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Large-Model-Driven Virtual Simulation Paradigm for Power Battery Engineering Education

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Abstract: Engineering education in power battery systems faces persistent bottlenecks, including prohibitively expensive experimental resources, severe safety risks during abuse testing, and a steep cognitive gap between abstract electrochemical mechanisms and dynamic operational phenomena. To overcome the limitations of traditional, static virtual simulation tools, this paper proposes a novel large-model-driven virtual simulation experiment paradigm tailored for power battery courses. First, we systematically review the current constraints of virtual experiment teaching regarding resource supply, boundary-condition exploration, cognitive barriers, and assessment limitations. Second, a comprehensive methodological framework is proposed, integrating a high-fidelity simulation engine, a model integration layer, and a domain-specific large-model interaction layer. By synergizing open-source battery simulators, scientific computing models, and domain large models, this architecture enables natural-language scenario generation, real-time diagnostic feedback, personalized AI tutoring, and process-oriented multidimensional assessment. Finally, we discuss the pedagogical value and implementation challenges of this approach. The proposed framework effectively transforms virtual simulation from a rigid verification tool into an intelligent, closed loop learning companion, offering a scalable and safe pathway to cultivate innovative engineering talents under the Emerging Engineering Education initiative.

1. Introduction

The rapid transformation of the global energy system has made power batteries a strategic technology. Modern power battery courses increasingly involve battery management systems, thermal safety, data-driven modeling, and artificial intelligence [1-3]. Under the background of Emerging Engineering Education, the goal of engineering talent cultivation is shifting from knowledge transmission to competency development. Experimental teaching is critical in this process, as it connects theory with physical phenomena and engineering judgment. However, conventional experimental teaching is constrained by expensive equipment, long-cycle degradation tests, and safety risks associated with destructive operations. While virtual simulation has become an important supplement, many conventional platforms rely on pre-defined animations or fixed procedures [1,4]. They generally lack high-fidelity physical modeling, intelligent guidance, and process-oriented assessment. Consequently, students may complete tasks mechanically without developing deep experimental reasoning or innovation abilities.

Recent advances in large language models and multimodal artificial intelligence provide new opportunities for virtual simulation teaching [5-7]. These models can process natural language instructions, generate experimental scenarios, explain physical phenomena, and provide adaptive feedback [5-6]. When combined with battery simulation engines and machine-learning algorithms, they can transform a virtual platform into an intelligent learning environment. This paper focuses on a large-model-driven virtual simulation experiment teaching paradigm for power battery education. First, the key issues of current virtual simulation teaching are systematically summarized. Second, a methodological framework is proposed, integrating a high-fidelity simulation engine, a model integration layer, a domain large-model interaction layer, and a multi-dimensional evaluation mechanism. This framework utilizes domain large models to support multimodal scenario generation, real-time diagnosis, and personalized tutoring. Ultimately, the proposed paradigm aims to convert virtual simulation from a static resource into an intelligent learning companion, offering a pathway for engineering talent cultivation under the Emerging Engineering Education framework.

2. Current Status and Key Issues in Power Battery Virtual Simulation

The integration of digital resources and intelligent tools has become a focal point in modern engineering education [5]. However, power battery courses face unique challenges due to high system complexity, significant safety risks, and the interdisciplinary nature of the field. The primary bottlenecks are summarized below.

2.1. Resource and Safety Constraints

A major limitation is the mismatch between high student demand and limited laboratory resources [1]. High-fidelity battery testers and environmental chambers are expensive to acquire and maintain, often restricting students to passive demonstrations rather than exploratory practice. Furthermore, essential experiments involving boundary conditions, such as overcharge, nail penetration, and thermal runaway, are restricted in routine teaching due to physical safety risks [8-9]. While traditional virtual tools offer a safe alternative, they often lack the fidelity required for inquiry-driven learning, presenting fixed outcomes rather than guiding students through mechanism analysis.

2.2. Cognitive and Intelligence Gaps

Power batteries involve coupled multi-physics processes, making it difficult for students to bridge the gap between abstract electrochemical equations and dynamic experimental data [10-11]. This cognitive barrier is intensified by the introduction of data-driven algorithms, where students may apply models without a deep understanding of their physical constraints [12-13]. Most existing virtual platforms function as fixed operation software; they cannot diagnose student errors or provide adaptive guidance based on specific experimental intentions. Consequently, students often remain passive users rather than active experimenters.

2.3. Assessment Challenges

Traditional evaluation methods primarily rely on final reports or written exams, which fail to capture a student's reasoning process, parameter adjustment logic, or error-correction ability. Although virtual environments can record detailed operation logs, these process data are rarely utilized for formative assessment [14-15]. There is a clear need for a multidimensional assessment system that evaluates theoretical mastery alongside the ability to solve open-ended engineering problems.

3. Methodological Framework of Large-Model-Driven Virtual Simulation

To address the above problems, this paper proposes a large-model-driven methodological framework for virtual simulation experiment teaching in power battery courses. The framework is not a single software function, but an integrated teaching system composed of technical architecture, experimental content, interaction mode and evaluation mechanism. Its basic logic is to use high-fidelity simulation as the scientific foundation, AI models as the intelligent support, course tasks as the pedagogical carrier, and learning data as the basis for continuous improvement.

3.1. Design Principles and Overall Architecture

The proposed framework is founded on four core design principles: scientific fidelity, student-centered inquiry, embedded AI assistance, and process-oriented evaluation. As illustrated in Figure 1, the overall architecture is structured into three hierarchical technical layers, complemented by a continuous teaching-learning closed loop.

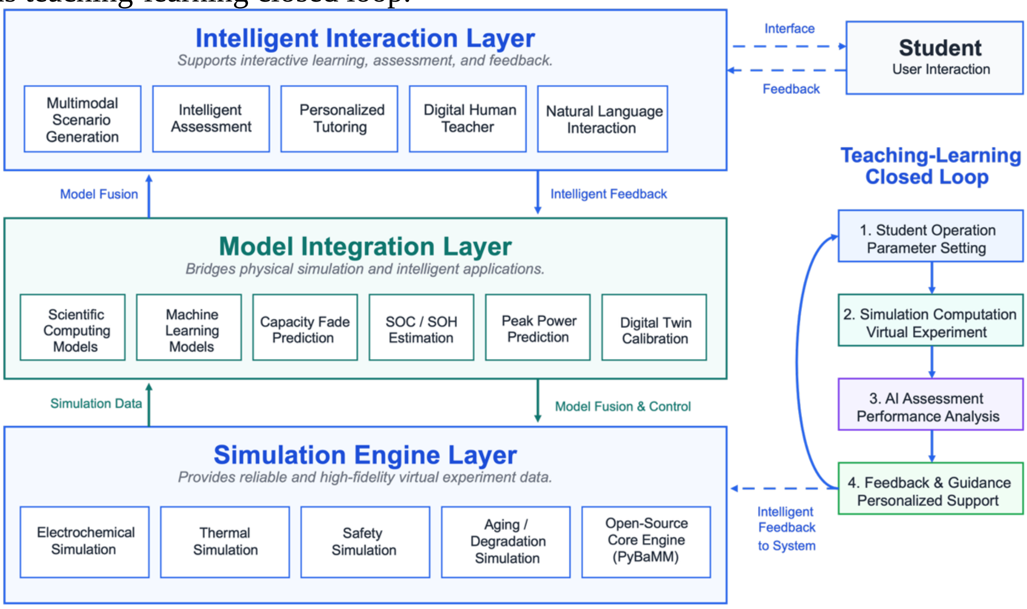

Figure 1: Methodological framework architecture.

1) Simulation Engine Layer: Serving as the foundation, this layer provides reliable, high-fidelity virtual experiment data. It utilizes open-source core engines (e.g., PyBaMM) to execute comprehensive physical models, including electrochemical, thermal, safety, and aging simulations.

2) Model Integration Layer: This intermediate layer bridges physical simulations with intelligent applications. By incorporating machine learning and scientific computing models, it facilitates digital twin calibration and advanced battery state predictions, such as SOC/SOH, peak power, and capacity fade.

3) Intelligent Interaction Layer: Positioned at the top, this layer manages direct interaction with the student. Driven by domain large models, it features natural language interfaces and digital human teachers to support multimodal scenario generation, intelligent assessment, and personalized

tutoring.

4) Teaching-Learning Closed Loop: Parallel to the technical stack, this operational workflow ensures iterative competency development. The cycle progresses through four continuous stages: (1) student operation and parameter setting, (2) virtual experiment simulation, (3) AI-driven performance assessment, and (4) personalized feedback and guidance, which seamlessly loops back to inform subsequent student operations.

3.2. High-Fidelity Simulation Environment

The Simulation Engine Layer provides the physical foundation of the virtual laboratory by fusing mechanism-based modeling and data-driven methods. At its core, open-source simulation engines, such as PyBaMM, are utilized to compute dynamic electrochemical reactions, lithium-ion transport, and coupled thermal processes. By solving these fundamental governing equations, the system can reliably simulate the transient behaviors of various cell chemistries under diverse operational profiles and environmental conditions.

To account for real-world engineering complexities, the Model Integration Layer applies data-driven calibration. Machine-learning algorithms and scientific computing models are integrated to address phenomena that simplified mechanisms struggle to capture fully, such as cell-to-cell inconsistency, non-uniform temperature distributions, and long-cycle capacity fading. This synergistic approach establishes a robust digital twin, accommodating both standardized protocols (e.g., CC-CV charging, HPPC tests) and open-ended exploratory investigations in a safe, repeatable environment.

3.3. Domain Large Model and Multimodal Interaction

Situated within the Intelligent Interaction Layer, a domain-specific large language model (LLM) functions as an interactive digital teacher. Its primary objective is to bridge the cognitive gap between abstract simulations and student understanding. A key capability is multimodal scenario generation. When a student inputs a natural language instruction, such as “simulate a 2C discharge at -20℃”, the LLM accurately extracts key variables, configures the corresponding simulation parameters, and verifies the physical reasonableness of the request before executing the virtual experiment.

Beyond executing commands, the digital teacher excels at providing multimodal explanations. It correlates abstract simulation curves (e.g., voltage drops, temperature spikes) with internal physical states and potential safety risks. Pedagogically, rather than supplying direct answers to experimental anomalies, the system employs targeted questioning and counterfactual prompts. This interaction style forces students to reflect on their parameter choices and stimulates independent engineering reasoning, transforming them from passive users into active investigators.

3.4. Intelligent Guidance and Personalized Feedback

As illustrated in Figure 2, the framework operationalizes intelligent guidance through a systematic, seven-step pedagogical workflow. The process initiates with task release, where specific learning objectives are published. Students then engage in parameter setting and virtual experiment execution. Rather than passively waiting for the final output, the system actively intervenes through a core AI-powered personalization phase directly integrated into the learning sequence.

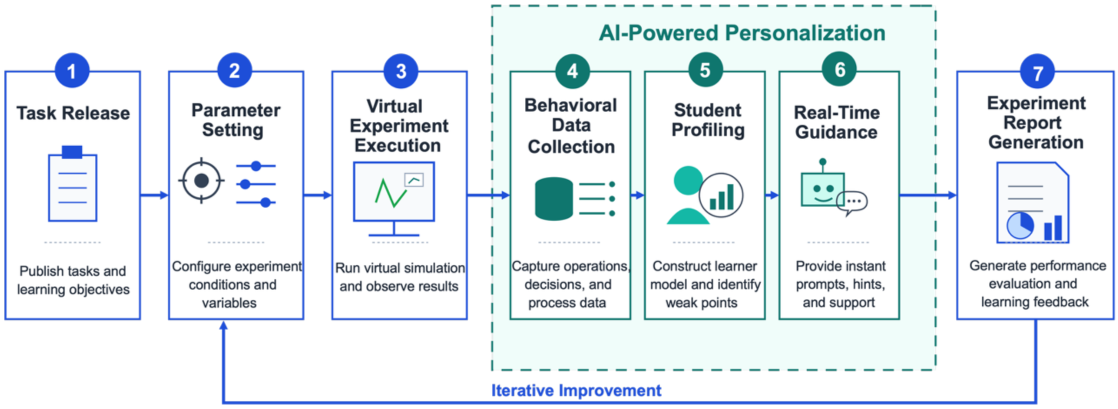

Figure 2: Intelligent guidance and personalized feedback workflow.

Within this personalization phase, the framework conducts meticulous behavioral data collection, capturing high-resolution operational data such as parameter choices, decision-making sequences, and interaction logs. These data drive dynamic student profiling, which maps student actions to competency indicators to construct a comprehensive learner model. By identifying weak points, the AI can accurately distinguish whether a suboptimal result stems from a conceptual misunderstanding, safety boundary ignorance, or a simple numerical error. Based on this profile, the system delivers real-time guidance through instant prompts and hints to prevent blind trial-and-error. Ultimately, the experiment report generation produces evidence-based evaluation, establishing an Iterative Improvement loop that guides students to refine their parameters and strategies in subsequent attempts.

3.5. Virtual Experiment Modules

To align with the interdisciplinary knowledge structure of modern power battery curricula, the application tier encompasses five progressive virtual experiment modules. These modules are carefully designed to transition students from basic component analysis to complex system-level engineering:

1) Cell Characterization: Evaluates basic performance indicators and parameter sensitivity through standardized charging and impedance-related tests.

2) BMS Algorithm Validation: Assesses the accuracy and robustness of SOC/SOH estimation and peak power prediction algorithms under varying conditions.

3) Thermal Management Design: Optimizes cooling structures and flow-rate strategies to maintain thermal uniformity and ensure safety margins.

4) Safety Boundary Exploration: Simulates extreme abuse conditions, such as overcharge and short circuits, allowing students to observe failure evolution without physical risk.

5) Life-Cycle Aging Simulation: Analyzes long-term degradation patterns and capacity fading across accelerated timeframes and usage strategies.

Rather than acting as isolated software demonstrations, these modules function as an interconnected task chain. For instance, parameters identified in the characterization module are subsequently utilized in BMS algorithm validation and thermal design. This continuity reinforces the critical understanding that battery engineering requires systematic, multi-physics trade-offs.

3.6. Process-Oriented Evaluation

Moving away from the traditional reliance on static final reports, this framework implements a comprehensive, process-oriented evaluation mechanism. This approach evaluates the entire trajectory of student inquiry, systematically assessing theoretical mastery, experimental strategy design, data interpretation, and the ability to effectively utilize AI assistance. Every iteration, mistake, and refined hypothesis tracked by the system contributes to the final assessment profile.

The outputs of this evaluation serve a dual, closed-loop purpose. At the individual level, they provide students with specific diagnostic feedback and targeted recommendations for subsequent practice. At the cohort level, the aggregated data offer instructors valuable insights into common student misconceptions and behavioral patterns. This macro-level analysis allows educators to iteratively optimize course difficulty, refine classroom lectures, and adapt teaching strategies to better meet student needs.

4. Discussion and Outlook

4.1. Pedagogical Value and Innovation

The proposed paradigm has three main pedagogical values. First, it expands the boundary of experimental teaching. Students can conduct experiments that are difficult, expensive or unsafe in physical laboratories, including destructive abuse tests and long-cycle aging simulations. This expands the scope of learning from standard verification to exploratory investigation. Second, it strengthens the connection between mechanism and data. Through visualization, explanation and parameter sensitivity analysis, students can observe how internal processes generate external signals and how algorithms infer hidden states. Third, it enables personalized learning at scale. The domain large model can provide timely support to each student, while teachers can focus on designing higher-level tasks and guiding complex discussions.

The major innovation of this framework lies in the integration of large models with high-fidelity simulation and teaching evaluation. Unlike a conventional virtual simulation platform, the proposed system does not merely present results. It understands experimental intentions, assists scenario construction, monitors learning behavior, explains mechanisms and produces personalized feedback. Unlike a general AI tutoring system, it is grounded in numerical simulation and course-specific experimental tasks. Therefore, it has the potential to improve both learning experience and engineering competency.

4.2. Implementation Challenges and Risk Control

Despite its potential, the implementation of a large-model-driven virtual simulation laboratory faces several challenges. The first challenge is model reliability. Battery simulation requires accurate parameters, appropriate boundary conditions and careful validation. If the simulation result deviates from physical reality, students may form incorrect understanding. Therefore, model verification, parameter management and uncertainty explanation must be included in platform development.

The second challenge is the accuracy and controllability of AI feedback. Large models may generate plausible but incorrect explanations if they are not constrained by domain knowledge, simulation outputs and teaching objectives. To reduce this risk, the AI system should be connected to a structured knowledge base, validated simulation results and teacher-designed rubrics. Important feedback should be evidence-based, and high-stakes assessment should involve teacher review.

The third challenge is the depth of pedagogical integration. Technology itself does not guarantee effective learning. If experimental tasks are poorly designed, students may still perform shallow clicking operations. Therefore, teachers need to design open-ended questions, comparative tasks, reflection prompts and project-based assignments. The platform should encourage students to explain why results occur and how engineering decisions can be improved.

4.3. Outlook for Broader Engineering Education

Although this paper focuses on power battery education, the framework can be generalized to other engineering fields that involve high-cost experiments, safety risks, complex mechanisms and large-scale data. Examples include intelligent manufacturing, vehicle engineering, energy systems, robotics, chemical processes and electrical equipment diagnosis. The common logic is to use AI-supported virtual simulation as an intermediate space between classroom theory and real engineering practice.

In the future, the integration between virtual experiments and real laboratories should be strengthened. Physical experimental data can be used to calibrate virtual models, and virtual experiments can prepare students before they enter the physical laboratory. Students may first explore parameters in the virtual environment, identify promising schemes, and then verify selected schemes in real experiments. This hybrid model can improve efficiency, reduce risk and deepen understanding.

Another important direction is the development of responsible AI literacy. Students should not only use AI tools, but also understand their limitations, assumptions and ethical implications. In battery engineering, AI-generated suggestions may influence safety-related decisions. Therefore, teaching should cultivate students' ability to question AI outputs, verify conclusions with mechanisms and data, and maintain engineering responsibility.

4.4. Future Development of the Platform

Future work can be conducted from three aspects. First, the platform should enrich the battery model library by including different chemistries, cell formats, pack configurations and multi-physics coupling mechanisms. This will make the virtual laboratory more representative of industrial scenarios. Second, the domain large model should be continuously refined using teaching data, expert feedback and structured battery knowledge. Its ability to diagnose misconceptions, generate experiments and explain mechanisms can be gradually improved. Third, the evaluation system should be further validated through classroom practice, including comparison with traditional teaching modes, analysis of learning gains and investigation of student acceptance.

From a long-term perspective, the large-model-driven virtual simulation laboratory may become a key component of digital engineering education. It can support pre-class inquiry, in-class exploration, after-class personalized practice, project-based learning and interdisciplinary collaboration. More importantly, it can help students develop the ability to learn with AI, reason with models and make engineering decisions under uncertainty.

5. Conclusion

This paper has restructured and expanded a large-model-driven virtual simulation experiment teaching paradigm for power battery education. By adding a systematic analysis of the current status and key problems, the paper clarifies why conventional experimental teaching and traditional virtual simulation tools are insufficient for the needs of Emerging Engineering Education. The main bottlenecks include resource constraints, safety restrictions, interdisciplinary cognitive barriers, limited intelligence of existing platforms and insufficient process-oriented assessment.

To address these problems, a methodological framework is proposed. The framework integrates a high-fidelity simulation engine, a model integration layer, a domain large-model interaction layer, virtual experiment modules and a process-oriented evaluation mechanism. It supports natural-language scenario generation, multimodal visualization, intelligent guidance, personalized feedback and iterative teaching improvement. Through this design, virtual simulation can evolve from a static supplementary resource into an intelligent experimental learning environment.

The proposed paradigm provides a feasible pathway for improving power battery experiment teaching and cultivating engineering talents with theoretical understanding, practical ability, AI literacy and innovation capacity. Future work should further validate the framework in real courses, improve the reliability of simulation and AI feedback, and extend the approach to broader engineering education scenarios. The ultimate goal is to build a student-centered, AI-enhanced and practice-oriented teaching system that supports high-quality talent cultivation in the era of intelligent engineering.

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