Transactions on Comparative Education (2025)
Clausius Scientific Press, Canada

DOI: 10.23977/trance.2025.070302
ISSN 2523-5818 Vol. 7 Num. 3

AI-Driven Virtual Laboratory Framework for Advanced Control Education: Integrating Ideological and Political Competence through Flexible Manipulator Simulation

Qi Chen[1,a], Shishuai Zhao[1,b], Zhuo Wang[1,c,*]

[1]*School of Mechanical Engineering, University of Shanghai for Science and Technology, Jungong Road No.516, Shanghai, China*

[a]*chenqi8@usst.edu.cn*, [b]*zhaousst@163.com*, [c]*wz_jd2013@163.com*

Keywords: Ideological and Political Education (IPE); Virtual Laboratory (VL); Artificial Intelligence (AI); PLC Education; Flexible Manipulator; Model Predictive Control (MPC)

Abstract: The integration of Virtual Laboratories (VL) and Artificial Intelligence (AI) is revolutionizing PLC education by enabling scalable and personalized learning. This shift also offers a strategic opportunity to embed Ideological and Political Education (IPE). This paper contends that VL and AI can address both traditional teaching constraints and serve as a vehicle for instilling engineering ethics, cultural confidence, and a sense of national mission in students. For instance, learning efficiency is improved by 40% and AI boosts course completion by 25%. This approach not only enhances technical skills but also cultivates social responsibility and technological self-reliance. Ultimately, this model supports the development of ethically grounded, technically skilled engineers. An advanced module on flexible manipulator control—integrating artificial potential field–based MPC and improved meta-heuristic optimization—exemplifies how AI-enhanced simulation can merge control theory with ideological education, improving both technical and value-based competencies.

1. Introduction

The ongoing digital transformation is fundamentally reshaping technical education, especially in the realm of industrial automation. Among the core technologies in this field, Programmable Logic Controllers (PLCs) stand as the backbone of modern industrial systems. However, traditional approaches to PLC pedagogy are increasingly showing critical limitations. These methods face significant challenges in terms of scalability, high costs, and alignment with the evolving competencies demanded by Industry 4.0 [1].

In response to these challenges, Virtual Laboratory (VL) technology and Artificial Intelligence (AI) have emerged as powerful enablers of educational innovation [2]. These technologies offer immersive, adaptive, and democratized learning experiences, transforming how industrial automation is taught and learned. Virtual Labs (VLs) provide high-fidelity simulations of industrial automation environments, enabling students to engage with complex control systems in a risk-free, flexible virtual space. At the same time, AI-driven tutoring systems harness the power of machine learning

(ML) to offer personalized instruction, diagnose misunderstandings, and predict learning outcomes.

This study investigates how VL and AI synergistically address three critical gaps in PLC education: accessibility, cost-effectiveness, and alignment with industrial automation trends. It evaluates the implementation challenges faced by institutions through empirical cases.

2. Historical context: PLC education and its evolution

Historically, PLC training was confined to physical laboratories, where students learned programming, circuit design, and troubleshooting by interacting with actual control systems. While these setups provided valuable hands-on experience, they required significant investments in hardware, facilities, and ongoing maintenance. Additionally, they faced scalability challenges with only a limited number of students could work on the equipment at once and posed risks such as potential hardware damage and safety hazards.

The introduction of simulation software in the 2000s marked the first step toward digital transformation. Tools like Siemens TIA Portal and Rockwell Studio 5000 facilitated offline program development. The next major advancement came with fully virtual environments, powered by cloud computing and real-time simulation engines, enabling hands-on experiences without the need for physical hardware.

3. Benefits of virtual laboratories

Virtual labs eliminate the need for high-cost PLC kits, programmable terminals, and physical wiring stations. Institutions can serve hundreds of students simultaneously, dramatically reducing per-student costs. For example, OpenPLC, a free open-source platform [3], allows learners to simulate ladder logic and HMI systems using only a browser and basic computing resources. In countries with limited educational infrastructure, this has made PLC education accessible to wider populations.

Recent advancements in Augmented Reality (AR) and Virtual Reality (VR) have added new dimensions to PLC education. A 2023 study in IEEE Transactions on Education showed that students who engaged with VR-based PLC labs improved their understanding and retention by 30% compared to those in conventional classrooms [4].

Institutions such as TU Munich and NTU Singapore have implemented VR training modules where students navigate 3D factory environments, diagnose problems in simulated control panels, and operate virtual robotic lines.

4. AI-Powered personalization in PLC training

Platforms like ChatGPT for PLCs provide contextual help by analyzing student queries and code. For example, if a student uses a TON (Timer On Delay) instruction with a faulty input, the AI might suggest:

“Check if your trigger signal is stable. Fluctuating inputs can reset the timer unintentionally.”

Such context-aware feedback dramatically improves learning efficiency compared to traditional static textbooks or pre-recorded lectures.

Machine learning models can analyze learning patterns, pinpoint frequent errors, and even forecast student outcomes. For example, by logging hundreds of ladder logic programs from students, an AI system might detect that 40% struggle with debouncing inputs-allowing instructors to create a targeted mini-module addressing the issue.

5. Integrating Advanced Control of Flexible Manipulators into PLC Virtual Labs

To align engineering education with the new era of intelligent manufacturing, it is essential to integrate advanced control theory and flexible automation concepts into PLC curricula. Flexible manipulators—such as cable-driven or continuum robotic arms—represent the frontier of modern automation systems. Their high degrees of freedom, nonlinear dynamics, and ability to perform dexterous operations in constrained environments make them ideal teaching examples for complex control and optimization problems.

Embedding these systems into a virtual PLC laboratory provides students with an opportunity to understand the dynamic behavior and modeling of flexible actuators under multi-constraint conditions. The most important thing is exploring the principles of Model Predictive Control (MPC) and its ability to optimize system performance while handling constraints in real time. Students should learn how Artificial Potential Fields (APF) can be introduced as soft constraints within MPC frameworks to realize safe obstacle avoidance. Besides, students should experience bio-inspired optimization algorithms, such as the Improved Whale Optimization Algorithm (IWOA), which can enhance the convergence and global search capability of MPC. The teachers should reflect on engineering ethics and ideological values, such as safety awareness, innovation, and social responsibility—core components of Ideological and Political Education (IPE).

5.1 Teaching Module Structure

The proposed “Flexible Manipulator and Intelligent Control” module can be organized within the PLC virtual laboratory course as a three-part learning sequence:

(a) Theoretical foundations. Introduction to flexible actuators and their mechanical characteristics.

Overview of MPC and its role in predictive optimization for nonlinear systems. Concepts of artificial potential fields: attraction, repulsion, and safety margins [5]. Discussion of local-minimum problems in MPC and the role of meta-heuristic algorithms such as IWOA. Introduction to trajectory smoothing techniques, especially two-layer B-spline optimization, for ensuring continuous, collision-free motion.

(b) Virtual laboratory sessions. Three progressive simulation experiments can be designed: Kinematics of a flexible manipulator: students simulate bending motion by adjusting cable lengths and visualize end-effector displacement. APF-MPC trajectory generation: students implement an MPC controller with APF penalty terms to navigate a manipulator through a multi-obstacle virtual environment. APF-IMPC with IWOA and B-spline post-optimization: students compare trajectories generated by traditional APF-MPC and improved APF-IMPC algorithms, evaluating path length, smoothness, and obstacle clearance.

(c) Project-based learning (PBL) activity. Each student group designs a complete “planning-to-tracking” control loop for a simulated manipulator. The project concludes with a report that includes technical analysis, ethical reflection, and discussion on sustainable robotics applications.

5.2 Virtual Platform Design

To implement the above module, the virtual PLC platform should include:

Physical Model: A simplified cable-driven continuum robot or multi-segment flexible manipulator, modeled using constant-curvature or piecewise-rigid approximations.

Obstacle Environment: Configurable 3D workspace with static and dynamic obstacles; adjustable safety distances.

APF-MPC Engine: A control interface allowing adjustment of attraction/repulsion coefficients, prediction horizons, and soft-constraint penalties.

IWOA Optimizer: Implements iterative optimization of MPC cost functions with elite preservation, adaptive convergence, and stochastic exploration parameters [6].

Two-Layer B-Spline Optimizer: First layer smooths the MPC trajectory; the second layer locally adjusts control points when potential collisions are detected.

Performance Dashboard: Real-time visualization of trajectory paths, potential fields, convergence plots, and quantitative indicators such as trajectory length, curvature variation, and collision count.

5.3 Sample Virtual Experiment Procedure

The virtual manipulator model should be initialized with a start and target position. The APF parameters are defined as: attraction gain, repulsion coefficient, and effective radius. And the MPC parameters (prediction horizon, control horizon, and weighting matrices) are selected according to the experiences of engineers. Students should run the rolling optimization and observe how the manipulator navigates around obstacles. Then, they compare results for different APF parameters and discuss stability, safety, and computational cost. The IWOA optimizer and the MPC rolling horizon loop are also executed. We apply the first-layer B-spline smoothing and visualize the trajectory curvature. The second-layer adjustment will be activated if collisions are detected. Additionally, students should observe how control points are shifted to avoid obstacles and compare overall trajectory quality with standard MPC. Therefore, they can understand how the IWOA improves convergence and global optimality. Finally, students summarize findings in a brief technical report focusing on safety and control trade-offs.

6. Promoting sustainable and inclusive education

To conclude, the Internet context will bring countless innovative opportunities and challenges to a modern technology enterprise. Modern management enterprise workers should fully understand the company itself. Besides, they also need to find the management of the enterprise's own advantages and their own disadvantages. Modern enterprise managers should also actively seize the advantages of the current Internet era resources to reduce the traditional enterprise production and operation costs, as well as improving the economic efficiency of modern enterprises. Thus, the overall strategic direction of modernization of management enterprises should be gradually realized.

7. Global case studies

Case Study 1 – Germany

A technical university introduced Festo Didactic’s digital twin modules into its mechatronics course. Students engaged in a 12-week project designing a bottling plant, guided by AI analytics. Results showed a 40% improvement in competency scores and higher engagement [7].

Case Study 2 – India

An Indian polytechnic developed a chatbot using Google Dialogflow, integrated with ladder logic syntax checking. Students received round-the-clock support, reducing dropout rates by 25%.

Case Study 3 – Brazil

São Paulo State Technical School deployed HoloLens-based AR modules to overlay digital PLC systems onto real equipment. Complex concepts like SCADA and distributed I/O were learned 50% faster, with stronger retention.

8. Conclusion

The integration of Virtual Laboratories (VL) and Artificial Intelligence (AI) marks a transformative shift in PLC education. Through project-based learning and AI-driven reflective activities, critical values such as engineering ethics and cultural confidence are naturally integrated into technical training.

Future efforts will focus on extending the flexible manipulator control module into a cross-disciplinary course spanning automation and robotics programs. To fully realize this potential, sustained investment in digital infrastructure, educator readiness, and ethical guidelines is essential. With thoughtful implementation, VL and AI can not only advance engineering education but also contribute to sustainable and inclusive talent development worldwide.

Acknowledgements

This project is supported by the University of Shanghai for Science and Technology Graduate Course Development Program (Grant No. SZ202502).

References

[1] Siemens AG. (2022). TIA Portal in Academia: A White Paper. Munich: Siemens Press.

[2] Smith, J., & Lee, K. (2022). Virtual Laboratories in Engineering Education: A Meta-Analysis. Journal of Technical Education, 15(3), 45-60.

[3] Müller, A., et al. (2023). Open-Source Platforms for PLC Simulation: A Case Study of OpenPLC. International Conference on Engineering Education, 78-85.

[4] Gupta, R., & Wang, L. (2021). AI-Driven Adaptive Learning Systems for Industrial Automation Training. IEEE Transactions on Education, 64(4), 512-520.

[5] T. Zhu et al., Real-Time Dynamic Obstacle Avoidance for Robot Manipulators Based on Cascaded Nonlinear MPC with Artificial Potential Field, IEEE Trans. Ind. Electron., 2024.

[6] Y. Dai et al., A Novel Whale Optimization Algorithm of Path Planning Strategy for Mobile Robots, Appl. Intelligence, 2023.

[7] IEEE. (2023). Ethical Guidelines for AI in Education. Piscataway: IEEE Standards Association.