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RESEARCH ARTICLE OPEN ACCESS

State-of-Charge Estimation of the Panasonic 18650PF Li-ion Cell using Deep Learning Models and Algorithms with Adaptive Learning Rates

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ABSTRACT
This article presents a novel empirical study for the estimation of the State-of-Charge (SOC) of the Panasonic 18650PF lithium-ion (Li-ion) cell using deep learning models and algorithms with adaptive learning rates. Specifically, we model a vehicle drive cycle designed for training neural networks. Our results suggest that the choice of the optimization algorithm affects the performance of the model and that a Deep Forward Network (DFN) with four hidden layers is the model of optimal capacity when considering 256 units per layer. This optimal DFN is able to estimate the SOC of the 18650PF Li-ion cell with an error smaller than 0.12 % over a 25^{o} C dataset using the Adam optimization algorithm.
Keywords **-** Deep Learning, Electrical Energy Storage, Li-ion battery, State-of-Charge.

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I. INTRODUCTION

In the last decade, government, industry and academia have given great importance to the electrification of the transport system, motivated by the need to reduce the emission of greenhouse gases. Hybrid electric vehicles, such as the Toyota Prius, or fully electric vehicles, such as the various Tesla models, the Nissan Leaf and the Chevy Bolt, are successful cases in the USA. The United Kingdom took a bold step in this direction in 2018 [1], [2].

The advancement of Electrical Energy Storage (EES) technologies enabled the emergence of the iPod, smartphones and tablets with lithium-ion (li-ion) batteries. Also, EES will be one of the critical components of the new electricity grid, given the intermittent nature of renewable energy sources [3]. EES systems are necessary even when renewable sources are connected to the grid, because it is necessary to smooth the energy supply. For example, the EES of a building or factory can be charged during hours of reduced demand and supply/supplement energy demand during peak hours.

EES technology consists of the process of converting a form of energy (almost always electrical) to a form of storable energy, which can be converted into electrical energy when necessary.

EES has the following functions: to assist in meeting the maximum electrical load demands, to provide time-varying energy management, to relieve the intermittency of renewable energy generation, to improve energy quality/reliability, to serve remote loads and vehicles, to support the realization of smart grids, improve the management of distributed/standby power generation and reduce the import of electricity during peak demand periods [4].

The efficient use of the Li-ion battery requires the supervision of a Battery Management System (BMS), as it is necessary that the battery operates under appropriate conditions of temperature and State-of-Charge (SOC). The BMS has to estimate, in real-time, the amount of energy stored in a given system, such as a battery pack of a Electric Vehicle (EV). Such a task is not trivial, since it is not possible to directly measure the amount of energy stored in the system. In fact, the estimation of SOC is probably one of the biggest challenges in the field of battery research [5].

For instance, SOC can be measured using the Coulomb counting method given by (1)[1]

$$SOC = SOC_0 - \int I_{bat}\, dt/Q_n \qquad (1)$$

where SOC_0 is the initial value of SOC, I_{bat} is the battery current and Q_n is the nominal capacity in Ah. It should be noted that the cell temperature produces deleterious effects on the open circuit voltage, internal resistance and available capacity and can

[1] The lower and upper limits of the integral in (1) are 0 and *t*, respectively, where *t* denotes time.

also lead to a rapid degradation of the battery if it operates above a given temperature threshold. Therefore, the modeling of the battery is of paramount importance, since it will be used by the BMS to manage the operation of the battery [6].

The recent literature suggests that the machine learning approach, based on deep learning algorithms is the state of the art in the area of SOC estimation [7], [8].

One of the great challenges in deep learning is the optimization of the neural network. Although the Stochastic Gradient Descent (SGD) algorithm (and its variants) is very popular, a learning rate too small leads to painfully slow convergence, while a learning rate too high can destabilize the algorithm, causing oscillations or divergence [9].

On the other hand, we have at our disposal algorithms with adaptive learning rates such as AdaGrad, RMSProp, and Adam[2].

This work uses Deep Forward Networks (DFN) or MultiLayer Perceptrons (MLP) as baseline models. We investigate the effect of choosing the optimization algorithm on the performance of the deep learning models, especially with regard to the SOC estimate of a lithium-ion cell. The questions we ask are: a) which optimization algorithm should we choose? b) Which DFN offers the optimal capacity[3]?

We model a vehicle drive cycle designed for training neural networks which were applied to a Panasonic 18650PF Li-ion cell [10]. More specifically, we compare the performance of the following optimization algorithms for training deep models: SGD, AdaGrad, RMSProp, and Adam (these last three use methods that adapt the learning rate parameter of the training algorithm).

The issue of regularization (parameter norm penalties, early stopping, dropout, etc.) is outside the scope of this paper.

The remainder of the work is organized as follows. Section II presents the state of the art and trends in Li-ion battery SOC estimation. Section III presents our experimental results. Finally, section IV presents our conclusions.

II. STATE OF THE ART AND TRENDS IN LI-ION BATTERY ESTIMATION

Energy storage acts as a mediator between variable loads and variable sources.

Hannan et al. [11] present a detailed taxonomy of the types of energy storage systems taking into account the form of energy storage and construction materials: mechanical, electrochemical (rechargeable and flow batteries), chemical, electrical (ultracapacitor or superconducting magnetic coil), thermal and hybrid. Li-ion battery technology has attracted the attention of industry and academia for the past decade. This is mainly due to the fact that Li-ion batteries offer more energy, higher power density, higher efficiency and lower self-discharge rate than other battery technologies such as NiCd, NiMH, etc.

There are two methods of battery modeling: i) model-driven and ii) data-driven (based on data that is collected from the device) [12].

Electrothermal models, which belong to the category of model-driven methods, are commonly classified as: i) electrochemical or ii) based on Equivalent Circuit Models (ECM).

Electrochemical models are based on partial differential equations and are able to represent thermal effects more accurately than ECM. However, the first class of models requires detailed knowledge of proprietary parameters of the battery manufacturer: cell area, electrode porosity, material density, electrolyte characteristics, thermal conductivity, etc. This difficulty can be eliminated by characterizing the battery using a thermal camera and thermocouples. But this solution is expensive, time consuming and introduces other challenges such as the implementation of dry air purge systems, ventilation, security, air and water supply, etc. Electrochemical models demand the use of intensive computing systems.

On the other hand, the ECM-based approach has been used for computational/numerical analysis of batteries. In this case, the objective is to develop an electrical model that represents the electrochemical phenomenon existing in the cell. The level of complexity of the model is the result of a compromise between precision and computational effort. Note that an extremely complex and accurate ECM may be unsuitable for application in embedded systems.

Estimating the SOC of lithium ion cells in a BMS by means of deep learning offers at least two significant advantages over model driven approaches, namely: i) neural networks are able to estimate the non linear functional dependence that exists between voltage, current and temperature (observable quantities) and unobservable quantities, such as SOC, with great precision and ii) the problem of identifying ECM parameters is avoided [7].

[2] Chapter 8 of reference [9] presents a brief, but very instructive, review of such algorithms.

[3] In deep learning, the number of learnable parameters in a model is often referred to as the model's capacity (determined by the number of layers and the number of units per layer) [9].

III. EXPERIMENTAL RESULTS

We selected the Panasonic 18650PF Li-ion Battery Data of [10]. This dataset contains a series of ten drive cycles: Cycle 1, Cycle 2, Cycle 3, Cycle 4, US06, HWFTa, HWFTb, UDDS, LA92, and Neural Network (NN). Cycles 1-4 consist of a random mix of US06, HWFET, UDDS, LA92, and Neural Network drive cycles. The drive cycle power profile is calculated from measurement for an electric Ford F150 truck with a 35kWh battery pack scaled for a single 18650PF cell.

We consider only the tests at the temperature of 25^{o} C for the NN drive cycle, which combines portions of US06 and LA92 drive cycles, and was designed to have some additional dynamics which are useful for training neural networks. Note that the objective of this paper is not to assess the performance of the DFN models at different temperatures, but to empirically investigate the question of stochastic optimization in the context of the problem of SOC estimation with deep neural nets.

For instance, Fig. 1 shows the following 2.9 Ah Panasonic 18650PF Li-ion cell characteristic curves:

- temperature (^{o} C) vs. SOC (%);
- amp-hours discharged vs. time (minutes);
- voltage (V) vs. time (minutes);
- current (A) vs. time (minutes);
- temperature (^{o} C) vs. time (minutes), and;
- voltage (V) vs. SOC (%).

We applied feature normalization on the input data using the formula

$$\boldsymbol{x}_{\text{normalized}} = (\boldsymbol{x} - \mu_x)/\sigma_x \qquad (2)$$

where μ_x and σ_x denote the mean and standard deviation of $\boldsymbol{x}$.

We divided the NN dataset into training and validations sets. The validation error is estimated by taking the average validation error across $K = 4$ trials. We use a simple, but popular solution, called K-fold cross-validaton, which consists of splitting the available training data into two partitions (training and validation), instantiating K identical models, for each fold $k \in \{1; 2; \ldots, K\}$, and training each one on the training partitions, while evaluating on the validation partition. The validation score for the model used is then the average of the K validation scores obtained. It is usual to use about 80% of the data for the training set, and 20% for the validation set. Note that the validation scores may have a high variance with regard to the validation split. Therefore, K-fold cross-validaton help us improve the reliability when evaluating the generalization power of the model [9].

We use Mean Absolute Error (MAE) and Mean Squared Error (MSE) as performance metrics for the generalization (test) errors. After the validation phase using K-fold cross-validaton, the DFN model is trained using the entire training data and its performance is evaluated against an unseen test set. This the test phase (final phase).

The features of the input layer are: voltage, current, and temperature. We vary the depth of the models, using DFN with two to five hidden layers, in order to assess the effect of depth on generalization power, each hidden layer having 256 units. We used the REctified Linear Unit (Relu) activation function, given by

$$g(z) = \max(0, z) \qquad (3)$$

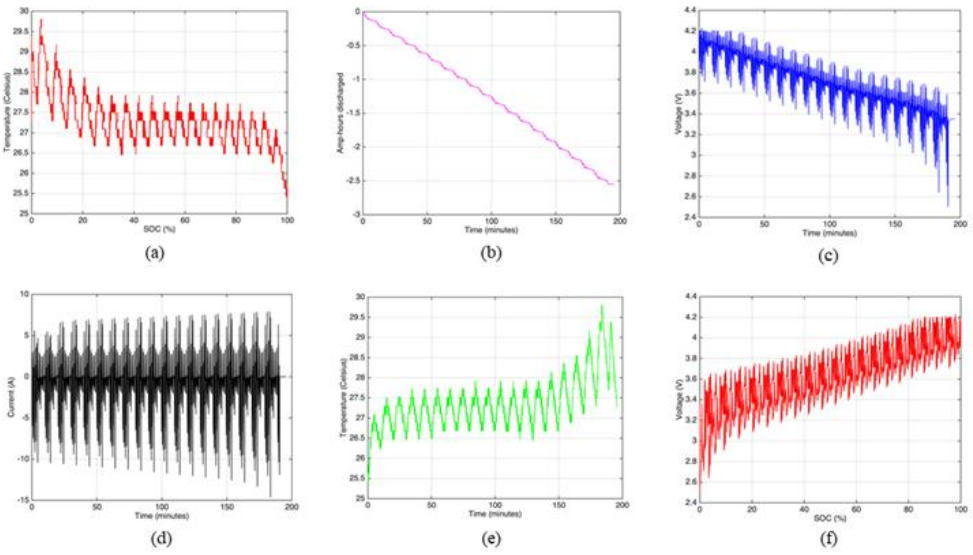

Figure 1: in (a), (b), (c), (d), (e), and (f) we have: temperature (^{o} C) vs. SOC (%), amp-hours discharged vs. time (minutes), voltage (V) vs. time (minutes), current (A) vs. time (minutes), temperature (^{o} C) vs. time (minutes), and voltage (V) vs. SOC (%), respectively.

Tables 1 and 2 show the MAE and MSE, respectively, for the SOC estimates obtained with SGD, AdaGrad, RMSProp, and Adam optimizers. Fig. 2 shows the learning curves (MAE and loss function) of the training phase for the DFN with four hidden layers using the Adam algorithm.

The results of Tables 1 and 2 show that:

- the choice of the optimization algorithm must be made on a case-by-case basis. Although the family of algorithms with adaptive learning rates (AdaGrad, RMSProp, and Adam in this paper) has become very popular in the deep learning community nowadays, one can not claim, a priori, that a given optimization algorithm is the best algorithm. For instance, the results obtained for the DFN with four hidden layers and the SGD algorihtm are better than those obtained for AdaGrad and RMSProp;
- the choice of the optimization algorithm affects the model performance;
- the DFN with four hidden layers is able to estimate the SOC with a MAE of 0.21% and MSE of 0.11% (best results) using Adam, being, therefore, the model of optimal capacity when considering 256 units per layer.

It should be noted that we do not perform ensemble-average, as we are dealing with a real dataset, i. e., we just have access to one realization of the data-generating process.

IV. CONCLUSION

We present a preliminary empirical study on the impact of the optimization algorithm on the performance of the deep learning model, in the context of the estimation of the SOC of a Li-ion battery. For this, we used the Panasonic 18650PF Li-ion Battery Data [10].

Our results indicate (for the 18650PF Li-ion cell) that: i) the choice of the optimization algorithm must be made on a case-by-case basis, ii) the choice of the optimization algorithm affects the model performance, iii) the DFN with four hidden layers (256 units per layer) is able to estimate the SOC with with a MAE of 0.21% and MSE of 0.11% using the Adam optimizer, being, therefore, the model of optimal capacity.

Table 1: MAE vs. optimization algorithms.

Optimizer	MAE (%) 2 hidden layers	MAE (%) 3 hidden layers	MAE (%) 4 hidden layers	MAE (%) 5 hidden layers
SGD	0.32	0.45	0.32	0.50
AdaGrad	0.84	0.63	0.53	0.49
RMSProp	0.41	0.67	0.56	0.32
Adam	0.46	0.26	0.21	0.22

Table 2: MSE vs. optimization algorithms.

Optimizer	MSE (%) 2 hidden layers	MSE (%) 3 hidden layers	MSE (%) 4 hidden layers	MSE (%) 5 hidden layers
SGD	0.25	0.42	0.25	0.51
AdaGrad	1.49	0.85	0.60	0.52
RMSProp	0.37	0.75	0.56	0.29
Adam	0.41	0.14	0.11	0.13

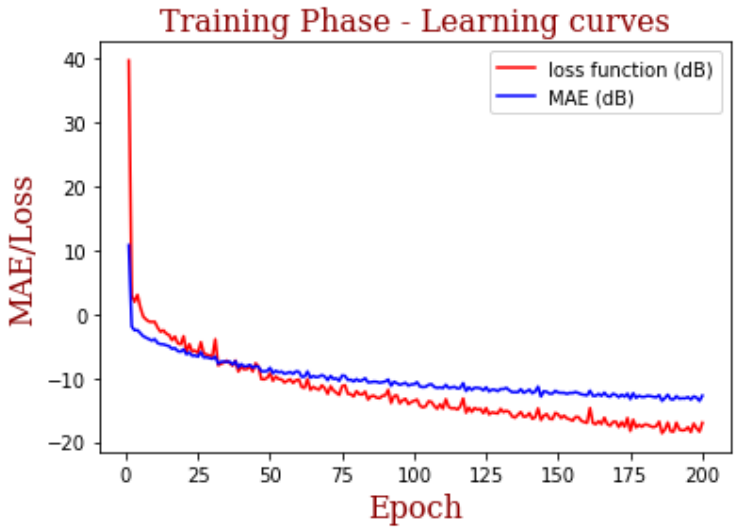

Figure 2. Learning curves of the training phase.

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