

Digital-Fluid Intelligent Learning: AI-Driven Visualization for Dynamic Demonstration in Fluid Mechanics Classes

Ruizi Zhang*

School of Energy and Power Engineering, University of Shanghai for Science and Technology, Shanghai 200093, China

**Author to whom correspondence should be addressed.*

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Abstract: Aiming at common pain points in current fluid-mechanics classes, including invisible flow phenomena, insufficient physical experiment supplies, high-threshold conventional CFD tools, and poor interactivity of digital resources, this paper takes the “Digital-Fluid Intelligent Learning” AI visualization demonstration system as the carrier to explore innovative paths for empowering dynamic demonstrations in fluid-mechanics classes with AI technology. From four dimensions: flow-field visualization, virtual-experiment library, real-time solving engine, and inquiry-based ecosystem, this study puts forward implementation strategies. It breaks the disconnection between theories and phenomena in traditional teaching, realizes real-time interactive generation of dynamic flow-field effects in class, effectively lowers the cognitive threshold for core knowledge points, and provides referable practical solutions for the digital transformation of engineering fluid-related courses.

Keywords: Digital-fluid intelligent learning; AI visualization; Fluid mechanics; In-class dynamic demonstration; Virtual fluid experiment

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1. Introduction

As a core basic course for multiple engineering majors, fluid mechanics has long been restricted by the inherent property that flow phenomena cannot be directly observed. Traditional classroom teaching constantly faces practical problems such as difficulty in understanding abstract theories, insufficient coverage of physical experiments, and low demonstration efficiency. A large number of students fail to establish corresponding connections between theoretical formulas and real flow laws, which directly affects learning outcomes of subsequent specialized courses. Against the backdrop of Emerging Engineering Education and the digital transformation of education, the construction of fluid-mechanics courses has gradually shifted from single theoretical lecturing to a teaching mode combining engineering cases, digital resources, and practical teaching

^[1]. In recent years, machine learning and physics-informed deep learning have been gradually applied in

flow-field modeling, order reduction and fast prediction, laying a technical foundation for lightweight flow-field generation for classroom use ^[2,3]. Meanwhile, three-dimensional dynamic flow-field visualization and virtual-reality systems based on CFD data have been adopted in fluid-mechanics teaching ^[4]. Therefore, it is feasible to reconstruct in-class dynamic-demonstration modes relying on data-driven models and interactive-visualization technologies. Taking the “Digital-Fluid Intelligent Learning” platform as a practical carrier, this paper explores new paths for dynamic demonstration adapted to classroom scenarios, and offers new solutions for addressing traditional teaching pain points of fluid mechanics.

2. Existing problems in fluid-mechanics classes

2.1. Lack of flow-feature visualization, difficult-to-break cognitive barriers for abstract theories

Behind fluid motion lie physical quantities including velocity distribution, pressure gradient, vortex evolution and shear-stress transfer, all of which are implicit parameters that cannot be directly observed. Conventional classroom teaching merely relies on static two-dimensional cloud charts and simplified streamline schematic diagrams, together with blackboard-writing derivation of the mathematical form of the Navier-Stokes equations. Students mainly understand flow laws indirectly through mathematical deduction and static images. They can hardly observe the continuous evolution of flow states varying with control parameters, which easily gives rise to insufficient connections among theoretical equations, physical-quantity distribution and real flow phenomena. Existing research on virtual-simulation teaching of fluid mechanics also regards abstract basic concepts, lack of direct student experience, and time-space constraints of offline experiments as important factors impairing teaching effects. Especially for turbulence problems, multi-scale vortex structures and their dynamic-evolution processes cannot be fully presented via single-frame static images.

2.2. Insufficient supply of physical fluid experiments, limited coverage of synchronous in-class demonstrations

Physical facilities such as traditional Reynolds-experiment devices, Venturi-tube test platforms, small-scale wind tunnels and circulating water tunnels involve procurement, operation and maintenance costs, and are restricted by equipment quantity, experimental venues and class hours. Under large-class-teaching conditions, students have relatively limited opportunities for close observation and synchronous operation. For working conditions hard to carry out in ordinary teaching laboratories, such as high-pressure, high-speed, and complex multi-phase flows, virtual experiments can provide repeatable and parameter-adjustable supplementary observation environments, yet they shall not replace necessary physical experiments and hands-on operational training ^[5-7].

2.3. High-operation-threshold of conventional CFD simulation tools, incompatible with real-time in-class demonstration rhythm

Mainstream commercial fluid-simulation tool Fluent and open-source tool OpenFOAM require hours or even days to finish full-process computation. The computing workflow covers meshing, physical-model selection and iterative convergent solving, and the whole process heavily depends on high-performance computing hardware. Teachers cannot adjust parameters on-the-spot in class to rapidly generate corresponding dynamic flow-field results. Such professional software features complex operational logic; students need considerable

class hours just to learn pre-processing operational skills, whose learning content deviates from the teaching objectives of core fluid-mechanics theories. Static images dominate post-processing outputs of such tools; even available dynamic animations need pre-computation several days in advance, failing to satisfy teachers' and students' demands for real-time interactive debugging of flow-field patterns in class. Existing studies on ANSYS-aided practical teaching of fluid mechanics and construction of computational-fluid-mechanics courses indicate that professional simulation tools can expand engineering-practice teaching, yet corresponding software training, numerical-method foundations and curriculum-organization design are also required ^[8,9]. Hence, direct application of general-purpose CFD software for high-frequency parameter interaction in class still has considerable thresholds.

3. Strategies for empowering dynamic demonstration in fluid-mechanics classes via AI visualization

3.1. Construct a full-dimensional dynamic flow-field visualization module to break cognitive barriers of abstract theories

Aiming at the difficulty of continuous observation of flow features in traditional classes, the “Digital-Fluid Intelligent Learning” platform converts physical fields such as velocity, pressure, and vorticity into interactive dynamic visual content. During teaching, teachers can adjust control parameters such as Reynolds numbers via sliders, and the interface invokes or generates representative flow-fields under corresponding parameter conditions synchronously, enabling students to continuously observe the process where steady streamlines lose stability and gradually form complex vortex structures. For turbulence-related content, the system provides layered-display functions for multi-scale vortex structures, which present large-scale energy-containing vortices, intermediate-scale energy-transfer processes and small-scale dissipative structures in layers, helping students understand multi-scale features and energy-cascade processes of turbulence ^[10]. Existing three-dimensional flow-field virtual-reality systems based on CFD data can dynamically display complex vortex structures. Research on virtual-simulation experiments in fluid mechanics also proves that interactive flow-field presentation helps improve the intuitive experience of abstract concepts and supports inquiry-based learning. As shown in **Figure 1**, through dynamic flow-field demonstration and multi-scale layered display, the platform establishes connections among theoretical equations, physical-quantity distribution and flow phenomena.

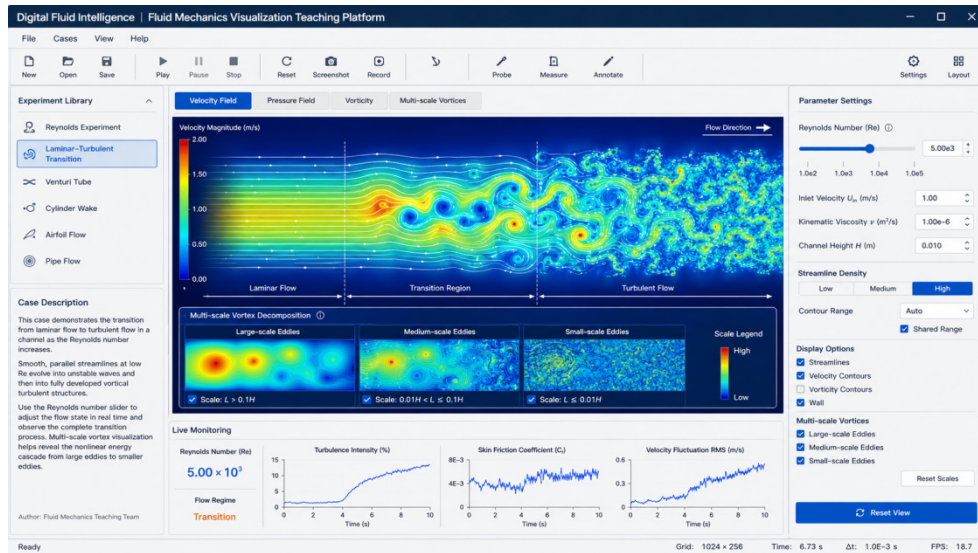


Figure 1. Visualization Interface for Laminar-Turbulent Transition and Multi-Scale Vortex Structures on the “Digital-Fluid Intelligent Learning” Platform.

3.2. Develop a full-scenario virtual-fluid-experiment library to make up for shortages in physical-experiment resource supply

Centering on core teaching knowledge points of fluid mechanics, the Digital-Fluid Intelligent Learning system builds a virtual-fluid-experiment library covering three categories of scenarios: basic verification, engineering application and extreme working conditions, making up for resource shortages of traditional physical experiments. Basic-category experiments fully restore the operational logic of classic physical experiments, including Reynolds experiments, Venturi-tube flow-rate tests, and airfoil flow-around tests. Physical laws corresponding to all experimental phenomena are consistent with real-experimental results. After teachers launch demonstrations in class, all students can observe detailed flow-field changes synchronously through their own terminals, breaking the restriction that only two to four students can watch demonstrations around one single physical device. For scenarios hard to conduct in ordinary teaching laboratories, such as high-pressure, high-speed, or complex multi-phase flows, the platform delivers supplementary visual demonstrations without replacing physical-experiment training on device cognition, data acquisition, and error analysis. The system supports one-click switching of boundary conditions; new flow-field results can be generated within several seconds after parameter adjustment. More than ten groups of comparative demonstrations for different working conditions can be completed within one class hour. Teachers can show in real time how variations in pipe diameter, flow velocity, pressure, and other parameters affect flow-field patterns, solving the problems of low demonstration efficiency and narrow coverage of traditional physical experiments.

3.3. Build zero-code AI real-time solving engine to adapt to high-frequency interactive demonstration rhythm in class

The Digital-Fluid Intelligent Learning system eliminates complicated operational workflows of traditional CFD tools. It is equipped with a zero-code AI real-time solving engine specially customized for classroom teaching, which directly lowers technical thresholds for fluid dynamics demonstrations. Machine learning and physics-informed deep learning have been applied in flow-field order-reduction, governing-equation solving

and flow-state prediction, providing methodological foundations for such fast surrogate models. For airfoil flow-around problems, deep-learning models have also been adopted to rapidly infer RANS velocity fields and pressure fields according to geometric conditions ^[11]. The system completes pre-training and lightweight encapsulation for different geometric models in advance. Teachers do not need to manually perform meshing, physical-model selection, iterative-parameter debugging and other professional operations. They only need to select corresponding demonstration cases on the visualization interface to enter the interactive-demonstration state. High-frame-rate dynamic flow-field outputs are available within several seconds after parameter adjustment. This design avoids the problem that considerable class hours are consumed for pre-processing-operation learning required by traditional CFD tools. All operation logics are designed around core knowledge points of fluid mechanics. Teachers' and students' attention can be fully focused on exploring flow laws without distraction caused by complex software operations. The system supports real-time two-way interaction in class. Students can submit parameter-adjustment demands on their own terminals. Teachers click for confirmation, and corresponding dynamic flow-field images will be generated synchronously. It breaks the restriction that traditional demonstrations can only adopt pre-generated animations, enabling on-demand observation and instant feedback in class and delivering immersive interactive-demonstration effects.

4. Conclusion

Facing the long-term trend of digital transformation in engineering education, the deep integration between AI visualization and fluid-mechanics classes is far more than simple teaching-tool upgrading. It serves as a core driving force to promote curriculum transformation from “theoretical indoctrination” to “phenomenon-oriented inquiry”. The platform helps strengthen connections among theoretical knowledge, physical-quantity distribution and flow phenomena, and offers technical support for improving intuitive presentation of abstract concepts and enhancing classroom interactivity. In the future, platforms similar to Digital-Fluid Intelligent Learning can further connect with more subdivided engineering-fluid-related scenarios, continuously optimize real-time solving accuracy and interactive experience, and render abstract flow laws truly perceivable, explorable, and interactive. It helps students consolidate theoretical foundations and establish engineering thinking within immersive demonstration scenarios, comprehensively foster an inquiry-based learning atmosphere in class, and provide stronger digital support for cultivating high-quality engineering-technical talents.

Disclosure statement

The author declares no conflict of interest.

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