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Influence of the temperature on energy management in battery-ultracapacitor electric vehicles

Akif Demircalı [a], Peter Sergeant [b, c], Selim Koroglu [a], Selami Kesler [a], Erkan Öztürk [d, *], Mustafa Tumbek [a]

[a] Dept. Electrical Electronics Engineering, Pamukkale University, 20070, Denizli, Turkey
[b] Dept. Electrical Energy, Systems and Automation, Ghent University, B-9000, Ghent, Belgium
[c] Flanders Make, The Strategic Research Centre for the Manufacturing Industry, Belgium
[d] Dept. Automotive Engineering, Pamukkale University, 20070, Denizli, Turkey

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ABSTRACT

Energy management strategies for an electric vehicle (EV) with multiple power sources have been widely described in literature. The investigated energy sources are batteries, ultracapacitors, fuel cells, flywheels and solar panels. The management strategy decides how to combine two or more sources in an optimal way. However, the behavior of these sources and also the behavior of the electric drives depend on their temperature. Moreover, the temperature can have extreme values in automotive applications and affect the energy management task. In this paper, to investigate the temperature effect on battery/ultracapacitor powered EV, temperature dependent models are presented for these storage components, as well as for the drive train components itself: power electronics and motor. The average motor iron loss and ultracapacitor loss tend to decrease with increasing temperature, while the average motor copper loss and power electronics loss tend to increase with increasing temperature. These two opposing trends cause the total loss of the drive train to have a rather small variation with temperature for the considered EV and in the considered temperature range. By consequence, the energy management strategy of the EV does not have to depend on the temperature in order to obtain maximal efficiency.

1. Introduction

In recent years, there has been an increase in research and practice on electric vehicles (EVs), along with advances in power electronics and processor technologies. A review for internal combustion engine vehicles (ICEV), hybrid electric vehicles (HEV) and all electric vehicles (AEV) is presented in (Tie and Tan, 2013). That paper summarized the construction of power electronic components, energy storage units and management methods. The efficiency of EVs and the subcomponents used has become very important because of the petroleum prices and environmental concerns. Therefore, the energy storage units that affect the efficiency of the vehicle the most and the use of these units together are examined from all the aspects. None of today's energy storage units such as battery, fuel cell (FC), ultracapacitor (UC), flywheel and solar panel are enough to meet all the requirements of the EV (Hu et al., 2015b; Rezzak and Boudjerda, 2016; Trovao and Antunes, 2015). Hence, the use of two or more of these units is an acceptable and common solution. Providing the high-energy density required by the vehicle from the battery and fuel cell, the high-power density from the components such as the flywheel on the ultracapacitor eliminates the disadvantages of the use of the weaker sides of all these components (Hu et al., 2015a). However, the combined use of two energy storage system (ESS) is not a simple matter and requires a good design in all details (Rosario, 2007).

The design and optimization studies about Energy Management Systems (EMSs) for electric vehicles with multiple energy storage units in the literature are quite numerous. It is possible to divide the studies made in this subject into two main groups, rule-based and optimization-based. Rule-based EMSs including classical and fuzzy rule based EMSs are preferred because of their simplicity and real-time ease of implementation (Castaings et al., 2016; Ferreira et al., 2008; Florescu et al., 2015; Rezzak and Boudjerda, 2016; Rosario, 2007). However, rule based methods do not guarantee that the

* Corresponding author.
E-mail addresses: akifdemircali@pau.edu.tr (A. Demircalı), peter.sergeant@ugent.be (P. Sergeant), skoroglu@pau.edu.tr (S. Koroglu), skesler@pau.edu.tr (S. Kesler), erkanozturk@pau.edu.tr (E. Öztürk), mustafatumbek@pau.edu.tr (M. Tumbek).

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most appropriate management is made and there are some difficulties in determining the rules. Optimization-based EMSs aim at optimizing energy management in the framework of established constraints such as energy consumption, carbon emissions, or conservation of the healthy operation of energy storage units used (Hu et al., 2016). In optimization-based EMS, many methods such as genetic algorithm (GA) (Koroglu et al., 2017; Koubaa and Krichen, 2017), particle swarm optimization (PSO) (S.Y. Chen et al., 2015; Z. Chen et al., 2015; Koroglu et al., 2017, 2016; Koubaa and Krichen, 2017; Trovão et al., 2013; Trovao and Antunes, 2015), simulated annealing (SA) (Trovão et al., 2013; Trovao and Antunes, 2015), convex programming (Hu et al., 2016, 2015a, 2015b) and dynamic programming (Wang et al., 2013) are used and better results are obtained compared to rule based EMS. Heuristic optimization methods are highly preferred methods in electric vehicle EMS. Many studies have compared methods such as PSO and SA and conclude that the PSO is slightly better than the others in terms of both accuracy and fast results (Trovao and Antunes, 2015). In a similar research, PSO, GA and a differential evolution algorithm are used and compared for the EMS of a battery-UC powered EV and it is concluded that PSO is a fast and more accurate method (Koroglu et al., 2017). Therefore, PSO is preferred in many studies thanks to its simple structure, fast response and accurate results.

However, these studies usually focus on minimizing the use of fuel or electricity, and some other parameters and equipment that may be important for electric vehicles are neglected or included in a simplest way. For example, almost all of the papers about optimization based EMS use the simplest models of the ESS, not including temperature effect on the component models, mechanical dynamics of the components and converter-inverter-motor specialties. In some studies made in this regard, the temperature-dependent performance changes are included for only one component (Hu et al., 2016). The effect of temperature on the whole drivetrain and on the several vehicle components have not been included in efficiency studies. The literature lacks studies that consider the temperature influence of all components in the drivetrain.

The novelty of this paper is twofold. Firstly, temperature dependent component models are developed for all drive train components: the battery, ultracapacitor, inverter, motor and gearbox. The second novelty is that these component models are integrated in a system level model of the EV, in order to observe the effect of the temperature in these components on the global EMS of the vehicle. The energy management of the vehicle is achieved in two stages. The first stage is to restrict the search space of the optimization method according to conditions of storage devices and power demand of the vehicle. After determination and restriction of the search space, in stage two, power sharing optimization is implemented with PSO. Finally, comparative results and conclusion that present the effect of temperature are given.

This paper is structured as follows. Section 2 presents the temperature dependent component models of the vehicle components and their validation. Section 3 explains the structure of the EMS: how the system level model for the energy management is built up consisting of the several component models from Section 2. Section 4 and Section 5 present the effect of temperature on the components and EMS, respectively. Finally, conclusions are given in Section 6.

2. Temperature dependent component models for battery, ultracapacitors, motor and inverter

2.1. Battery

The battery model is developed according to studies (Chen and Rincón-Mora, 2006; Erdinc et al., 2009; Gao et al., 2002; Lo, 2013) and the datasheet of the used batteries of the designed vehicle. As indicated in those studies, the battery output voltage can be calculated by making a temperature dependent Thévenin equivalent scheme, consisting of the battery open circuit voltage U_{OC}, the battery equivalent internal impedance Z_{eq} and the temperature correction of the battery potential. So, it can be expressed as in Eq. (1).

$$U_{bat} = U_{OC} - i_{bat}{*}Z_{eq} + \Delta E(T) \tag{1}$$

As the value of battery open circuit voltage is strongly dependent on battery SOC, it has to be modelled with empirically determined equations or lookup tables for a specific battery. For the use case in this paper, the U_{OC} of the considered battery can be calculated by interpolating U_{OC} according to the battery SOC. The relation between U_{OC} and SOC can be found empirically or obtained from the datasheet of the battery as shown in Fig. 1.

$\Delta E(T)$ is a potential correction term used to represent the temperature effect on the battery output voltage as described by (Gao et al., 2002). Also, this term is very “battery-specific”. An example of the behavior of $\Delta E(T)$ for the $LiFePO_4$ batteries described in (Lo, 2013) is visualized in Fig. 2.

Also, the battery SOC can be expressed as in Eq. (2) for the simulation process according to ampere count principle.

$$SOC = SOC_{initial} - \int i_{Bat}\, dt \tag{2}$$

2.2. Ultracapacitors

A temperature dependent UC model is developed according to (Shi and Crow, 2008; Vural et al., 2009; Zhang et al., 2016; Zubieta and Bonert, 2000) and datasheets of used UC (Maxwell Technologies, n.d.). The UC equivalent circuit used in this paper is illustrated in Fig. 3, and the equations to obtain the parameters of this equivalent circuit from the datasheet values are presented in Table 1 (Shi and Crow, 2008). The first branch is called the fast-term branch composed of R_f and C_f and represents the charge and discharge characteristics of the UC for the time interval of a few

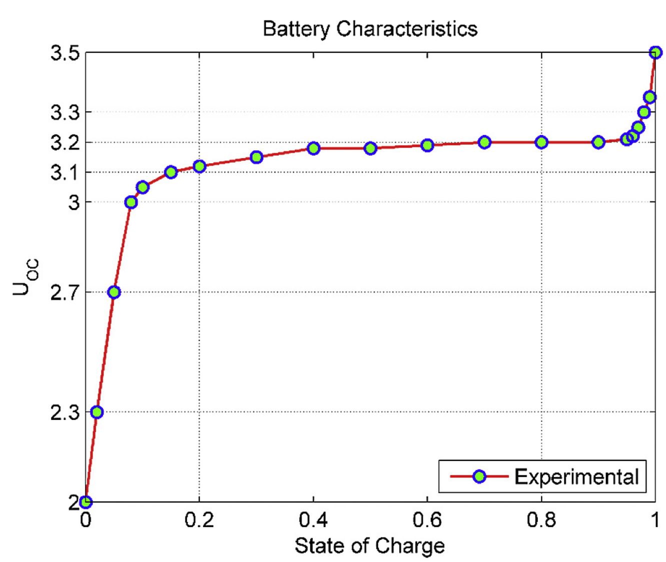

Fig. 1. Experimental curve for the battery open circuit voltage versus battery SOC for $LiFePO_4$ battery.