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Enhancing battery system identification: nonlinear autoregressive modeling for Li-ion batteries

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ABSTRACT

Precisely characterizing Li-ion batteries is essential for optimizing their performance, enhancing safety, and prolonging their lifespan across various applications, such as electric vehicles and renewable energy systems. This article introduces an innovative nonlinear methodology for system identification of a Li-ion battery, employing a nonlinear autoregressive with exogenous inputs (NARX) model. The proposed approach integrates the benefits of nonlinear modeling with the adaptability of the NARX structure, facilitating a more comprehensive representation of the intricate electrochemical processes within the battery. Experimental data collected from a Li-ion battery operating under diverse scenarios are employed to validate the effectiveness of the proposed methodology. The identified NARX model exhibits superior accuracy in predicting the battery's behavior compared to traditional linear models. This study underscores the importance of accounting for nonlinearities in battery modeling, providing insights into the intricate relationships between state-of-charge, voltage, and current under dynamic conditions.

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1. INTRODUCTION

In response to the growing concern over fossil fuel scarcity and climate change, there has been a rapid shift from internal combustion engine (ICE) vehicles to electric vehicles (EVs) [1]. This transition hinges on two pivotal objectives: augmenting and customizing battery capacity, preferably on-board, and developing high-speed battery chargers [2]. EV batteries and on-board chargers are also emerging as potential solutions to the mass-energy storage challenges faced by the electric power sector. Integrating EVs into the smart grid capitalizes on their predominantly parked status, enabling them to accumulate grid energy during periods of low demand and supply energy to the grid during peak demand [3]. Various battery technologies, such as those employing lead, nickel, and lithium, are integral to this transition, albeit characterized by instability and sensitivity to reaction conditions [4]. Consequently, meticulous monitoring and control of chemical reactions within cells are imperative to safeguard batteries from a spectrum of damages, ranging from irreversible capacity loss to catastrophic explosions. Particularly, lithium-ion batteries demand specialized handling to prevent performance deterioration and mitigate scenarios that could lead to severe damage or explosions [4].

Ensuring the simplicity of the model identification process aligns with specific requirements. In the context of electric vehicles, an accurate representation and simulation of battery behavior are crucial for assessing storage system performance. A model serves as a streamlined mathematical depiction of a battery, enabling the prediction of its behavior and the observation of phenomena that are often challenging to measure under real-world electric vehicle usage [5]. For instance, a model facilitates the simulation of several years of a storage system's life cycle in a matter of minutes, eliminating the need for recurrent construction of physical prototypes and costly experiments. Effective predictive engineering entails the development of a model that closely mirrors reality, addressing pertinent engineering inquiries [6].

The study and control of electric vehicles heavily depend on modeling lithium-ion batteries, a task that numerous researchers are actively engaged in [7]. Their efforts are directed towards enhancing the accuracy, robustness, and speed of lithium-ion battery models, considering the myriad factors and uncertainties that influence the complex electrochemical reactions within batteries. Establishing mathematical battery models is a multifaceted problem, posing challenges in both academic and industrial realms. Measurable quantities in battery management systems (BMS) include current input, output observation, terminal voltage, and temperature [8], [9]. BMS, functioning as an electronic guardian, monitors battery operation, shielding it from damage during charging and discharging. It ensures that the voltage, temperature, current, and state of charge of each cell remain within safe parameters, thereby enhancing the battery's lifespan and autonomy [10]. Consequently, BMS research has been pivotal in fostering innovation, leading to various types with diverse functions and solutions for improving battery operation [11].

One primary task of BMS is to determine the state of charge, representing the residual potential of the battery. Given that the state of charge is typically not immediately measured, various estimation strategies based on battery models have been developed [12]. Electrochemical models, describing battery performance through chemical processes, offer high accuracy but are often deemed impractical due to their complexity. Alternatively, circuit modeling, demonstrated by the Thevenin battery model and other variations, has proven effective [13]. However, limitations persist, such as constant parameter values concerning the state of charge and temperature. Innovative models, including those incorporating high-frequency cycling effects and battery self-discharge, offer potential improvements [14].

The application of artificial neural networks (ANNs) emerges as a highly efficacious strategy for modeling intricate and dynamic systems, transcending the constraints imposed by battery models or mathematical correlations [15]. Nevertheless, the computational intricacies inherent in the ANN algorithm pose significant challenges, manifesting as slow convergence, susceptibility to overfitting, and vulnerability to local minima. Mitigating these challenges necessitates a meticulous selection of the learning algorithm, activation function, number of hidden layers, neuron count, learning rate, spread value, and input and output specifications [16].

To enhance the computational efficiency of ANN, careful consideration and optimization of these parameters become imperative. Various sophisticated ANN methodologies have been advanced for the estimation of state of charge (SOC), encompassing backpropagation neural network (BPNN) [17], radial basis function neural network (RBFNN) [18], and recurrent neural network (RNN) [19]. Nevertheless, it is noteworthy that existing ANN approaches often lean on a laborious trial-and-error paradigm for the identification of optimal parameter values. This approach, unfortunately, proves inefficient and obstructs the realization of an optimal solution within a reasonable timeframe. Hence, a more strategic and efficient exploration of parameter spaces is imperative for advancing the effectiveness of ANN applications in this domain [20].

The Shepherd equation, presenting a generic model with a controlled voltage source in series with a fixed internal resistance, is a notable advancement. Although literature elaborates on this model by incorporating temperature and lifecycle effects, it lacks integration of the state of charge effect. Meanwhile, ANN have gained widespread application as intelligent mathematical tools for data-driven modeling [21]. Their suitability for handling nonlinear and intricate frameworks makes ANN a compelling choice. In this study, a neural network (NN) approach is employed to assess the parameters of a Li-ion battery. The selection of this methodology is motivated by its exceptional ability to address intricate problems. Specifically, recurrent neural networks of the nonlinear autoregressive models with exogenous inputs (NARX) type are employed for the estimation process. This approach relies not only on the input data but also takes into account the feedback from the outputs. This paper employs a well-organized structure, providing a comprehensive understanding of the neural network model's theory and features in section 2. The experimental setup is thoroughly explained in this section, laying the foundation for the subsequent discussions. Section 3 delves into the test results, presenting simulations and engaging in a detailed analysis of the obtained outcomes. The concluding remarks, encapsulating key insights and potential avenues for future research, are presented in section 4. This structured approach enhances the clarity and coherence of the paper, ensuring a systematic and logical flow of information.

2. RESEARCH METHOD

With the swift progress in computer processing capabilities and the ongoing refinement of learning techniques, the prevalence of neural networks is undergoing significant expansion, particularly in fields like image processing and automatic translation [22]. The ANN serves as a cornerstone model for information processing, drawing inspiration from the intricacies of the human brain. Consequently, the fundamental structure of an ANN comprises a network of interconnected computing nodes, intricately linked by directed and weighted connections. These nodes, akin to neurons, symbolize information-processing units, while the weighted connections signify the strength of synaptic links between neurons. In this model, a neuron can be envisioned as the accumulation of potentials derived from incoming synaptic signals. This cumulative sum, in turn, conveys information through a non-linear transfer function [12].

The activation of an ANN occurs by inputting data into some or all of its nodes and subsequently propagating this information through the weighted links. Following information propagation, the activation levels of some or all nodes can be collected and employed for system control, prediction, or classification purposes [23]. ANNs possess the capability to model variations in real data by continuously adjusting the weights between nodes based on the information flow during the learning phase. They are well-suited for capturing intricate relationships between inputs and outputs, demonstrating the ability to adapt and refine their understanding, making them a potent tool for modeling nonlinear statistical data. The foundational mathematical model of ANNs is depicted in Figure 1. The mathematical expression for a neuron is formulated as (1):

$$Y = F(\sum(Xi * Wi + Bi)) \tag{1}$$

where Xi represents the input of the neuron, Wi is the weight of the interconnection between input Xi and the neuron, and Bi is the bais of the neuron. The determination of all weights and baises take place during the training phase.

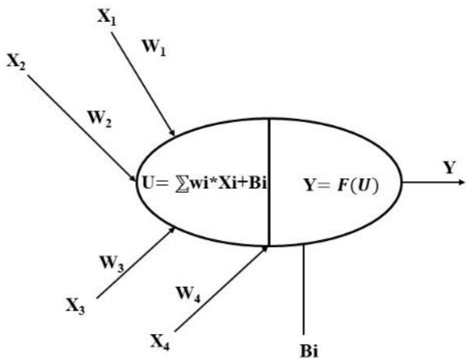

Figure 1. The basic mathematical model of ANN

Artificial neural networks have demonstrated effectiveness in various tasks related to the prediction and modeling of time-series data, including applications in financial time series prediction [3] and the forecasting of communication network traffic. Particularly in scenarios characterized by noisy time series and nonlinear underlying dynamical systems, ANNs consistently outperform traditional linear techniques, such as the well-known Box-Jenkins models [5]. The enhanced predictive capabilities of ANN models in these situations can be attributed to their inherent nonlinearity and heightened resilience to noise. Within the domain of recurrent neural architectures, NARX represent a distinctive class with limited feedback architectures stemming exclusively from the output neuron rather than hidden neurons [24]. The NARX constitutes a significant class of discrete-time nonlinear systems, and its mathematical representation is articulated as (2):

$$y(n+1) = f[y(n), \ldots, y(n-d_y+1); u(n-k), u(n-k-1), \ldots, u(n-k-d_u+1)] \tag{2}$$

In this context, $u(n) \in R$ and $y(n) \in R$ represent, respectively, the input and output of the model at discrete time step n. The parameters $du \geq 1$ and $dy \geq 1$, with the condition $du \leq dy$, denote the input memory and output memory orders respectively. The parameter $k (k \geq 0)$ represents a delay term referred to as the process dead time. For the sake of generality, we consistently assume $k = 0$ throughout this study, resulting in the following NARX model:

$$y(n+1) = f[y(n), \dots, y(n - d_y + 1); u(n), u(n-1), \dots, u(n - d_u + 1)] \quad (3)$$

$$y(n+1) = f[y(n); u(n)] \quad (4)$$

In this context, the vectors $y(n)$ and $u(n)$ represent the output and input regressors, respectively.

Identifying nonlinear relationships poses frequent challenges and can be approximated through conventional means, exemplified by a standard multilayer perceptron (MLP). This feed-forward neural network (FFNN) comprises an input layer, one or more hidden layers, and an output layer, with interconnections established between nodes within each layer and those of the preceding layer [25]. The resultant interconnected structure is termed the NARX network, representing a robust class of dynamic models reminiscent of Turing machines in the realm of computer science. The NARX topology employed in this manuscript is depicted in Figures 2 and 3.

To conduct the experiments, the setup necessitates the utilization of two power supplies and an active load, specifically the EA Power Control. The EL9000B, functioning as an active load, boasts a formidable power capacity of 2,400 W and a current rating of 170 A. Complementing this, the PS9000 3 U power supply, with an impressive power capacity of 10 kW and a current output of 340 A, is employed. Furthermore, a constant voltage supply is integrated for relay power, maintaining the ambient temperature at a controlled 23 °C, Figure 4. The EA Power Control plays a pivotal role in the experimentation process, serving to record current, voltage, and power profiles. MATLAB takes charge of the subsequent data processing, while LabView acts as the interface for efficient data acquisition. This comprehensive setup ensures meticulous control and monitoring of the experimental conditions.

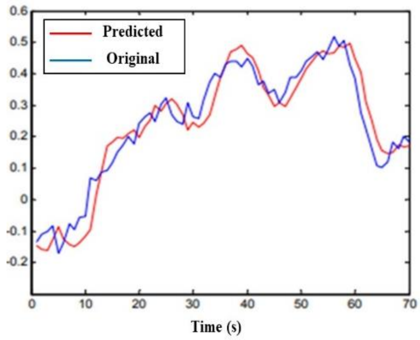

Figure 2. Prediction results of the NARX method

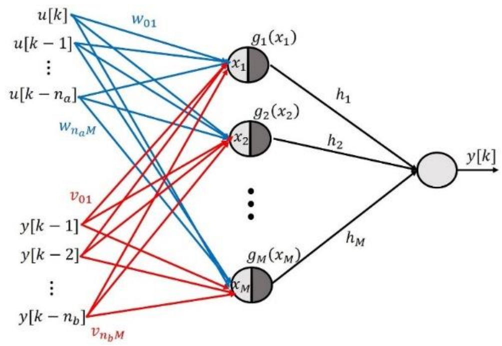

Figure 3. NARX model

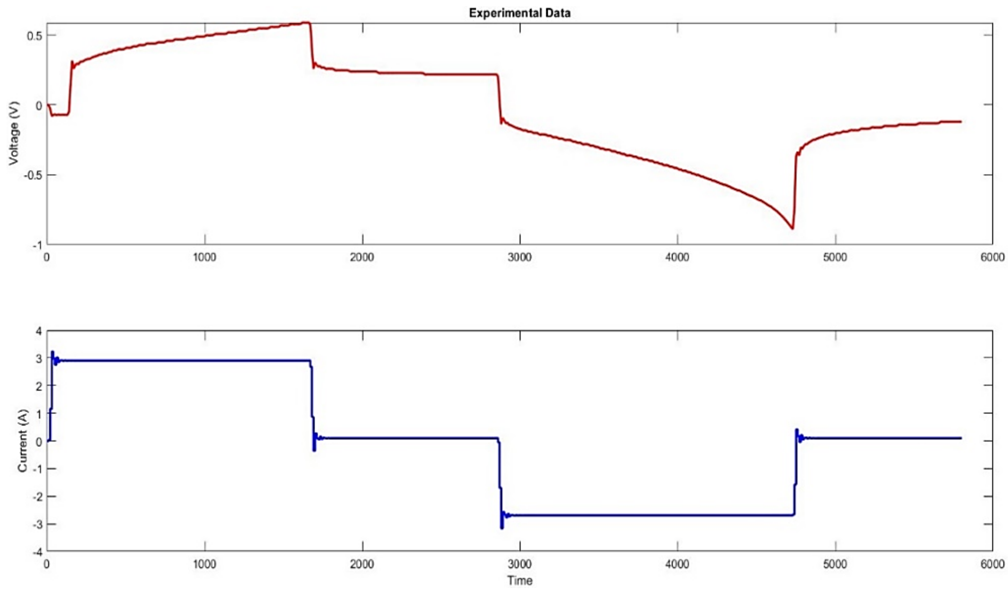

Figure 4. Experimental data

It is noteworthy that the EL9000B and PS9000 3 U are selected for their substantial power capabilities, ensuring a robust and versatile platform for experimentation. The constant voltage supply and controlled ambient temperature contribute to the stability of the experimental setup. Following data acquisition, MATLAB simulations are conducted, and the results are meticulously compared with the experimental data, leading to a thorough performance analysis. This meticulous integration of cutting-edge equipment and sophisticated software underscores the precision and reliability of the experimental procedures, facilitating a comprehensive evaluation of the proposed model [12].

3. RESULTS AND DISCUSSION

The battery underwent a complete charging cycle from 0% to 100% and discharging from 100% to 0%, resulting in negligible integration errors due to the precise calibration of the current sensor. The subsequent figures depict a comparison among the proposed models, the measured voltage, and the standard model. Figures 5 and 6 specifically illustrate this comparison using the training database. As evident in Figures 5 and 6, a notable similarity is observed between the proposed and measured voltages in contrast to the voltage derived from the standard model. The uniqueness of our approach lies in the dynamic nature of the battery model, which accounts for the influence of temperature and state of charge (SOC) on the battery models.

While the maximum error of the proposed model is limited to 10%, it is crucial to note that certain error peaks are discernible, particularly during instances of high battery discharge. These peaks, far from being shortcomings, actually serve as indicators of the robustness of our model. The ability of our model to quickly converge to the experimental curve, even in the presence of these error peaks, highlights its resilience and adaptability under challenging conditions. These occasional peaks in error, associated with intense battery discharge, underscore the realistic and dynamic nature of the proposed model. The fact that our model effectively captures and responds to such discharge-induced fluctuations reinforces its reliability and suitability for real-world applications. In essence, these error peaks contribute to validating the robustness of our model, showcasing its capacity to navigate and accurately represent the complex dynamics inherent in various battery operating scenarios.

The DST data at 10C serves as a crucial component in validating the proposed model. Figures 5 to 7 vividly present the simulation results during the validation phase. Notably, the rapid convergence of the proposed model curve to the measured voltage is evident in the figures. Furthermore, a strikingly low error is observed between the curves of the proposed model and the measured voltage, underscoring its efficacy in comparison to the standard model. This robust validation process reaffirms the accuracy and reliability of our proposed model in capturing the intricate dynamics of the battery system under consideration.

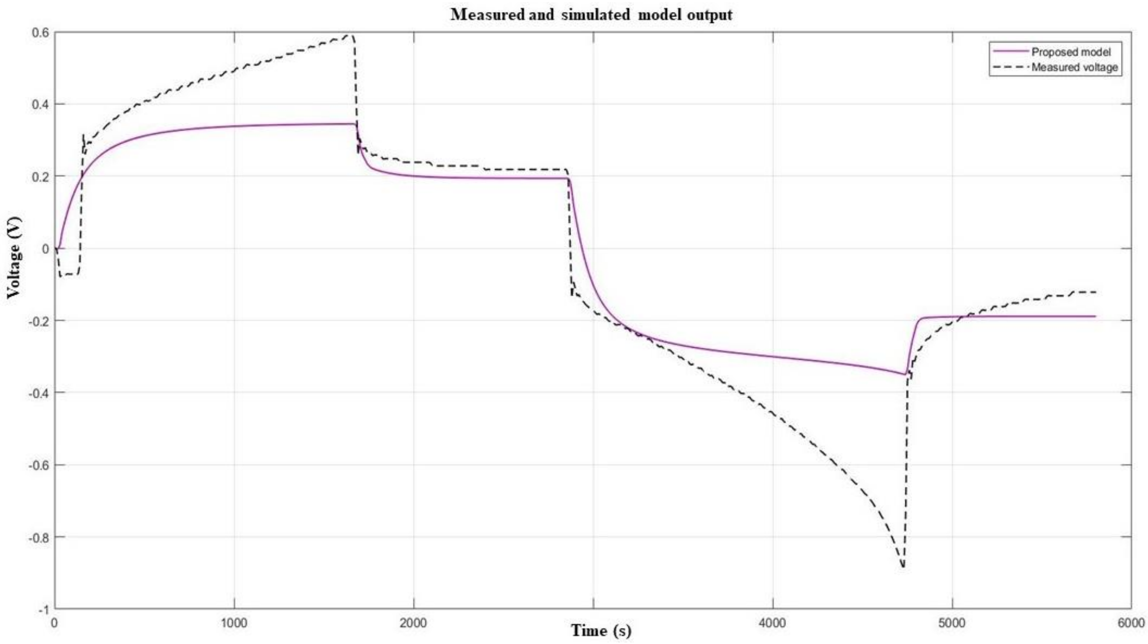

Figure 5. Contrast between a conventional battery model and the proposed battery model

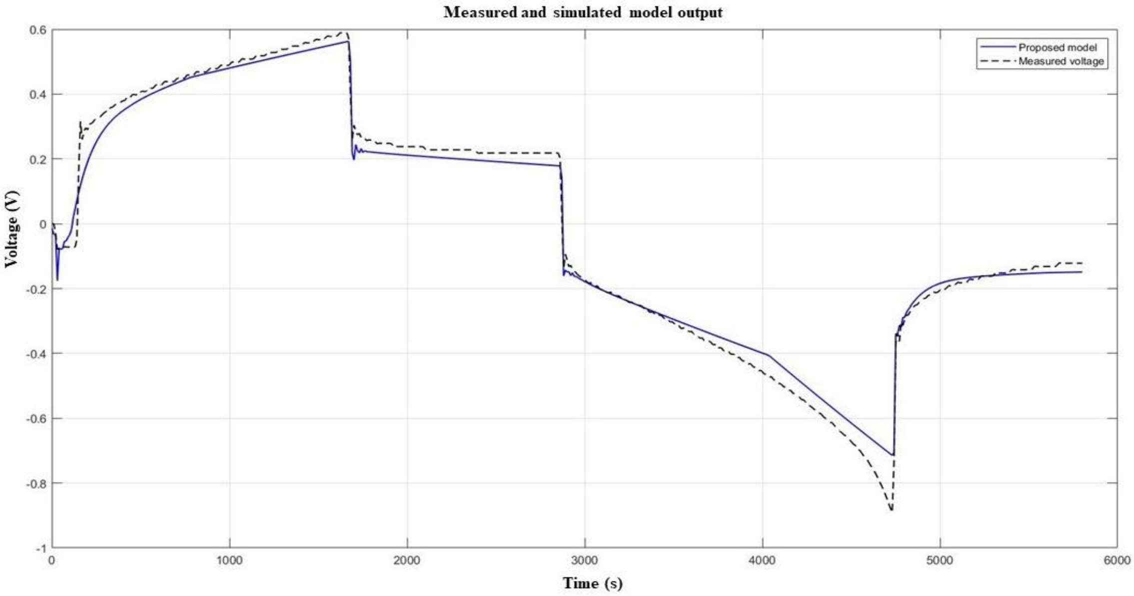

Figure 6. Contrast between a conventional battery model and the proposed battery model

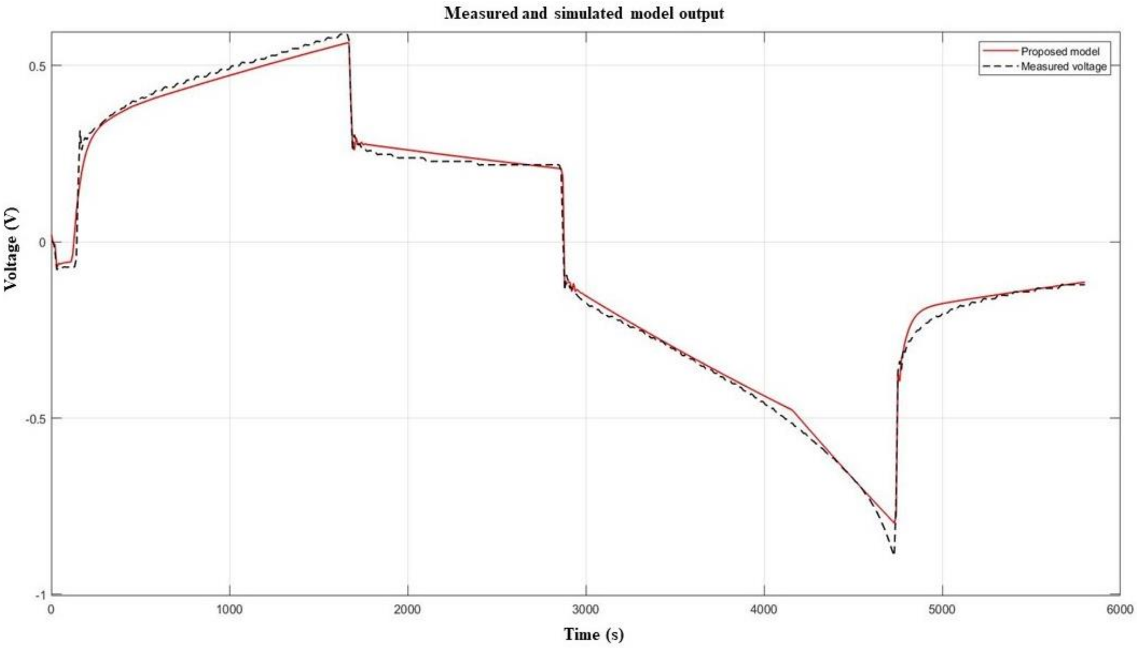

Figure 7. Contrast between a conventional battery model and the proposed battery model

4. CONCLUSION

In conclusion, this study presented a battery model founded on ANN. The ANN underwent thorough offline training to ascertain the necessary battery model, utilizing experimental data sourced from The CALCE battery group website. The simulation results demonstrated not only a remarkable accuracy but also swift convergence to experimental outcomes, irrespective of the charging and discharging conditions. The adaptability of the proposed model extends its applicability to a wide array of rechargeable batteries. Nevertheless, certain challenges associated with the model necessitate careful consideration. For the implementation of this model in a battery pack, the calculation of the SOC for each cell is imperative. Considering the varied environmental conditions in which batteries operate, the database used for designing the model should encompass all potential operational scenarios.

Looking ahead, future endeavors will revolve around leveraging the state space of this model to estimate SOC through a robust algorithm. This holistic approach will not only enhance the model's predictive capabilities but also contribute to addressing the challenges inherent in applying such models to real-world battery systems. Overall, the findings underscore the potential and significance of the proposed ANN-based battery model in advancing the understanding and practical application of rechargeable batteries.

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