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Modeling and adaptive control for supercapacitor in automotive applications based on artificial neural networks

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ABSTRACT

The behavior of a supercapacitor is a complex and nonlinear function of its current rate, temperature, chemistry and history, and hence cannot easily be determined. In this study, we use a one-layer feed-forward artificial neural network (ANN), trained using the back-propagation algorithm, to model the behavior of supercapacitors used in automotive applications. Possible improvements of the neural network model using a multilevel approach are discussed. Then, on the basis of this model, a neural controller is developed in order to control the supercapacitor voltage. Simulation results confirmed the accuracy of the model compared to measurements from supercapacitor module power-cycling.

1. Introduction

Electric energy sources have attracted a great deal of attention, especially in the context of the development of Hybrid Electric Vehicles (HEV) and, more recently, Electric Vehicles (EV) for a large number of applications such as advanced, light, fuel-efficient and heavy duty vehicles and cleaner urban transport. These technological innovations rely on a common component, the Energy Storage System (ESS), designed to meet the requirements of each application and enhance on-board energy management (auxiliaries, regenerative braking energy, etc.) [1]. Electrochemical energy storage, such as lithium-ion batteries, fuel cells and supercapacitors, has been identified as a critical enabling technology for these systems.

Supercapacitors are gaining more attention as electrical energy storage elements for renewable energy sources which tend to have a high charge–discharge cycle frequency, and demand high cycle efficiency and good depth-of discharge (DOD) properties. Recently, several researches focused on hybrid ESS system, where the advantages of the high power capabilities of supercapacitors would store the surplus energy that can be combined with the suitability of a high volumetric energy density Li-ion battery that can effectively work in variable high power applications such as EV, fuel cell vehicles and HEV [2].

In such a system, fuel cell or lithium battery is only operating in nearly steady state conditions. However, the supercapacitors are functioning during transient energy delivery or transient energy recovery [3]. The role of the supercapacitor is to supply transient power demand and peak loads required during acceleration and deceleration.

However, current systems present several drawbacks:

There is obviously an acute need for tools able of simulating ESS behavior based on current understanding of the phenomena involved and taking into account the environmental conditions (power profiles and temperature) that affect them strongly [4].

On one hand, it is difficult to build an accurate model for supercapacitor, due to their complex electrochemical characteristics [5]. The dynamic behavior of a supercapacitor is strongly related to the ion mobility of the electrolyte used and the porosity effects of the porous electrodes [6]. On the other hand, we have to ensure that supercapacitor operate in a reliable range and are capable of delivering the required power and energy in a safe way [7].

In literature, many equivalent circuit models have been developed in order to simulate supercapacitor behavior. These models, based on simplification and approximation, remains approximative since it cannot take all nonlinearities occurring inside the supercapacitor into account [8,9]. Recently ANN has brought a new and advancing frontier in power electronics which is already a complex and interdisciplinary technology. Besides, there is no doubt that ANN techniques can solve complex problems which are difficult to solve by traditional methods [10–12].

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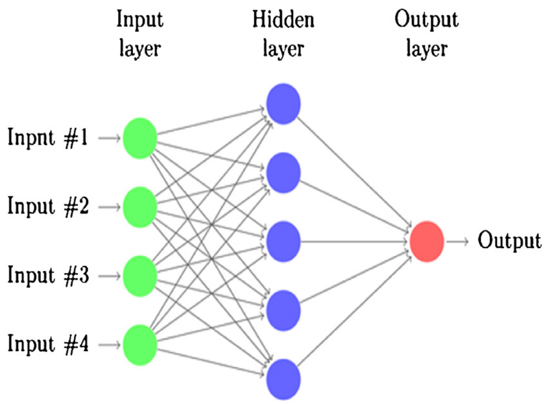

Fig. 1. Artificial neural network with a single hidden layer.

In this work, we aim to model and control the behavior of supercapacitors using a neural network approach. Current knowledge of supercapacitor was then applied in a neural network capable of reproducing nonlinear and complex behavior, to develop a model for analyzing and describing supercapacitor behavior and to control its voltage in a second step. Thus, the supercapacitor modeling, the simulation results and the model validation are presented. Then, we focus on the model improvement using a hierarchical multilevel approach. After that, based on the developed model, we consider the adaptive control of the supercapacitor voltage using an inverse neural controller.

2. Neural network based modeling

Recently, ANNs have been widely used to predict the characteristics and the performances of electrochemical sources such as lithium batteries, fuel cells and supercapacitors [13–15]. Here, we employed this technique to model and control supercapacitor behavior. Neural network modeling was chosen for its simplicity of implementation and the high performance in predicting the behavior of complex systems [16,17]. In this work, we used a multilayer artificial neural network with a single hidden layer (Fig. 1) to model a supercapacitor module. Actually, theoretical works have proven that, even with just one hidden layer, neural network can uniformly approximate any continuous function over a compact domain, provided that neural network has a sufficient number of synaptic connections.

2.1. Experimental data

Actually, to reduce the environmental impact of their fleet, many companies have made investments in researching and testing alternative technologies such as hybrids as well as electric vehicles. Experimental studies were conducted on a supercapacitor module composed of 4 cells connected in series with 3000F/2.7V each. Each cell is equipped with a thermocouple to measure its temperature. The cells in question are commercialized ones and used in a HEV application. The power cycling tests are performed on a Battery Testing System from Digatron provided with specific features for supercapacitor testing. The power bench characteristics are a voltage range of 70 VDC and a maximum current of ±1000 A.

This bench is equipped with an easy used software namely BTS-600 which has the flexibility to program any electrical profile in accordance with a given driving cycle made of engine start, boost and regenerative braking phases (microhybrid electric vehicle operation). The designed profile parameters are the current levels in charge and discharge (±100 mA/F, −300 mA/F), the duration of the pulses and the rest periods, and also the upper and lower limits of the total voltage of the SC module. Moreover, current profile is conceived in order to obtain both cell accelerated aging as well as a possibility to achieve online device characterization according to the IEC standard [18]. During the experiment, in addition to the current, the voltage and the temperature of each cell are acquired.

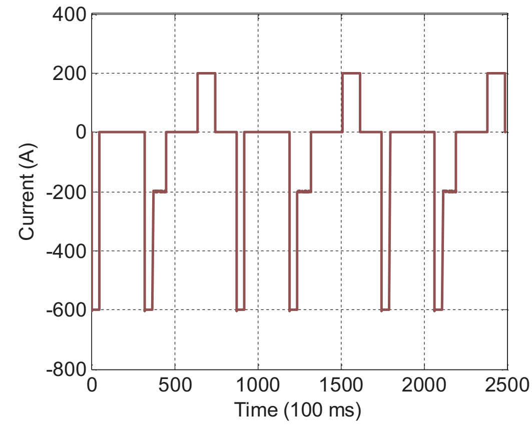

Fig. 2. Measured module current.

The supercapacitors were placed in an isothermal chamber during tests to ensure temperature control. Experiment is carried out at 40 °C. Figs. 2 and 3 represent the current profile applied to the module and the corresponding voltage respectively. These measurements have been used to build a database for the NN-based model training and validation.

2.2. Back propagation algorithm

The back propagation algorithm is a widely used training algorithm for multilayer neural networks. This algorithm is a modified version of the gradient method, designed to minimize the difference between network output and the desired values and has proved its efficiency in updating the network weights [19]. The expression (1) represents the error calculation; e_p:

$$e_p = \frac{1}{2}\sum_{k=1}^{l}\left(y_k^p - y_k^{p^d}\right)^2 \qquad (1)$$

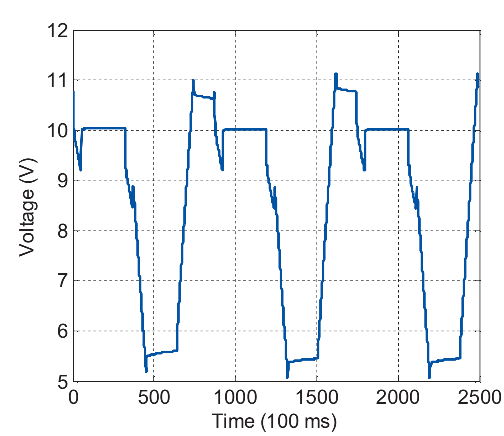

Fig. 3. Measured module voltage.