Article

Teaching Intelligent Fluid Dynamics through Engineering Cases: Design and Preliminary Practice of a Graduate Teaching Case Library

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Abstract: Effective integration of classroom instruction and research practice is essential to the quality of graduate engineering education. To address three persistent weaknesses in the teaching of fluid dynamics simulation courses, a graduate teaching case library, Intelligent Fluid Dynamics, was established. Specifically, theoretical instruction is delivered in isolation from research practice, systematic training in the application of acquired knowledge is absent, and assessment fails to reflect the stated course objectives. The reform takes the CFD simulation skills already acquired by students as its point of departure and targets research competence in intelligent fluid dynamics. Two complete teaching cases are under development: physics-informed neural network (PINN)-based flow field reconstruction and inversion, and deep reinforcement learning (DRL)-based active flow control of airfoils. Each case is supported by a knowledge-to-competence map and an instructor-oriented teaching guide. Learning is organized as a three-level progression, applied foundations, specialized depth and innovative practice, and is supported by purpose-built teaching procedures and an assessment scheme combining coursework with a final examination. Preliminary results indicate improved transfer of prior learning and enhanced specialized competence, and the experience is expected to be informative for comparable graduate courses.

Keywords: teaching case library; case-based teaching; intelligent fluid dynamics; physics-informed neural network; deep reinforcement learning

1. Introduction

Graduate education occupies the highest tier of the higher education system in China, and the cultivation of innovative ability has long been regarded as its central task. In practice, however, instruction in many specialized graduate courses remains a one-way transmission of knowledge, with limited exposure to research practice. A serious curricular disconnection has thus emerged, manifested in poorly sequenced content, objectives inconsistent with delivered instruction, and coursework that excludes research training [1].

A representative example is provided by the discipline considered in this study. The graduate course 'Fluid Dynamics Simulation and Analysis' is organized around three units: the finite volume method, mesh generation, and solver settings with post-processing. It is taught alongside 'Computational Fluid Dynamics' and 'Integral Equations and Inversion' in the same training program. Complete velocity and pressure fields for airfoil flows can be obtained through numerical simulation. Two demands that are not yet covered by these courses are posed by engineering practice. The first is the reconstruction of complete flow fields from sparse experimental data, such as the sparse velocity vectors obtained by PIV in a wind tunnel or the readings of a few wall-mounted pressure sensors; the second is the autonomous learning and optimization of control

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strategies by a simulation system. As AI for Science reshapes research in fluid mechanics [2-4], such topics are becoming standard extensions of the traditional syllabus. Nevertheless, many graduate courses still commence from first principles and disregard the simulation skills already acquired by students. Basic material must therefore be re-learned before the frontier of intelligent fluid dynamics is reached, resulting in inefficient use of instructional time and discontinuity in learning.

Students are frequently uncertain about the relationship between conventional numerical simulation and AI-based specialization. The material in some graduate courses is dense and difficult to assimilate within a single semester, and complete, executable, engineering-grounded cases integrating fluid mechanics with artificial intelligence are scarce. Both factors undermine teaching effectiveness and leave the extent of student mastery unclear. Graduate curriculum reform [5] must therefore address a practical question: how a case-driven pathway from simulation foundations to intelligent specialization can be constructed. In response to this need, the 'Intelligent Fluid Dynamics' graduate teaching case library was launched at the University of Shanghai for Science and Technology in September 2026. Two high-quality cases are being constructed around the core course 'Fluid Dynamics Simulation and Analysis', from which 'Computational Fluid Dynamics' and 'Integral Equations and Inversion' also benefit. Each case comprises a complete engineering background, physical and mathematical models, executable code, sample data, guided thinking questions and teaching slides.

2. Theoretical Basis and Reform Framework

2.1. Theoretical Perspectives on Case-Based Instruction

Innovative talent is fostered through the integrated development of curricula, whereby high-quality educational resources are consolidated into a coherent training system. Simulation courses constitute prerequisites for research training, and a graduate case-based curriculum is expected to align theory with practice. In such a curriculum, the theory and skills of the simulation courses are retained while advanced knowledge, interdisciplinary perspectives, frontier theory and innovative practice are progressively introduced. Professional knowledge is thereby acquired in a structured manner, the needs of advanced research are met, and innovative talent is developed [5, 6].

A clear instructional sequence is suggested by existing practice. Foundational knowledge points are introduced first, the content is subsequently extended in breadth and depth, and the process is concluded with project work [7]. It has further been argued that student demand should be taken as the point of departure, innovation awareness should be cultivated, differential course weighting should be applied at different stages, and the connections between courses should be strengthened [8]. A further methodological basis for the cases presented here is provided by physics-informed machine learning. Governing equations are embedded in data-driven models so that predictions remain physically consistent even when observations are sparse [2, 3], and machine learning has been developed into a distinct research paradigm in fluid mechanics [4]. These studies provide theoretical support for the case-library construction.

2.2. Reform Design

On this basis, the 'Intelligent Fluid Dynamics' case library serves as the vehicle for a reform that takes the simulation knowledge already acquired by students as its point of departure and is directed toward research competence. First, the theory and skills acquired in 'Fluid Dynamics Simulation and Analysis' are mapped onto the competence requirements of intelligent fluid dynamics. The content and teaching procedures of the graduate courses are then restructured around two complete engineering cases, PINN-based flow field reconstruction and inversion and DRL-based active flow control of airfoils, and learning is organized as a three-level progression: applied foundations, specialized depth and innovative practice. The objective is to convert simulation knowledge into specialized competence in intelligent fluid dynamics.

3. Design and Practice of the Case Library

3.1. Reorganizing Course Content Around Complete Engineering Cases

The reorganization of course content constitutes the first step of the case-library reform [9]. The syllabi of 'Fluid Dynamics Simulation and Analysis' and the two related courses were reviewed, and for each chapter the delivered content, the stated requirements and the competence developed were recorded; a complete inventory of simulation knowledge was thereby compiled. This inventory was then cross-referenced against every chapter of the two cases to identify the simulation knowledge on which each specialization topic depends, and the result was compiled as a knowledge-to-competence map linking prior student knowledge to the requirements of each case.

The case contents are organized according to the map. The course is opened with a two-credit-hour 'Opening Lecture: From CFD Simulation to Intelligent Fluid Dynamics', in which the relevance of the accumulated simulation knowledge to the specialization is outlined and the subsequent cases are introduced. Each case is then opened with a short segment of 'Fundamentals Revisited', in which the relevant simulation knowledge is first reviewed and the specialized theory and its applications are subsequently introduced. Each case is built around a single engineering object, the flow around a NACA0012 airfoil, and covers the full chain from engineering background and physical and mathematical models through executable code and sample data to guided thinking questions and teaching slides.

A teaching guide is prepared for each case. The prior knowledge on which each case builds, the extension of its concepts into practice, reference answers to the guided thinking questions, common errors and debugging methods, suggestions for further experiments and grading standards are recorded, so that the prerequisites and objectives of each case are immediately apparent to both instructors and students. This material has also been converted into concrete teaching checklists, thereby enhancing the precision of case-based instruction.

3.2. Three-Level Training Objectives

The objectives of a course determine the design of its teaching activities and the allocation of instructional effort. Traditional graduate objectives emphasize the mastery of specific knowledge and the development of research ability; the transformation of simulation competence into the specialized competence of intelligent fluid dynamics, however, is not addressed [10, 11]. The training objectives adopted here are therefore arranged as a three-level progression: applied foundations, specialized depth and innovative practice.

At the applied-foundation level, the simulation principles, software operation and data handling skills already possessed by students are applied to elementary problems in intelligent fluid dynamics. For instance, on the basis of the finite volume method, a PINN solution of the NACA0012 flow is compared with a high-fidelity CFD benchmark, the regions in which equation residuals concentrate are identified, and the mechanism by which a few sparse observations determine the global solution is explained.

At the specialized-depth level, student simulation knowledge is extended, and a practical understanding is acquired of the training of physics-informed neural networks and the state-action-reward structure of deep reinforcement learning. The design of data assimilation schemes and active flow control strategies is also required, for example the reconstruction of the full field around an airfoil from a few wall pressure readings. At the innovative-practice level, simulation foundations are combined with graduate-level specialized knowledge through participation in research projects on intelligent fluid dynamics, in which improvements to specialized techniques are proposed and complex computational data are interpreted, for instance by extending the PINN case to a three-dimensional wing or tuning the SAC controller for separation suppression. The three levels build on one another, and as each level is succeeded by the next [12], both the expected competence and the focus of learning are shifted.

3.3. Instructional Design for the Two Cases

The teaching procedures translate course objectives into classroom activities. Specialized theories are often presented in graduate teaching without reference to the simulation skills established earlier; three purpose-built procedures are therefore adopted to address this limitation.

The first is a problem-oriented opening: each case is initiated with a concrete problem that draws on a limited body of prior knowledge and stimulates curiosity [13]. Before 'PINN-based flow field reconstruction and inversion', for example, students are required to explain why the conventional CFD solvers previously employed cannot be directly applied when only a few PIV vectors are obtained experimentally. In answering this question, the mastered forward simulation workflow must be retrieved and the specific difficulties of data assimilation confronted, thereby facilitating a natural transition to the new topic.

The second procedure is case-driven extension: two specialized cases are built on the simulation foundations. In Case 1 a fully connected network $(x, y) \rightarrow (u, v, p)$ is trained to reconstruct the steady flow around a NACA0012 airfoil at Re = 3000 with U∞ = 1 m/s and chord c = 1 m; the two-dimensional incompressible Navier–Stokes equations are embedded in the total loss $L_{\text{total}} = \alpha L_{\text{data}} + \beta L_{\text{eqns}} + \gamma L_{\text{bc}}$ alongside the sparse observation error and the boundary condition residual. With only 500 observation points, about 1% of the grid points, the predicted velocity field matches the CFD benchmark in velocity distribution, stagnation point position, leading-edge acceleration region and wake morphology, with a relative error of about 3.2%, and the method is further verified on water-tunnel PIV data of a turbulent boundary layer with missing regions. In Case 2 the CFD solver serves as the environment of a DRL agent. The state consists of velocity readings from a few probes; the action adjusts the jet fluxes of a synthetic jet actuator at $x/c = 0.2$ on the upper surface at an angle of attack of 10; the three jet slots operate at zero net mass flux ($Q_i = U_{\text{jet},i} \cdot L_{\text{jet}}, Q_3 = Q_1 + Q_2$); and the multi-objective reward $R_C = (C_D)_{t_0} - (C_D)_t - a\left|(C_L)_{t_0} - (C_L)_t\right|$, balances drag reduction against lift retention with an energy penalty [14, 15]. The implementation is carried out in three stages. The OpenFOAM environment is built with a Python interface, the soft actor-critic agent is trained with the Tianshou library until the reward curve converges, and the uncontrolled, open-loop and DRL-controlled configurations are compared in terms of vorticity fields, reward curves and lift-drag coefficients.

The third procedure introduces a computational experiment. On the existing CFD platforms, extended computational projects are carried out in Jupyter Notebooks. The observation data are resampled at different sparsity levels (100, 500 and 2000 points) and noise levels (0%, 5% and 10%) to quantify the robustness of PINN, and the trained controller is tested under changing inflow conditions. By reusing existing computational resources, reform costs are minimized, and the simulation skills acquired in course exercises are linked to research practice [16].

3.4. Assessment Design and Feedback

Assessment design exerts a direct influence on teaching behavior. Conventional graduate examinations assess specialized knowledge and research ability; however, the ability to apply the knowledge acquired in simulation courses is not examined, and consequently the degree of integration between fundamentals and specialization cannot be demonstrated. Two complementary forms of assessment are therefore used.

Transfer-oriented assignments are now incorporated into the coursework: a comparative essay on AI-based and conventional methods of flow field prediction, written on the basis of previously acquired simulation experience, and laboratory reports in which each case is traced back to the simulation skills on which it builds. The ability to apply simulation knowledge in unfamiliar settings accounts for 30% of the final grade.

The final examination is supplemented with integrative questions that link fundamentals with specialization, such as Based on the Navier–Stokes equations and the PINN loss function, analyze how the weights (α, β, γ) affect reconstruction accuracy and design a stable training scheme for a flow field reconstruction system, so that the

integration of knowledge at every level can be evaluated. The course paper, in which the application of simulation foundations to a specific research topic must be demonstrated, accounts for the remaining 40% of the grade. Feedback from questionnaires, student interviews, homework and test papers is collected continuously, so that deficiencies in teaching can be identified and content and methods adjusted promptly.

4. Discussion

4.1. Early Evidence

Improved transfer of learned knowledge to new settings has been observed. Through the knowledge-to-competence map and the opening lecture, the connection between student simulation knowledge and the specialized content of intelligent fluid dynamics is made explicit, and the confusion typically associated with the transition from numerical simulation to AI-based research is alleviated. In discussion, the simulation background is drawn upon more actively in the resolution of concrete problems, such as explaining the physical meaning of individual PINN loss terms or evaluating the rationality of a reward design.

An improvement in learning efficiency has also been observed. By anchoring specialized instruction in simulation studies, repeated coverage of previously mastered material is avoided and access to in-depth specialized work is advanced. Homework and test data indicate increased mastery of specialized content and improved performance on integrated questions combining simulation and specialized knowledge.

The student response has been positive. At the end of the semester, the case design was reported by most students to have improved the comprehensibility of the course and the efficiency of learning, and favorable ratings were given to both the problem-oriented openings and the case-driven extension work. A total of 58 students were enrolled in the two most recent offerings of the related courses. More than ten AI teaching cases accumulated in the undergraduate course ‘Engineering Fluid Mechanics’ are also drawn upon as prototypes for the case library.

4.2. Remaining Issues and Outlook

The same evidence, however, also reveals several limitations. First, student backgrounds are heterogeneous. Python programming, deep learning and numerical methods have not been fully mastered by some students, and the code implementation and mathematical derivation of the cases are found difficult to follow. Remedial support is required for students with insufficient prior preparation without reducing the progress of the cohort; effective approaches to such support remain to be established.

Second, higher requirements are imposed on instructors by case-based teaching. Both CFD techniques and AI methods must be mastered, thorough familiarity with the engineering background of the cases is required, and teaching procedures that effectively integrate the two must be designed. This capacity is strengthened through team collaboration, collective lesson planning, and the involvement of a team member from the Energy Science and Technology Research Institute of State Power Investment Corporation, who reviews the engineering background and supplies authentic engineering data; such measures underpin the sustained development of the reform.

Third, the evidence base remains insufficient. The present assessment relies mainly on classroom performance, coursework scores and questionnaires; systematic before-and-after comparisons and long-term follow-up evidence are not yet available. In future work, a quasi-experimental evaluation will be conducted with a control group, so that the effect of the reform can be estimated more rigorously. All case materials, including code, data and courseware, will also be released on the college platform and GitHub so that a broader range of courses and students can benefit from the library.

5. Conclusion

Postgraduate education in this field depends critically on the connection between simulation foundations and intelligent fluid dynamics specialization. The ‘Intelligent

Fluid Dynamics' graduate teaching case library represents one attempt to establish such a connection, implemented through a reform that takes the simulation competence already acquired as its point of departure and research capability as its objective. The practice reported here demonstrates that two complete cases, PINN-based flow field reconstruction and inversion and DRL-based active flow control of airfoils, can be constructed with an explicit knowledge-to-competence map and an instructor-oriented teaching guide; that a three-level progression of applied foundations, specialized depth and innovative practice can provide direction for training; and that purpose-built teaching procedures and a comprehensive assessment scheme can convert fragmented knowledge into applicable competence. The gap between graduate coursework and research practice is thereby narrowed, and the ability to apply specialized knowledge in practice is gradually acquired by students.

This experience can be drawn upon by other graduate specialization courses at the same institution that likewise rest on simulation foundations, as well as by similar courses at other institutions. A case-based curriculum nevertheless extends beyond the classroom to encompass program design, curriculum structure, teaching methods and assessment, and these dimensions will need to be examined in an integrated manner in future research.

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