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Development of a decentralized smart charge controller for electric vehicles

Tianxiang Jiang [a], Ghanim Putrus [b,*], Zhiwei Gao [b], Matteo Conti [c], Steve McDonald [a], Gillian Lacey [b]

[a] School of Electrical and Electronic Engineering, Newcastle University, Newcastle Upon Tyne NE1 7RU, UK
[b] Faculty of Engineering and Environment, Northumbria University, Newcastle Upon Tyne NE1 8ST, UK
[c] School of Design, Royal College of Art, London SW7 2EU, UK

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ABSTRACT

Existing commercial battery charging posts for electric vehicles (EV) offer limited controllability and flexibility. These chargers are not designed to allow users to specify important criteria such as desired energy for next trip and waiting time whilst charging. In addition, the charging regime is not set to take into consideration the impact of charging (e.g. rate of charge) on the battery cycle life and the grid supply.

With increased penetration of EVs and distributed generators (DG), complying with grid regulations will become more challenging, e.g. network voltage levels may deviate from the statutory limits. Moreover, as the battery is the most expensive part of an EV, consideration should be given to extending battery life and reduce the effective EV cost. Therefore, there is a need to develop a smart EV charge controller that can meet users' requirements, extend battery cycle life and have minimum impact on the grid supply.

In this paper, a smart controller is proposed which determines the optimal charging current based on grid voltage, battery state of health and user's trip requirements. Models of a typical UK power distribution network and an EV battery (that allows simulation of battery aging process) are developed to investigate the performance of the "smart" charging system. Simulation and experimental results are presented to demonstrate the effectiveness of the proposed controller.

Introduction

Renewable energy and electric vehicles (EV) are intended to replace conventional electricity generation and transport systems, which is expected to result in a significant reduction in greenhouse gas emissions [1,2]. However, the intermittent nature of renewables combined with uncontrolled EV charging can have significant adverse impacts on power networks, e.g. overloading of transformers and voltages exceeding the statutory limits [3–5].

Deilami and Masoum [6,7] suggested a centralized EV charge aggregator that employs "objective functions" to solve voltage sag problems. The aggregator collects information from every charging point (such as EV arrival, departure, charging priority and charging time) and runs the network load flow every 5 min, to generate effective commands to the chargers, in order to avoid exceeding the voltage statutory limits. Practically, this centralized control method has difficulties in responding to frequent changes in grid voltages, especially with high penetration levels of embedded intermittent renewable generation. In addition, it is difficult to identify an individual EV's charging status and its user's needs. As a result, there is a need for a decentralized control strategy to meet the user's requirements without compromising the grid quality of supply.

Singh et al. [8] developed a decentralized controller based on fuzzy systems to realise a real-time EV charging/discharging (V2G) control, where 50% of the EV battery pack energy was reserved for EV use and the rest was used to support ancillary services for the grid (e.g. voltage control). The suggested control strategy aims to support the grid, but does not consider the user's requirements or the battery state of health (SOH).

Battery capacity degradation affects the overall EV cost and range. Therefore, it is important to consider this aspect during charging. Battery capacity loss includes cycle loss and calendar loss [9]. Spotnitz [10] indicated that cycling causes capacity loss at a greater rate than from calendar losses alone. Marra et al. [11] and Lunz et al. [12] concluded that the four main factors that affect the battery cycle life are temperature, state of charge (SOC), charging current (normally presented as "C-rate") and depth of

* Corresponding author. Tel.: +44 (0)191 227 3107.
E-mail addresses: Tianxiang.Jiang@newcastle.ac.uk (T. Jiang), ghanim.putrus@northumbria.ac.uk (G. Putrus).

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discharge (DOD). Battery capacity fading accelerates when it is cycled at high temperature, high SOC, high C-rate and large DOD.

A comparison between the functions of conventional EV charging controllers is presented in Table 1. It can be seen these controllers have limited functionality and do not simultaneously provide a smart control to meet EV user's requirements, prolong EV battery life and support active network operation.

This paper proposes a new EV charging control "concept" and a decentralized real-time smart controller for 3-phase single EV charging that meets all the functions listed in Table 1. The proposed controller may be designed to be part of an on-board or off-board EV charger. The smart controller interacts with the EV, user and network, as shown in Fig. 1. The controller determines a suitable current to charge the EV battery based on information collected from the smart-meter, battery management system (BMS) and user input. As the input data to the smart controller is largely non-linear, Fuzzy Logic (FL) rules, which use linguistic representation to express ambiguous information rather than complex mathematical equations [13], are employed in the proposed charging system.

The paper is organized as follows. Section 'The proposed controller' presents the structure of the proposed controller. In Section 'Modelling of the distribution network', a typical model of a UK 33/0.4 kV distribution network is developed. Section 'Modelling of Lithium-ion Battery' presents a model for a typical EV battery with capacity fading prediction. In Section 'Design of the Fuzzy Logic Controller', the fuzzy system used in the proposed controller is described. A range of smart charging scenarios are simulated and discussed in Section 'Results and Discussion'. Section 'Experimental work' presents details of the experimental laboratory model of the smart charger that was developed to demonstrate the effectiveness of the smart charging. Conclusions are given in Section 'Conclusions'.

The proposed controller

The proposed decentralized controller is intended for a single EV charger (on-board or off-board), where the control strategy is optimized based on the battery status of the specific EV to be charged. A block diagram of the controller is depicted in Fig. 2. The smart controller receives information about the battery state from the BMS (A), user requirements (B) and grid conditions (C). The three signals to the fuzzy logic controller are battery SOH (S_1), user defined charging current (S_2) and grid node voltage (S_3). The output of the controller is the maximum charging current "C-rate", which can be used to set the charging current (in Amperes) based on the battery capacity. The charging current and battery terminal voltage determine the loading on the grid.

Battery Information

For the battery pack of a specific EV to be charged, the information required by the smart controller, such as cycle number and SOC remaining (initial SOC) is obtained from the on-board battery management system (BMS). The battery SOH is defined as a 'measure' which reflects the general condition of a battery and

Table 1
Comparison between EV charging controllers.

Controller	Objectives		
	User's requirements	Network support	Battery life extension
Standard EV charger	Yes	No	No
Centralized aggregator [6,7]	Yes	Partially (not in real-time)	No
Decentralized controller [8]	No	Yes	No

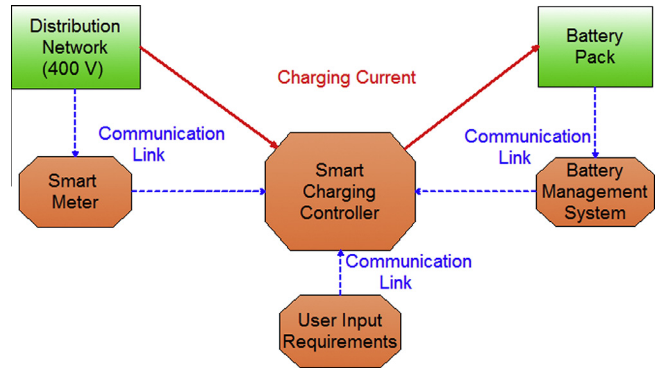

Fig. 1. The smart controller interface links.

its ability to deliver usable capacity in comparison with a fresh battery [14]. In this paper, the battery SOH is described as the difference between the usable capacity and the end of life capacity (usually 80% of the rated capacity [11]) as a percentage of the rated (fresh) capacity%. The proposed controller calculates the SOH based on information received from the BMS with respect to the total number of charge/discharge cycles. Assuming the usable capacity of a fresh battery is 100%, the SOH can be defined as:

$$SOH = 100\% - 80\% - f(cycles) \tag{1}$$

where f is a function of number of charging cycles, and it is obvious that $0\% \leqslant SOH \leqslant 20\%$.

The tests reported by [15] show that the battery usable capacity decreases almost linearly as the charging cycle number increases (assuming constant temperature). The SOH can thus be expressed as:

$$SOH = 20\% - (\Sigma\alpha \times cycle\ number) \tag{2}$$

where the degradation coefficient α changes as the battery cycling conditions vary and is determined from experimental data of battery cycling. Therefore,

$$\alpha_{particular\ \ condition} = \frac{20\%}{cycle\ number_{particular\ \ condition}} \tag{3}$$

In (1)–(3), it is assumed that the BMS can assess the cumulative loss of capacity under different cycling conditions. It is usual to normalise the loss under different conditions into a single equivalent value rated at ½ C and 70% DOD. Therefore, the BMS may be designed to show the cycle life at different cycling conditions according to (3).

The SOC is defined as the percentage of the maximum possible charge that is present in a battery:

$$SOC = \frac{\int idt}{C_{usable}}, \quad 0 \leqslant SOC \leqslant 1 \tag{4}$$

where C_{usable} is the battery usable capacity in ampere hours.

EV user requirements

The EV user requirements are defined in terms of the next journey length and "wait-able" charging period. As mentioned earlier, battery capacity fading accelerates with increasing SOC and DOD [11]. Therefore, charging only the necessary amount of energy required for the next journey can help protect the battery and extend its life. The energy required for the next journey is transferred into the relative SOC_{target} and may be represented as:

$$\Delta SOC = SOC_{target} - SOC_{remain} \quad 0 \leqslant \Delta SOC \leqslant 1 \tag{5}$$

where SOC_{remain} represents the energy left in the battery (before charging starts). This information is provided by the BMS.