use of any mathematical load models or historical time series of load or weather datasets. There are three differences between the proposed method and forecasting: (1) typical meteorological year weather data is used as the input, (2) the load profile generated is for a region different from the training region (where measured data are available), (3) the load profile generated is in the same time frame as the training load profile rather than for the future.

The accuracy of the proposed technique has been evaluated by simulation case studies carried out on three real datasets. The first two case studies provide analysis and validation. In the third case study a modified version of the method is developed for application to a dataset based on research surveys. Results indicate that the synthetic load profiles generated closely resemble real ones and therefore can be used as benchmarks. A comparison of load profiles synthesised by ANN and regression demonstrate the superiority of ANN over regression for synthetic generation of load profiles.

The remainder of the paper is organized as follows: the datasets used in this study are described in Section 2. In Section 3, the formulation of the proposed synthetic load profile generation model is described. The feasibility of the method is investigated and validated by case studies in Section 4. Finally, conclusions from this work are presented in Section 5.

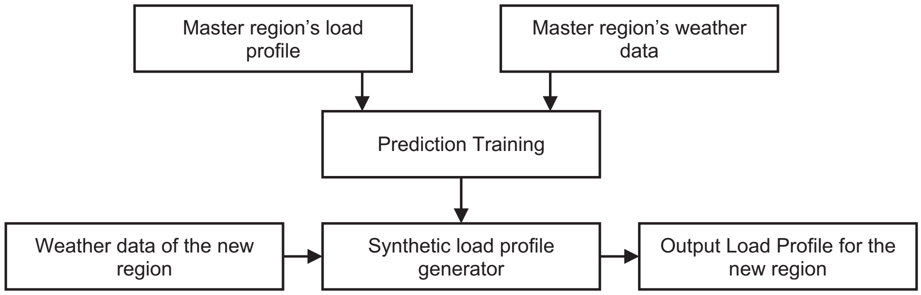

Fig. 1. Proposed synthetic load profile generation method.