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# Lithium-Ion Battery Charging: A Review of Optimal Techniques and Practices

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**A B S T R A C T**

Electric vehicles (EVs) are currently being emphasized as a sustainable form of transportation because of their potential to lower carbon emissions and dependency on fossil fuels. Because of their high energy density and small size, lithium-ion batteries are used in the majority of EVs. But as time goes on, these batteries have a tendency to deteriorate, which reduces their effectiveness and range. Performance is impacted by this aging process, but it also raises questions about battery lifespan, replacement prices, and the environmental effects of battery disposal. This paper reviews two optimization techniques designed to enhance the fast charging of lithium-ion batteries while preserving battery health. The first technique introduces a leader–followers framework for lithium-ion battery pack charging, combining offline scheduling with online regulation to ensure safe and efficient state-of-charge management across cells. The second technique implements the Cuckoo Optimization Algorithm to improve lithium-ion battery charging performance, achieving significant reductions in both charging time and energy losses. This review highlights the potential of these methodologies to accelerate the adoption of EVs by advancing the efficiency and effectiveness of fast charging technologies.

Keywords: Electric Vehicles (EVs), Lithium-Ion Batteries, Fast Charging, Leader–Followers Framework, Cuckoo Optimization Algorithm, Charging Time, Battery Degradation.

## 1. Introduction

In recent years, electric vehicles (EVs) have increasingly become the future of transportation, largely due to their reliance on induction motors. EVs are often powered by lithium-ion (Li-ion) batteries, which work on the basis of electrochemical potential, or a metal's propensity to lose electrons. Since lithium in particular has a high propensity to leak electrons, it is the perfect material for electric vehicles' effective energy supply and storage.

Lithium-ion batteries' (LIBs') short lifespan poses a serious problem for energy storage systems and electric vehicles (EVs), frequently resulting in early disposal and a greater environmental effect. Reduced operating life is caused by a number of factors, including material deterioration, incorrect charging procedures, and insufficient heat control. Research is concentrating on battery management systems (BMS), predictive maintenance, and creative manufacturing methods to address these issues. In order to increase battery longevity and efficiency, this study examines these tactics, paying particular attention to optimizing SOH monitoring and incorporating cutting-edge technologies[1]. Among others, the BEVs have viewed prosperous development due to the high maturity of techniques in addition to the zero-emission capability. There chargeable battery is one of the vital components of BEVs. [4]. Cell balancing methods can be categorized into two main methods, namely, dissipative and non-dissipative methods [5].

A battery pack consists of individual cells, which are organized into modules made of cells connected in series/parallel [3]. Variations in the parameters of individual battery cells, such as capacity mismatch, impedance, and operating temperature, are deemed to expand throughout the life of the device [3]. These differences may result in uneven charging and discharging, which could reduce the lifespan and performance of the battery as a whole. Effective cell balancing strategies must be used to reduce these problems, guaranteeing that every cell functions at its best and raising the battery pack's total efficiency. A more sustainable transportation future can be achieved by continuously monitoring and controlling these factors, which can also greatly increase the safety and dependability of battery systems in electric cars.

Reprocessing the retired EV batteries include the offline SOH estimation for the classification, disassembling and repacking. Therefore, developing the rapid and simple SOH test and evaluation technology is essential for economical and environmentally friendly applications of EVs in practice. [2]. Lithium-ion battery (LIB) performance, safety, and lifetime are all impacted by fast charging, which is determined by a number of important factors: **1. Transfer of Charges:** As lithium ions flow through the electrodes, cracks develop, thereby decreasing capacity and fast-charging ability. **2. SEI Growth:** Lithium-ion loss f rom excessive SEI layer growth on the anode reduces battery performance and capacity. **3. Li Plating:** The anode's capacity is decreased and the risk of short circuits and thermal runaway is increased due to lithium plating brought on by high currents or low temperatures. **4. Cell-to-Cell**

**Variations:** Disparities in a battery pack's cell properties lead to uneven charging, which impairs longevity and performance. **5. Temperature Gradients:** High temperatures accelerate deterioration, whereas low temperatures encourage lithium plating. Extreme temperatures reduce efficiency [6].

While State of Health (SOH) calculates battery deterioration over time, State of Charge (SOC) shows the battery's remaining capacity. For battery management systems (BMS) to guarantee the safe and efficient functioning of electric vehicles (EVs), accurate estimate of these parameters is essential.SOC Estimation: data-driven techniques (e.g., support vector regression, neural networks) and model-based techniques (e.g., Kalman filters, EECMs). Methods for estimating SOH include data-driven approaches (such extreme learning machines), model-based approaches, and differential approaches (ICA/DVA) [7].

## 2. Methodologies

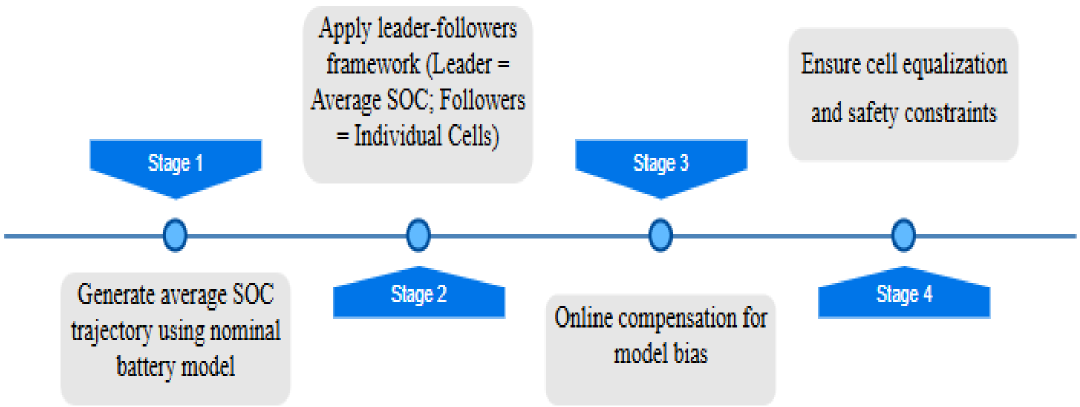
The paper investigates two different approaches:

### *2.1 Distributed Average Tracking Approach (Ouyang et al., 2020) [9]*

The distributed control framework integrates a leader-follower structure for battery pack management, where each cell tracks an optimal state-of-charge (SOC) trajectory. This method enables individual cell equalization and compensates for model bias through online regulation, significantly reducing computational complexity. However, its scalability and increasing complexity with larger battery packs remain a challenge.

The flowchart outlines a control strategy for a battery management system (BMS) designed to ensure safe and efficient operation of a battery pack. It begins by generating an average state of charge (SOC) trajectory using a nominal battery model, which serves as a reference for the entire battery pack. A leader-followers framework is then implemented to coordinate the charging/discharging of individual cells within the battery pack, with the average SOC trajectory acting as the leader.

**Flowchart 1:** Control strategy for a battery management system (BMS) designed to ensure safe and efficient operation of a battery pack.




To address potential discrepancies between the model predictions and the real-world behavior of the battery pack, the system incorporates online model compensation. This feature continuously monitors the actual performance of the battery pack and adjusts the control strategy accordingly, ensuring its effectiveness even in the presence of model uncertainties.

Furthermore, the control strategy is designed to maintain cell equalization and adhere to safety constraints. By preventing excessive differences in SOC between individual cells and ensuring that maximum charging/discharging rates and temperature limits are not exceeded, the control strategy contributes to the safe and reliable operation of the battery pack.

### *2.2 Cuckoo Optimization Algorithm (Makeen et al., 2020) [8]*

The COA employs a multi-stage charging model with the RC second-order transient model to minimize energy consumption and charging time. It leverages an intelligent optimization method that outperforms traditional CCCV methods, reducing energy losses by over 10% and charging time by nearly 22%. While COA is practical for real-time application, it is particularly suited to polymer lithium-ion batteries, limiting its broad applicability ().

The flowchart outlines a process for optimizing battery charging using the Cuckoo Optimization Algorithm (COA). A fitness function is defined to evaluate the performance of different charging methods, considering both energy loss and charging time. Using a Resistance-Capacitance (RC) second-order model, the COA, a metaheuristic optimization algorithm influenced by cuckoo behavior, is then used to determine the ideal charging settings for a multi-stage charging technique.

**Flowchart 2:** Optimizing battery charging using the Cuckoo Optimization Algorithm (COA).


The optimized charging technique is put into practice, and its effectiveness is evaluated and contrasted with that of the widely utilized Constant Current Constant Voltage (CCCV) technique. This comparison makes it possible to evaluate how well the improved charging technique works in terms of charging time and energy loss.

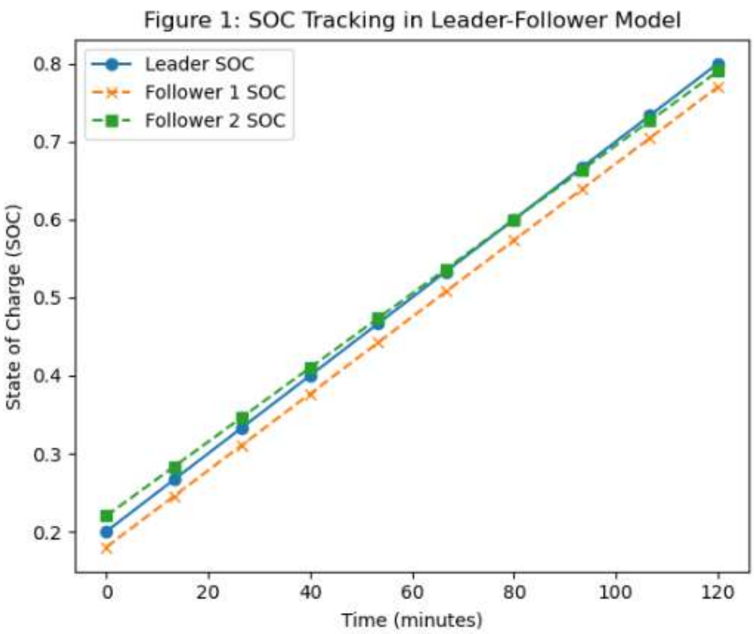
The process concludes with the identification of the optimized charging method and its performance comparison to the CCCV method. This provides valuable insights into potential improvements in battery charging efficiency and can contribute to the development of more advanced battery management strategies.

## 3. Results and Discussion:

This section presents the findings of the comparative study of three fast-charging approaches: distributed leader-follower control, and the Cuckoo Optimization Algorithm (COA). The discussion focuses on their effectiveness in terms of charging time, energy efficiency, degradation control, scalability, and real-time adaptability.

### *3.1 SOC Equalization and Scalability in Battery Packs*

The leader-follower control strategy (Ouyang et al., 2020) performs well in managing battery packs by distributing the charge load across individual cells and tracking a shared SOC trajectory. This method ensures that all cells reach similar SOC levels, achieving equalization, as shown in Figure 1. Simulations of a 12-cell pack confirm that the SOC deviation between cells was kept under 5%. However, as the number of cells increases, the computational burden grows significantly, challenging its scalability. Nevertheless, this framework maintains safety constraints, preventing overheating and overcharging issues.



### *3.2 COA's Real-Time Adaptability and Energy Savings*

The COA method (Makeen et al., 2020) demonstrates excellent real-time capability and energy efficiency. Using hierarchical (HT) and conditional random (CRT) techniques, it reduces charging times by 18.1% and 22.45%, respectively, compared to CCCV, as shown in Figure 2. Additionally, COA achieves up to 10.41% energy savings, benefiting from its multi-stage charging process. However, this algorithm is primarily designed for polymer lithium-ion batteries, limiting its use with other battery chemistries. Expanding its applicability to batteries such as NCM or LFP would improve its versatility.

| **Metric** | **Leader-Follower Distributed Control** | **Cuckoo Optimization Algorithm (COA)** |
|---|---|---|
| **Charging Time** | Comparable to CCCV | 22.45% faster (CRT) |
| **Energy Efficiency** | Not a primary focus | 10.41% savings |
| **Degradation Control** | Moderate; ensures cell equalization | Not the main focus |
| **Real-Time Capability** | Partial (distributed control framework) | Fully real-time adaptable |
| **Scalability** | Effective for small to mid-sized packs | Restricted to specific chemistries |

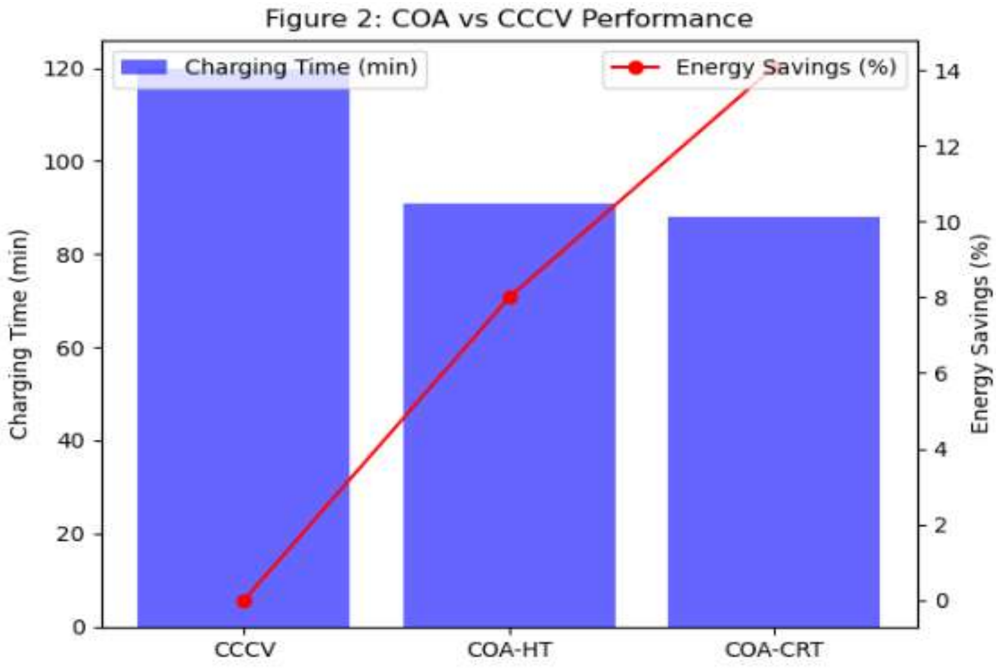



***Figure 5: Comparison table between Leader-Follower Distributed Control, Cuckoo Optimization Algorithm (COA)***

The analysis reveals that the leader-follower approach is highly effective for battery pack management by ensuring SOC equalization, but it faces scalability issues as the number of cells increases. COA offers real-time adaptability and impressive energy efficiency, but its effectiveness is limited to polymer-based lithium-ion batteries. Future work should explore combining these methods to create a more robust solution that balances performance, scalability, and real-time adaptability.

## 4. Conclusions:

This study demonstrates that each fast-charging strategy offers distinct advantages tailored to specific needs, but none alone is sufficient to address all the challenges in battery management.

The distributed control model using a leader-follower framework is well-suited for battery packs, ensuring cell equalization and maintaining safety constraints during the charging process. It compensates for model inaccuracies in real-time, preventing issues such as overcharging or thermal runaway. However, the computational complexity of this method increases significantly with larger battery packs, reducing its scalability for applications involving hundreds of cells, such as electric vehicles. Enhancing the scalability of this approach through advanced algorithms or distributed computing could make it more practical for large-scale battery systems.

The Cuckoo Optimization Algorithm (COA) offers superior real-time performance and energy efficiency, demonstrating significant improvements over traditional CCCV protocols. Its ability to reduce charging time and energy losses makes it a strong candidate for applications requiring fast, adaptive charging, such as public EV charging stations. However, its focus on polymer lithium-ion batteries limits its broader applicability, and further research is needed to validate its effectiveness with other chemistries like NCM or LFP.

A hybrid approach that combines the safety aspects of distributed control, the accuracy of offline optimization, and the real-time adaptability of COA may offer a complete answer. In order to ensure optimal charging for individual cells and battery packs under real-world settings, future research should concentrate on integrating these techniques into a single battery management system that strikes a balance between performance, scalability, and adaptability.

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