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Research on Teaching Reform and Optimization of University Fuel Cell Courses Integrated with Machine Learning

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Abstract: Driven by the global low-carbon energy transition and China's dual-carbon strategy, fuel cell technology has become a core compulsory course for energy chemistry, new energy science and engineering, and other related majors in universities. This course features obvious interdisciplinary attributes covering electrochemistry, catalytic materials, fluid mechanics, and automatic control. However, microscopic reaction mechanisms and multiphysics coupling processes are invisible and abstract, bringing great learning difficulties to students. At present, domestic fuel cell teaching faces prominent bottlenecks including fragmented curriculum content, insufficient visual demonstration of microscopic mechanisms, high cost and safety risks of physical experiments, disconnection between teaching and industrial frontiers, and lack of intelligent technology integration. Traditional lecture-based teaching only focuses on theoretical knowledge indoctrination, failing to cultivate students' data analysis, modeling optimization, and engineering innovation capabilities, which cannot meet the talent demand of intelligent upgrading of the fuel cell industry. Machine learning (ML) has outstanding advantages in nonlinear data fitting, performance prediction, multi-objective optimization, and microscopic mechanism inversion, which provides a new path for fuel cell curriculum reform. Targeting practical teaching pain points of energy majors, this paper summarizes five major teaching dilemmas of existing fuel cell courses, and explores multi-dimensional integration paths of ML and classroom teaching, virtual simulation experiments, project training, and university-enterprise collaborative education. Furthermore, this paper puts forward targeted reform strategies from four aspects: hierarchical knowledge system construction, inquiry-based teaching innovation, practical teaching system expansion, and teacher training and evaluation mechanism optimization. The research results integrate data-driven thinking and intelligent modeling methods into the whole teaching process, effectively solving the problems of abstract mechanism explanation, limited experimental conditions, and lagging frontier technology updates. It provides theoretical support and practical reference for intelligent curriculum reconstruction and innovative engineering talent cultivation of fuel cell courses under an emerging engineering education background.

Keywords: Fuel cell course; University energy chemistry education; Machine learning; Curriculum reconstruction; Emerging engineering talent cultivation

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1. Introduction

Against the background of fossil energy shortage and global carbon neutrality goals, hydrogen energy and the fuel cell industry have been listed as China's key strategic emerging industries. Proton exchange membrane fuel cells (PEMFCs) and solid oxide fuel cells (SOFCs) have been widely applied in new energy vehicles, distributed power generation, and special power equipment due to high energy conversion efficiency and zero pollution emissions. With industrial digital and intelligent transformation, enterprises no longer only require graduates to master basic fuel cell theories, but also need interdisciplinary talents equipped with data modeling, fault diagnosis, and intelligent algorithm application capabilities.

Fuel cell courses cover electrode reaction kinetics, membrane conduction mechanism, flow field design, hydrothermal management and system integration, with characteristics of strong theoretical abstraction, multi-discipline crossing and close connection with engineering practice. Compared with general hydrogen energy courses, it involves more invisible microscopic interfacial reactions and complex multi-parameter coupling relations, accompanied by a large number of thermodynamic formulas and mathematical derivations, leading to a high learning threshold for undergraduates [1].

Currently, AI-assisted energy curriculum reform has become a hot spot in higher education research. Many domestic universities have built "AI + energy materials" talent training systems, embedding high-throughput computing and digital twin technology into traditional professional courses [2,3]. Meanwhile, machine learning has been widely used in fuel cell basic research and engineering applications: multiple ML models have achieved high-precision prediction of fuel cell power density; neural networks and genetic algorithms have realized efficient optimization of cathode flow fields; data-driven methods have also been applied in catalyst screening and stack degradation prediction. Nevertheless, the integration of mature ML research achievements and undergraduate classroom teaching is still insufficient [4]. Simply adding algorithm knowledge cannot match professional teaching logic. It is essential to take fuel cell professional knowledge as the core and ML as an analytical tool to make up for the defects of traditional teaching, visualize abstract mechanisms and cultivate students' data thinking, so as to transport high-quality interdisciplinary talents for the hydrogen energy industry.

2. Current situation and major challenges of university fuel cell courses

2.1. Fragmented knowledge system lacking systematic engineering logic

Fuel cell-related knowledge points are scattered in electrochemistry, fluid mechanics, materials science, and other independent courses without overall teaching planning. Teachers mostly explain single theoretical points separately, ignoring the internal correlation between material microstructure, interfacial reaction, operating parameters, and macroscopic output performance. Besides, the interdisciplinary integration of the course is insufficient, and students cannot build a complete systematic cognition of multi-physics coupling operation of fuel cells, resulting in fragmented and unsystematic knowledge reserve [5].

2.2. Abstract microscopic mechanisms and poor visualization effect of traditional teaching

The core teaching difficulties focus on invisible microscopic dynamic processes including proton conduction, gas-liquid two-phase mass transfer, and catalytic reaction evolution. Traditional teaching methods such as static PPT and two-dimensional diagrams can only display static results, failing to dynamically show real-time reaction changes under variable working conditions. Students can memorize basic concepts mechanically but cannot understand internal mechanisms or analyze parameter sensitivity, forming a prominent learning barrier.

2.3. High risks and high costs restrict the development of exploratory experiments

Physical fuel cell experiments are restricted by three practical problems: expensive testing equipment, strict hydrogen supply supporting conditions, and hydrogen explosion safety risks. Most universities cut experimental hours and simplify experimental content for safety and cost control. Current experiments are limited to basic principle verification, lacking design-oriented experiments such as flow field optimization, fault diagnosis, and life prediction. The disconnection between experimental content and industrial practice also restricts the cultivation of students' engineering practice ability. Virtual simulation platforms developed by some universities have verified that virtual-real combined experiments can effectively solve the above pain points, but such intelligent experimental modes have not been popularized nationwide [6].

2.4. Outdated teaching content mismatched with industrial intelligent frontiers

Textbooks and conventional teaching content focus too much on classical basic theories, with slow content update speed. Cutting-edge research directions including new non-precious metal catalysts and anion exchange membrane fuel cells are rarely involved. More importantly, mature industrial applications of machine learning in fuel cell performance prediction, health management, and intelligent optimization are not incorporated into the curriculum system, leading to the disconnection between talent training objectives and industrial intelligent transformation demands.

2.5. Insufficient teachers' intelligent teaching ability with an imperfect evaluation mechanism

Most professional teachers have a solid professional foundation but lack systematic training in machine learning and data mining. They are incompetent in integrating intelligent algorithms into professional teaching links. Meanwhile, colleges lack targeted AI teaching training and cross-disciplinary teaching teams. The existing teaching evaluation system still takes theoretical written examination as the core, ignoring students' modeling ability and innovative practice performance, which further hinders the promotion of ML integrated teaching reform [7].

3. Teaching content reconstruction strategies based on machine learning empowerment

3.1. Establishing a hierarchical, progressive, and multidisciplinary integrated knowledge system

Combined with emerging engineering talent training requirements, this paper reconstructs a modular and progressive curriculum knowledge system divided into five levels: basic cognition, microscopic reaction mechanism, material and structural design, system operation management, and intelligent simulation optimization. The curriculum progresses from basic theoretical knowledge to engineering practice and intelligent application step by step. Supported by knowledge graph technology, the new system breaks disciplinary barriers of multiple majors and takes machine learning as a universal quantitative analysis tool throughout the whole course. It guides students to transform from qualitative theoretical cognition to quantitative data analysis and build a complete engineering-oriented knowledge network.

3.2. Deep integration of machine learning modeling to enhance academic depth and inquiry-based learning

Aim at core difficult knowledge points, embed targeted machine learning modeling cases into classroom teaching. In polarization curve teaching, introduce regression models to fit experimental data and analyze the influence of temperature, humidity, and catalyst loading on cell performance; in flow field design chapters, adopt genetic algorithm and Bayesian optimization to carry out multi-objective simulation optimization of bipolar plate structures. Convert existing high-quality academic research results into undergraduate-oriented teaching cases, let students complete the whole process from data processing, model training to simulation optimization, and realize the transformation from passive knowledge reception to active problem analysis [8].

3.3. Anchoring scientific research and industrial frontiers to strengthen the research-oriented and open nature of the course

Track the latest fuel cell research progress and industrial intelligent application cases dynamically, and add frontier content such as stack fault diagnosis based on deep learning and life degradation prediction based on time-series algorithms. Meanwhile, combine material characterization means including XRD and EIS, guide students to use ML algorithms to realize intelligent denoising and feature extraction of experimental data. Connect classroom teaching with scientific research projects and industrial actual demands, expand students' academic vision, and lay a foundation for their subsequent discipline competitions and graduation design.

4. Practical implementation paths of teaching reform

4.1. Developing discipline-specific intelligent teaching resource database

Integrate open-source fuel cell experimental datasets, simulation cases, and algorithm templates to build an online lightweight intelligent teaching platform. Establish a correlation database covering "professional knowledge points-machine learning algorithms-engineering application cases" with a knowledge graph. Meanwhile, use literature crawler tools to update frontier cases and industrial standards in real time, providing convenient self-learning resources for teachers and students to support hierarchical teaching and after-class extended learning.

4.2. Optimizing classroom teaching mode and carrying out project-based inquiry teaching

Based on students' learning data, implement differentiated personalized teaching according to students' differences in theoretical foundation and modeling ability. Develop visual virtual simulation modules to visualize invisible microscopic reaction processes. Promote problem-oriented group projects including fuel cell power prediction and flow field intelligent optimization, combine Project-Based Learning (PBL) and Outcome-Based Education (OBE) teaching concepts to integrate theory, algorithm, and engineering problems, and improve students' independent inquiry ability and teamwork ability [9].

4.3. Building a virtual-real integrated practical teaching system combining university and enterprise

Optimize traditional physical experiments by adding data modeling and intelligent analysis links. Replace high-risk and high-cost physical experiments with virtual simulation platforms to realize repeated parameter debugging and fault simulation. Strengthen university-enterprise cooperation, introduce real industrial operation data to build joint practical training platforms, and open teachers' scientific research projects to undergraduates [10]. The combination of virtual simulation experiment, physical experiment, and scientific research training effectively makes up for the deficiency of the practical teaching system.

4.4. Optimizing teacher training and diversified teaching evaluation mechanism

Carry out regular targeted training on Python programming and common machine learning algorithms for professional teachers, and build cross-disciplinary teaching teams composed of energy, materials, and big data teachers to realize collaborative lesson preparation and joint development of teaching resources. Reform the traditional single final examination mode, build a five-dimensional evaluation system covering theoretical examination, virtual simulation operation, modeling project, experimental performance, and scientific innovation achievements. Shift the evaluation focus from mechanical knowledge memorization to comprehensive ability assessment, guiding the dual transformation of teaching and learning modes.

5. Conclusion

The integration of machine learning and fuel cell courses is a targeted curriculum reform adapting to educational digital transformation and industrial intelligent upgrading, rather than simple superposition of intelligent technology and professional courses. This reform optimizes the curriculum knowledge system, classroom teaching mode, practical training system, and teaching evaluation mechanism in four dimensions, effectively solving long-standing teaching difficulties such as abstract microscopic mechanism explanation, insufficient experimental conditions, and lagging frontier content update.

The reform practice helps students establish data-driven engineering thinking, master intelligent modeling and parameter optimization capabilities on the basis of solid professional theories. In the future, universities should further adhere to the talent training path dominated by professional knowledge, supported by machine learning tools, and carrierized by university-enterprise practical education, and continuously promote the intelligent upgrading of fuel cell courses. The research results can help universities cultivate high-level interdisciplinary innovative talents for the hydrogen energy industry, and provide talent support for China's energy structure transformation and dual-carbon strategic goal realization.

Disclosure statement

The author declares no conflict of interest.

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