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Hybrid Particle Swarm and Gravitational Search Optimization for Intelligent Battery Health Estimation

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***Abstract*— This paper presents a novel hybrid optimization framework for data-driven estimation of the state of health (SoH) of lithium-ion batteries (LIBs). Existing data-driven SoH estimation methods struggle to select suitable model hyperparameters that consider capacity regeneration phenomena and to identify meaningful data samples from LIB parameters. The specific contribution to this research lies in the integrated optimization strategy, which bridges the limitations mentioned. The dataset has 31 features, comprising MIT-Stanford lithium-ion battery profiles. It employs an intelligent hybrid approach that combines the gravitational search algorithm (GSA) with particle swarm optimization (PSO) to fine-tune recurrent neural network (RNN) parameters, such as the hidden layer neurons and learning rate. The combined GSA and PSO algorithms integrated with RNN improve the SoH estimation accuracy through better search efficiency and faster convergence. The 31 LIB parameter samples are closely linked to capacity degradation and are well-suited to form the data framework. The proposed model demonstrates high accuracy in SoH estimation, particularly when applied to cell c33 from MIT-Stanford lithium-ion battery profiles. Results show that the RNN optimized with the GSA-PSO algorithm for the c33 dataset achieved a mean squared error (MSE) of 1.30×10^{-8}, a root mean square error (RMSE) of approximately 0.0142, and a mean absolute percentage error (MAPE) of 0.0096.**

Keywords—Lithium-ion battery, state of health, data-driven, recurrent neural network, optimization

I. Introduction

Issues related to climate change and the rapid growth of lithium-ion battery (LIB) technology, which features characteristics like low self-discharge rate, low maintenance, high energy density, and lightweight design, have increased the popularity of LIBs in various applications, including electric vehicles (EVs) [1]. However, for LIBs to advance, it is essential to accurately assess performance deterioration. Nonetheless, accurately identifying LIB performance degradation is necessary for their continued advancement. Determining the state of health (SoH) of EV batteries is a significant challenge for EV owners, as their condition worsens over time [2]. Additionally, LIB fatigue could lead to explosions or fires if not handled carefully. Monitoring the SoH and controlling the lifespan of LIBs are therefore crucial responsibilities for the battery management systems (BMS) in the future.

Throughout its expected lifespan, the SoH, which frequently displays power and capacity loss, represents the health of the LIB [3]. While LIB capacity declines with decreasing energy, LIB power declines with increasing internal resistance (IR) with aging [4]. Determining SoH in real time is not feasible since LIB deterioration impacts both capacity and power decay. The SoH can currently be found using IR and capacity, which is a simple and appropriate method. Because the LIB needs to be completely charged and drained, capacity estimation takes time. Furthermore, because of its modest IR, the accuracy of EV battery parameter estimation is relatively low [5].

The SoH can be estimated using model-based methods such as empirical models (EM) and equivalent circuit models (ECM) [6]. The model-based methods are used to assess the LIB's health by examining the complex electrochemical process taking place inside the LIB. Although the performance of LIBs varies under diverse operating conditions, an ECM tries to capture the electrical behaviour of the LIBs using resistors, capacitors, etc., and then varies or tunes the values of the circuit elements using several filter techniques, such as a particle filter or Kalman filter. The EM predicts the SoH by illustrating the relationship between the LIB health factors and SoH [7]. Additionally, it is investigated that the ECM model exhibits notable error rates when noise and environmental factors are present [8]. However, to accomplish accurate SoH estimation outputs of the LIB, a considerable amount of data is required to depict its chemical features perfectly.

Since data-driven methodologies rely on actual historical data rather than mathematical models, they are currently widely used by researchers worldwide [9]. With the correct quantity of data, developing a data-driven model is easier. The data-driven model may be created with SoH and RUL by utilizing various LIB parameters from various operational profiles, including capacity, impedance, voltage, time, etc. For instance, a way for calculating SoH using the relevance vector regression (RVR) technique was proposed by Zheng and Fang [10]. Although the data framework was created using capacity data that provided acceptable error metrics, the results might be further enhanced by using more LIB parameters and related features. Three data-driven models for the SoH estimate framework were presented by Li et al [11]. A crucial feature selection process was performed, considering time, voltage, and current. Nonetheless, the unsatisfactory SoH estimation accuracy might have resulted from a poor choice of model parameters. Li et al. [12] used ant lion optimization (ALO) to predict the health of LIB using an SVR model. The generality of the suggested model was compromised since a small number of LIB datasets from the NASA database were used in the study without being validated.

The estimation accuracy from the previous works was deemed satisfactory under the associated constraints. However, the challenges with obtaining and critically evaluating the LIB