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State-of-charge estimation of Li-ion batteries using deep neural networks: A machine learning approach

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HIGHLIGHTS

- Deep neural network used to map battery signals directly to SOC.
- Deep neural network self-learns network weights.
- Neural network SOC estimator is shown to be computationally efficient.
- Increased SOC estimation accuracy and robustness by adding noise to training data.
- One deep neural network learns to estimate SOC over many ambient temperatures.

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ABSTRACT

Accurate State of Charge (SOC) estimation is crucial to ensure the safe and reliable operation of Li-ion batteries, which are increasingly being used in Electric Vehicles (EV), grid-tied load-leveling applications as well as manned and unmanned aerial vehicles to name a few applications. In this paper, a novel approach using Deep Feedforward Neural Networks (DNN) is used for battery SOC estimation where battery measurements are directly mapped to SOC. Training data is generated in the lab by applying drive cycle loads at various ambient temperatures to a Li-ion battery so that the battery is exposed to variable dynamics. The DNN's ability to encode the dependencies in time into the network weights and in the process provide accurate estimates of SOC is presented. Moreover, data recorded at ambient temperatures lying between $-20\,^{\circ}\mathrm{C}$ and $25\,^{\circ}\mathrm{C}$ are fed into the DNN during training. Once trained, this single DNN is able to estimate SOC at various ambient temperature conditions. The DNN is validated over many different datasets and achieves a Mean Absolute Error (MAE) of 1.10% over a $25\,^{\circ}\mathrm{C}$ dataset as well as an MAE of 2.17% over a $-20\,^{\circ}\mathrm{C}$ dataset.

1. Introduction

Li-ion batteries are not only heavily used in most portable electronics and Electric Vehicles (EV) but are also used in smart-grid technology for load levelling as well as in newer technologies like Unmanned Aerial Vehicles and passenger drones aimed for medium to short range distances [1]. This can be attributed to many advantages that Li-ion batteries offer over other batteries. These include a high specific energy and energy density which allows electrified vehicles longer electric-only driving range, high cycle life, high Coulombic efficiency (up to 98%) and low self-discharge [2,3]. In 2015, 50% of all nitrogen oxide air pollutants in the world, corresponding to 53 million tonnes of airborne nitrogen oxide emissions, can be attributed to the transportation sector. Furthermore, half of the overall health-related economic cost, estimated to be $865 billion in 2010, is credited to air pollution [4]. Nowadays, some countries are taking proportionate action to counteract these negative effects by banning new petrol and diesel powered vehicles by 2030 or as early as 2025, in the case of Norway. Due to the advantages of the Li-ion batteries outlined above, electrified vehicles powered by Li-ion batteries are currently one of the best ways to mitigate these issues.

A reliable state of charge estimation is required to ensure an accurate gauge of a vehicle's remaining driving range as well as proper balancing of the battery pack [3,5,6]. Due to unpredictable driving habits and the repeated acceleration and deceleration of a vehicle, the battery can be exposed to highly dynamic load demands. As a result of

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these dynamic load demands, SOC estimation is a tedious task. SOC is not an observable quantity, therefore its accurate estimation becomes essential for reliable and safe operation of the vehicle [5,7].

SOC is defined as the remaining charge within the battery and is defined as the ratio of the residual capacity of the battery to its nominal capacity [3]. The relationship between the battery's observable signals to the estimated SOC is a highly non-linear one, varying with temperature and discharge/charge currents [8,9]. Traditionally, the two main estimation methods have used *open circuit voltage* based techniques and *coulomb counting* [7,10]. These methods are known to have their limitations and have been generally displaced by more sophisticated methods. They include Luenberger observer [7,11], adaptive observer [7,12], sliding mode observer [7,13,14], and Kalman filters [15–17]. Typically, in observer methods, the parameters of an equivalent circuit model like resistances and open circuit voltage are fit to observed battery current and voltage data. An estimate is issued by mapping these parameters to SOC. In Kalman filter-based algorithms, it is typically required to linearize around an operating point which can significantly increase computational load. The measured current, voltage and the previously estimated SOC are provided to the algorithm and the filter issues an estimate of SOC at the next time step. These techniques are often tied to some battery model, like a lumped parameter model or an equivalent circuit model which require arduous model identification to adequately represent the non-linear behavior of a battery. In addition, they often require large numbers of parameters or different versions of the model to perform SOC estimation at varying ambient conditions.

Strategies involving classic machine learning algorithms have also been used in the past. The benefit of these types of techniques is that they can be trained with real world data and self-learn SOC estimation without the need for hand-engineered models. However, when neural network were solely used, the results were typically not accurate enough, and therefore required the additional use of Kalman filters or other inference mechanisms to achieve sufficient estimation accuracy. Although some works have used Kalman filters in conjunction with combined battery models or equivalent circuit battery models [18], many other works have also used them in conjunction with NN battery models. In Ref. [19], a trained 2-layer Neural Network (NN) with 30 neurons in the hidden layer estimates terminal voltage within a 4% Root Mean Square (RMS) error. However, to estimate SOC and to further reduce the RMS error to 2%, the NN is used as a battery model in an Extended Kalman Filter (EKF). In Ref. [20], an Extreme Learning Machine is used at a constant ambient temperature of 25 °C. An SOC estimation error of under 1.5% is claimed however this is only achieved in conjunction with a Kalman filter as well. Furthermore, the extreme learning machine is trained on constant discharge pulses hence their performance in transient load demand, experienced in real world scenarios, is unknown. In Ref. [21], a SVM is used with a moving window to increase computational efficiency when modeling the battery; a Mean Absolute Error (MAE) of less than 2% is achieved. However, as is the case for the above works, it achieves this MAE in conjunction with an EKF. In Ref. [22], a load classifying neural network is trained on 12 US06 drive cycles however different neural networks are used for idling, charging and discharging operation. The method achieves an average estimation error of 3.8% or 2.6% when additional filtering is performed. Furthermore, validation is performed on pulse discharge tests hence the method's performance in real world applications is unknown.

More recently, additional works have utilized model-based and machine learning-based approaches for battery SOC estimation. One such approach uses a moving average estimation with a reduced electrochemical model which is able to perform estimation without linearization error and allows for constraints on states like the internal resistance state and Li-ion concentration [23]. In Ref. [24], a fuzzy C-means and subtractive clustering method is used along with a SVM for SOC estimation. The work performed in Ref. [25] builds on the latter fuzzy-SVM approach by using a genetic algorithm-based fuzzy C-means clustering technique with a backpropagation algorithm to estimate SOC and is claimed to outperform classical fuzzy modeling techniques.

Advancements in modern machine learning techniques are accelerating faster than ever before due to constantly improving computing power and increased access to vast pools of data. Nowadays, machine learning algorithms have become deeply entrenched in our lives. They are now the dominant algorithms used for object recognition in images and video sequences, natural language processing on smartphones and predictive analytics in many industries, to name a few [26].

This work showcases how a machine learning technique like Feedforward Neural Networks (FNN) as well as Deep Feedforward Neural Networks (DNN), can accurately estimate SOC without the help of Kalman filters or any other inference methods. Specifically, this work contributes the following novelties. (1)A DNN can map observable signals from the battery like voltage, current and temperature directly to the battery SOC, avoiding additional filters and estimation algorithms like Kalman filters used in traditional systems. (2)The DNN can self-learn its own weights by using learning algorithms like gradient descent. This is markedly different than incumbent techniques like lumped parameter models, equivalent circuit or electrochemical models which require a great deal of time to hand-engineer and parameterize. (3)It will be shown that one DNN can learn to estimate SOC at different ambient temperature conditions. This is beneficial since traditional estimation techniques must use different models or different look-up tables for estimation at different ambient temperatures.

After a brief introduction, the second section will discuss the deep neural networks constructed in this work. In the third section, the experimental apparatus for the battery testing and data logging is described. In the fourth section, the performance of the DNN is tested with many validation datasets recorded at constant and at varying ambient temperatures.

2. Deep neural networks for SOC estimation

There are many examples where deep learning architectures have made significant improvements over conventional algorithms. In 2012, AlexNet, a deep convolutional neural network won the ImageNet competition where teams are tasked with classifying over 1 million high resolution images in 1000 different categories. AlexNet achieved a top-5 error rate of 15.3% compared to a more traditional model taking second place with a top-5 error of 26.2% [27]. Recently, Microsoft Research's deep learning algorithm, called a deep residual network, won the 2015 ImageNet challenge with an error rate of 3.57% which even surpasses human level accuracy valued at 5.1% [28].

Traditional machine learning techniques contain no more than one or two layers of non-linear and linear transformations [29]. With the advent of faster computational power and an abundance of available real world data, deeper architectures were investigated which, in many cases, allowed researchers to make striking improvements in many applications [27,30–33].

Feedforward neural networks, whose 2-layer and multi-layer DNN architectures are shown in Fig. 1, can, in principle, model any non-linear system by mapping the observables to a desired output. Once trained offline, FNN and DNN offer fast computational speeds online since they are composed of a series of matrix multiplications, as opposed to other strategies which can contain computationally intensive calculations like partial differentials equations. When FNN and DNN are applied for SOC estimation, a typical dataset that is used to train the networks is defined by $D = \{(\psi(1), SOC(1)^*), (\psi(2), SOC(2)^*), ..., (\psi(\tau), SOC(\tau)^*)\}$, where $SOC(t)^*$ and $\psi(t)$ are the ideal state-of-charge value and the vector of inputs at time step *t*, respectively. The current measurement used to determine the ideal $SOC(t)^*$ is described in more detail in the next section of this paper. The vector of inputs is defined as $\psi(t) = [V(t), T(t), I_{avg}(t), V_{avg}(t)]$ where $V(t)$, $T(t)$, $I_{avg}(t)$ and $V_{avg}(t)$ represent the voltage, temperature, average current and average voltage of the battery at time step *t*. The average current and voltage are both calculated over ξ precedent time steps, which ranged from 50 to 400 time steps. This is not to be confused with the total dataset time span defined by τ, where $\xi < \tau$. Many different types of inputs