Applied Energy 162 (2016) 763–771

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A data-driven approach for characterising the charging demand of electric vehicles: A UK case study

Erotokritos Xydas [a,*], Charalampos Marmaras [a], Liana M. Cipcigan [a], Nick Jenkins [a], Steve Carroll [b], Myles Barker [b]

[a] Cardiff University, School of Engineering, The Queen's Buildings, The Parade, CF24 3AA Cardiff, Wales, UK
[b] Cenex, Innovation Centre, Loughborough University Science & Enterprise Parks, Oakwood Drive, LE11 3QF Loughborough, UK

HIGHLIGHTS

- 21,918 charging events from 255 different charging stations in UK were analysed.
- A data pre-processing methodology for dealing with EVs charging data was presented.
- A data mining model was developed to analyse the EVs charging data.
- A fuzzy logic decision model was developed to characterise the EVs charging demand.

ARTICLE INFO

Article history:
Received 4 August 2015
Received in revised form 21 October 2015
Accepted 22 October 2015
Available online 11 November 2015

Keywords:
Characterisation model
Data mining
Data analysis
Electric vehicles charging events

ABSTRACT

As the number of electric vehicles increases, the impact of their charging on distribution networks is being investigated using different load profiles. Due to the lack of real charging data, the majority of these load impact studies are making assumptions for the electric vehicle charging demand profiles. In this paper a two-step modelling framework was developed to extract the useful information hidden in real EVs charging event data. Real EVs charging demand data were obtained from Plugged-in Midlands (PiM) project, one of the eight 'Plugged-in Places' projects supported by the UK Office for Low Emission Vehicles (OLEV). A data mining model was developed to investigate the characteristics of electric vehicle charging demand in a geographical area. A Fuzzy-Based model aggregates these characteristics and estimates the potential relative risk level of EVs charging demand among different geographical areas independently to their actual corresponding distribution networks. A case study with real charging and weather data from three counties in UK is presented to demonstrate the modelling framework.

1. Introduction

Electric Vehicles (EVs) offer reduced transportation related emissions, reduce the energy cost of driving and in some cases eliminate the use of fossil fuels. The total electricity demand is expected to grow as the number of EVs increases [1]. The impact of EVs charging on distribution networks has been investigated in the literature. The majority of these studies use synthetic data to assess the impact of the EVs charging load due to limited access to real EVs charging data. In [2–19] data from travel surveys are used to create EVs charging load profiles, assuming that EVs are travelling like conventional internal combustion engine vehicles.

Although EVs adoption is at an early stage, some utilities and aggregators are already collecting information from charging stations. A limited number of EVs pilots exist around the world, allowing some preliminary studies on charging demand profiles. In [20], statistical analysis of 4933 charge events in the Victorian EVs Trial in Australia was performed. Statistical models for charge duration, daily charge frequency, energy consumed, start time of charge event, and time to next charge event were estimated to express the uncertainty of usage patterns due to different user behaviours. Data from the Western Australian Electric Vehicle Trial (2010–2012) were analysed in [21,22], investigating the drivers' recharging behaviours and patterns. In [23], 7704 electric vehicle recharging event data from the SwitchEV trials in the north east of England were used to analyse the recharging patterns of 65 EVs. The results showed that minimal recharging occurred during off peak times. In [24] data from the same project were combined

* Corresponding author.
E-mail address: xydase@gmail.com (E. Xydas).

http://dx.doi.org/10.1016/j.apenergy.2015.10.151
0306-2619/

with low voltage smart meter data from Customer Led Network Revolution (CLNR) project and the impact of the combined demand profile was assessed on three different distribution networks. The results showed that the spatial and temporal diversity of EVs charging demand reduce its impact on those distribution networks. Finally, data from over 580,000 charging sessions and from 2000 non-residential electric vehicle supply equipment's (EVSE) located in Northern California were analysed in [25]. The scope of this analysis was to investigate the potential benefits of smart charging utilising the extracted information regarding the actual trips and customer characteristics.

Monitoring the charging events will inevitably create large volumes of data. These data require effective data mining methods for their analysis in order to extract useful information. In [26–28] various data mining techniques were utilized to address challenges in the energy sector, such as load forecasting and profiling. In [29–31] data mining modelling frameworks were applied to electricity consumption data to support the characterisation of end-user demand profiles.

In this paper, a framework was developed to characterize the EVs charging demand of a geographical area. The technical contributions of this paper are summarised below:

(i) Real EVs charging data from UK were acquired and analysed. The diverse data were organised and classified into attributes. To the authors' best of knowledge, this is the first time that real EVs charging data are presented using this level of detail.
(ii) A comprehensive data cleaning and formatting methodology is presented, developed specifically for dealing with EVs charging data.
(iii) A data mining model was developed to extract the useful information. Three key characteristics of EVs charging demand in a geographical area were investigated using the proposed methodology, namely shape of the typical daily profile, predictability with respect to weather and trend. Clustering, correlation and regression analysis were performed to study each characteristic, using factors to quantify them. Analysing these characteristics resulted in assessing the potential risks and uncertainties which affect the mid-term normal operation of the corresponding distribution network.
(iv) A fuzzy logic decision model was developed that aggregates the three factors into one "risk level" index. The "risk level" index was defined in order to characterize the EVs charging demand, reflecting its potential impact on the energy demand in a geographical area. Areas with high "risk level" values imply a potential risk for the mid-term normal operation of the distribution networks and such analysis could be important for the distribution network operator (DNO). No similar research work that quantifies the mid-term relative risk of the EVs charging demand among different geographical areas independently to their actual corresponding distribution networks was done so far.
(v) Furthermore, this paper fills a gap in the literature related to handling real EVs charging data, by proposing a complete data analysis methodology.

The rest of the paper is organized as follows: Section 2 describes the real EVs charging data analysed. In Section 3 the proposed methodology to characterize the EVs charging demand is illustrated. A case study is presented in Section 4, applying the model on real EVs charging events from UK to study the charging demand characteristics, and assess their potential impact. Finally, conclusions are drawn in Section 5.

2. Data description

EVs charging demand data were obtained from the Plugged-in Midlands (PiM) project (http://www.pluggedinmidlands.co.uk/). The Plugged-in Midlands project, managed by Cenex, is one of the eight 'Plugged-in Places' projects supported by OLEV, the Office for Low Emission Vehicles in the UK. Two datasets were provided by Cenex, with information regarding the charging events and charging stations respectively. The charging events dataset consists of 21,918 charging events from 255 different charging stations and 587 unique EVs drivers. The charging event dataset includes information about the connection/disconnection times and the energy of each charging event for the period of 2012–2013 with event-occurrence granularity. The charging station dataset contains time-independent information regarding the location and technical specifications of all charging points (e.g. the charging power rate). The contents of the two datasets are listed in Tables 1 and 2.

An additional dataset was acquired from the UK Met Office, with information regarding the weather in the Midlands, the geographical area under study. This dataset includes the values of various weather information (e.g. air temperature) with daily granularity for the period of 2012–2013. The weather attributes are listed in Table 3.

3. Methodology

The characterisation framework consists of three models: (i) *Data Pre-processing Model*, (ii) *Data Mining Model* and (iii) *Fuzzy Based Characterisation Model*. The *Data Pre-processing Model* provides data merging, cleaning and formatting to prepare the data

Table 1
Charging event data.

Attribute name	Attribute description
Connection time	Start time of charging event in dd/mm/yyyy hh:mm format
Disconnection time	End time of charging event in dd/mm/yyyy hh:mm format
Energy drawn	Energy demand of charging event in kW h
User	Unique ID for every EVs, e.g. EV1, EV2 etc.
Charging station	Unique ID for every charging station

Table 2
Charging station data.

Attribute name	Attribute description
Charging station	Unique ID for every charging station
Latitude	Latitude of charging station's location
Longitude	Longitude of charging station's location
Road	The road name of charging station's location
Post code	The post code of charging station's location
County	The county name of charging station's location
Location category	e.g. Private Parking, Public Parking etc.
Location subcategory	e.g. Public Car Park, Public On-street etc.
Ownership	e.g. Dealership, Hotel, Train Station
Host	Name of the charging station host
NCR	Whether or not the charging station is registered on the National Charging Registry (NCR) of UK
Manufacturer	The charging station manufacturer
Supplier	The operator of charging station
Charger type	Power rate of charging station in kW
Connector1	Socket Pin Type e.g. 3 Pin, 5 Pin etc.
Connector2	If exists, the second Socket Pin Type
Mounting type	e.g. Ground, Wall, Wall (tethered)