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Modelling carbon emissions in electric systems

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ABSTRACT

We model energy consumption of network electricity and compute Carbon emissions (CE) based on obtained energy data. We review various models of electricity consumption and propose an adaptive seasonal model based on the Hyperbolic tangent function (HTF). We incorporate HTF to define seasonal and daily trends of electricity demand. We then build a stochastic model that combines the trends and white noise component and the resulting simulations are estimated using Ensemble Kalman Filter (EnKF), which provides ensemble simulations of groups of electricity consumers; similarly, we estimate carbon emissions from electricity generators. Three case studies of electricity generation and consumption are modelled: Brunel University photovoltaic generation data, Elexon national electricity generation data (various fuel types) and Irish smart grid data, with ensemble estimations by EnKF and computation of carbon emissions. We show the flexibility of HTF-based functions for modelling realistic cycles of energy consumption, the efficiency of EnKF in ensemble estimation of energy consumption and generation, and report the obtained estimates of the carbon emissions in the considered case studies.

1. Introduction

Following the European Union legislations on CE (the so-called "20-20-20 target", which requires, in particular, 20% reduction of CE by 2020 [1]), the United Kingdom has committed to reducing CE by at least 15% across national industries. CE are reported in grams equivalent of carbon dioxide (gCO_2eq) and can be measured directly, using on-site tools, or indirectly, using carbon factors derived by Life Cycle Assessment techniques [2].

The reduction of CE in energy generation at power plants and in households has gained much attention in order to meet the national need for sustainability. The UK Government has targeted several low carbon energy plans: to ensure the transition together with the Europen Union (EU) as a low carbon economy, and development of the new Carbon Capture and Storage technology (CCS) and in power plants before the year 2030 with investment worth £110 billion in generation, transmission and distribution of electrical power [3]. The large amount of investment by the UK government indicates that there is a serious concern about the carbon footprint of the energy industry throughout the generation and distribution of electrical power. A good balance between traditional and renewable electricity is important in keeping the financial costs down and for environmental benefits. Studying dynamical changes of electricity consumption is therefore important in reducing of the total CE. It is therefore necessary to study both profiles of electricity usage based on different types of consumers and electricity generation patterns for the purpose of reducing CE and energy losses.

1.1. Modelling background overview

Numerous models have been proposed for the description of electricity data. Shang [4] used the univariate time series forecasting method and regression techniques in predicting very short-term (in minutes) electricity demands. This method avoided seasonality considerations (daily, weekly and yearly). Dordonnat et al. [5] presented a model for hourly electricity forecasting based on stochastically time-varying processes with various parametric trends (including seasons, short-term dynamics, weather regression effects and non-linear function for heating effects) using Fourier series for the daily cycle base function.

However, Dordonnat et al. [5] reported that multiple unknown parameters were introduced if the variance matrices in the regression model became very large and consequently various assumptions and restrictions were required. Brossat [6] stressed the sophistication, efficiency and high specifications of Fourier series, except for the difficulties in fitting many parameters into the

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Nomenclature

ANNs	Artificial Neural Networks
ANOVA	Analysis of Variance
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
CE	Carbon emissions
EnKF	Ensemble Kalman Filter
HTF	Hyperbolic tangent function
MA	Moving Average
NIR	Near Infrared Spectroscopy
PV	Photovoltaic
SARIMA	Seasonal Autoregressive Integrated Moving Average
SME	Small-medium Enterprise

model. According to McLoughlin et al. [7], the use of Fourier series in the electrical load is applicable when electricity demand is stable, but the performance is relatively poor in response to sudden changes in demands.

Autoregressive Integrated Moving Average (ARIMA) models have been extensively used in forecasting due to the need for fewer assumptions to be made. Jia et al. [8] reported that ARIMA is more flexible in application and more accurate in prediction compared with the Autoregressive (AR), Moving Average (MA), and Autoregressive Moving Average (ARMA) models. ARIMA models are often associated with seasonality for better prediction of future demands. The stochastic modelling of monthly inflows into a reservoir system using an ARIMA model based on 25 years of data by Mohan and Vedula [9] showed that ARIMA models were applicable in long-term forecasting. Based on quantitative analysis using an ARIMA model, Jia et al. [8] concluded that they were effective in simulation and prediction of ecological footprints. A comparison of ARIMA forecasting and heuristic modelling by Wang et al. [10] showed that ARIMA models are more accurate than heuristic models. However, the benefits of ARIMA models are contested by the findings of Sumer et al. [11], who employed ARIMA, Seasonal Autoregressive Integrated Moving Average (SARIMA) and regression models with seasonal latent variables in forecasting electricity demand and the results indicated both ARIMA and SARIMA models were unsuccessful in forecasting these data. Mečiarová [12] also challenged the possible difficulties in the interpretation of results based on ARIMA models. In forecasting aggregated diffusion models, ARIMA models tended to provide inaccurate results for long-term predictions [13].

Meanwhile, a large number of Artificial Neural Networks (ANNs) have been proposed to handle seasonal variations, but with several potential drawbacks. The simulation study in Zhang and Qi [14] has demonstrated that ANNs are unable to model seasonal trends accurately unless the raw data is pre-processed (deseasonalising and detrending) along with an adequate neural forecaster.

Hippert et al. [15] highlighted the two main features of ANNs: (a) forecast ANNs might be over-parameterized with a large number of components (neurons) resulting in (at least) hundreds of parameters to be estimated in a small data set; and (b) the results generated using ANNs were not always adequate and realistic. In electric power systems, ANNs can be classified as a 'black box approach', where the coefficients of variables do not represent temporal and magnitude components of the electrical load profile [7,16]. Other ANNs issues raised by Maier and Dandy [17] were: (i) possible lack of appropriate model inputs; (ii) availability of data and pre-processing data in the backpropagation algorithms; and (iii) inadequate process of choosing the stopping criteria and optimising the system. These factors could affect accuracies of seasonal trends. On the other hand, several recent studies, particularly in the energy field, showed the use of ANNs to provide accurate results. The statistical test completed by Schellong [18] showed that using the backpropagation technique with "momentum term" and "flat spot elimination" as a learning rule, together with measured consumption in the previous week, forecast results would be more accurate. A comparative study by Jebaraj et al. [19] demonstrated tha ANNs provided better results in forecasting coal consumptions. The recent approach with the combination of ANNs and regression model based Analysis of Variance (ANOVA) showed accurate forecast of annual electricity consumption [20].

Still, there is a need for a model that would be able to reproduce realistic behaviour of electricity data, as well as being computationally light, requiring a reasonably small number of parameters and providing adequate flexibility in fitting diverse types of data profiles. To this end, the HTF can be applied in fitting the model of seasonal trends. It is one of the most common sigmoid transfer functions in forecasting trajectories of dynamical systems in many fields. Earlier, HTF was applied in forecasting energy related demands in ANNs [21–24]. The HTF in multi-layer perceptron did not work well in the calibration model based on gasoline Near Infrared Spectroscopy (NIR) performed by Balabin et al. [25]. Schellong [18] also recommended the use of HTF along with logistics and limited sine function in training neurons in ANNs for adequate forecasting of the heat and power demand in Germany.

In order to build an electricity data model, a valid seasonal trend of the power consumption is needed for further state-estimations of CE. In this paper, HTF is chosen as the base in stochastic modelling of seasonal trends in power consumptions due to its need for fewer parameters and high flexibility in fitting the distribution curves. Since we are interested in building a basic stochastic model for various consumption profiles, HTF is implemented without the application of ANNs. Methods in modelling the seasonal trends using HTF will be explained in detail in the following sections.

1.2. Electric system structure

In Fig. 1, we show a schematic representation of the electricity network that includes generation, transmission, distribution and consumption of electricity. Generation and consumption of electricity require different approaches in modelling and different carbon factors for estimation of CE.

In the electrical industry, it is crucial to model electricity consumption in order to be able to organise energy generation, because electricity has very low storage capacity due to the current technologies. Once the electricity consumption is known, CE can be calculated with the up-to-date carbon footprints provided, for the UK energy industry, in the two post notes of the Parliamentary of Science and Technology [26,27] and Carbon Trust [28].

Calculation of the national carbon footprints in the UK is performed by the company Ricardo-AEA [29], with quality assurance performed by DEFRA and DECC and published by DEFRA in annual reports. The latest data are available in the form of Microsoft Excel spreadsheets on the website [30], where statistics are currently stored for the years 2002–2013 inclusive. The carbon factors for the year 2013 are valid until 31/05/2014, after which date they will be revised.

The electricity network is changeable, with consumers and generators connecting and disconnecting from the grid depending on