This article has been accepted for publication in a future proceedings of this conference, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/ICMCR64890.2025.10962807, 2025 3rd International Conference on Mechatronics, Control and Robotics (ICMCR)

A self-aware robotic machining architecture based on physics-informed neural networks

Yuanhui Zhang
Shien-Ming Wu School of Intelligent Engineering
South China University of Technology
Guangzhou, China
zyh351713@163.com

Mingfeng Wang
Department of Mechanical and Aerospace Engineering Brunel University
London, UK
Mingfeng.Wang@brunel.ac.uk

Kai Wu*
Shien-Ming Wu School of Intelligent Engineering
South China University of Technology
Guangzhou, China
whphwk@scut.edu.cn

***Abstract*—Industrial robots have been widely used in various industrial scenarios due to their flexibility and expandability. However, robots are susceptible to instability at high speeds and load conditions due to their low stiffness and dynamic characteristics variation with posture. Enhancing the processing stability of industrial robots through data-driven modeling and physical modeling approaches suffers from different drawbacks, such as solution complexity and weak interpretability. With the emergence of physics-informed neural networks (PINNs), new methodologies can be developed to enhance the self-aware processing of robots. In this paper, typical industry application scenarios and dynamics of robotics as well as PINNs are introduced and analyzed, and a framework and method based on PINNs are proposed to enhance the self-aware operation of industrial robots. This framework and methodology contribute to the researcher's efforts to apply PINNs more intensively to robot operation in the future to improve the stability and intelligence of robot operation.**

Keywords—industrial robot, self-aware machining, physics-informed neural networks

I. INTRODUCTION

In modern manufacturing, robots have become a driving force for enhancing productivity, precision, and flexibility across various industries [1, 2]. The integration of robotic systems in processes such as milling, grinding, and drilling has demonstrated remarkable efficiency and flexibility advantages, particularly in handling complex and large-scale components [3, 4]. However, industrial robots with an open-architecture design exhibit low stiffness and dynamic nonlinear time-varying characteristics, leading to unpredictability in the operation process [5, 6]. By integrating the robot's spatial static and dynamic information with the operational parameter system, the robot's self-awareness and operational capabilities would be enhanced.

The Physics-Informed Neural Networks (PINNs) were proposed by a research group from Brown University's Applied Mathematics Department [7]. These PINNs can learn the distribution patterns of training data samples just like traditional neural networks, while also learning the physical laws described by mathematical equations, enabling the model to learn more generalized pat[1]terns with fewer data samples [8]. PINNs have been applied to industrial scenarios such as condition monitoring and stability analysis [9, 10]. However, the nonlinear time-varying characteristics of the dynamics and the posture-dependent characteristics of the static parameters of the robotic operating system make modeling and solving its work processes difficult.

This paper analyzes the spatial information and parameter flow of the robot operation process and the self-awareness modeling process. A solution and learning framework are proposed for PINNs with robot self-awareness enhancement. This framework enables researchers to apply PINNs to the robot operation modeling and physics-solving process, which is conducive to enhancing the robot's self-perception operation capability.

II. ROBOTIC OPERATION FLOW AND INHERENT CHARACTERISTICS

A. Robot systems and operating procedures

With the improvement of robot load capacity and control algorithms, robots have been widely used in various fields of manufacturing processes. Typical application scenarios for industrial robots include welding, drilling, grinding and milling, etc. These different tasks require auxiliary end-effector equipment and control codes. The operational flow of a task-oriented industrial robot is shown in Fig. 1(a). The first step is to design and plan the robot path according to the task, design the robot motion parameters based on empirics, then generate the robot control code through offline programming tools, verify and debug the robot operation through the simulation environment, and finally import the debugged control program into the robot control system to perform the task. In the above process, the robot's task execution process is open-ended and lacks self-awareness of the machining process. Therefore, the robot is weak in controlling unexpected situations and non-stable phenomena, and it is difficult to ensure the stability of the machining process. The instability in the machining process, especially vibrations, may lead to the deterioration of the workpiece surface quality, rapid tool wear, and even damage to the robot's structure.

This work was supported by the Ministry of Education of the People's Republic of China, Grant No. 202201789 and the GJYC program of Guangzhou, Grant No. 2024D03J0005

This article has been accepted for publication in a future proceedings of this conference, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/ICMCR64890.2025.10962807, 2025 3rd International Conference on Mechatronics, Control and Robotics (ICMCR)

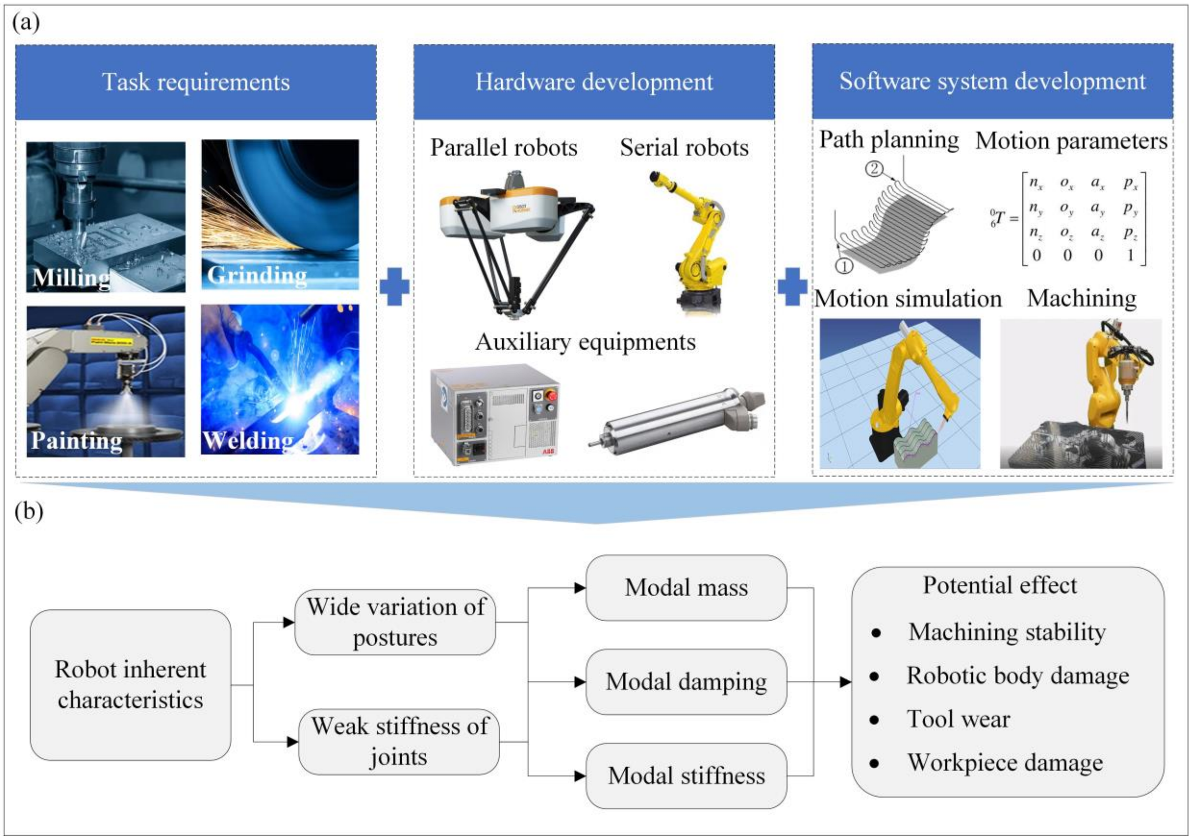

Fig. 1. Typical robot application scenarios, operational processes, and inherent characteristics.

B. *Inherent characteristics of robotic machining*

As shown in Fig. 1(b), there are differences in the characteristics of robots and CNC machine tools, mainly as follows：(Ⅰ) Due to the articulated tandem structure, the dynamic and static stiffness of the robot is spatially variable and much lower than that of the machine tool. (Ⅱ) A robot's modal characteristic parameters (such as modal mass, modal damping, modal stiffness, modal frequency, etc.) exhibit nonlinear variation with pose. Therefore, it is necessary to consider the inherent characteristics of robots in the process of improving their self-awareness operation capabilities.

C. *Robot operation modeling and self-awareness process*

Robot self-awareness mainly consists of advance prediction before operation and online monitoring during operation. Advance prediction consists of establishing the motion characteristic equations of the robot for a stable domain solution.

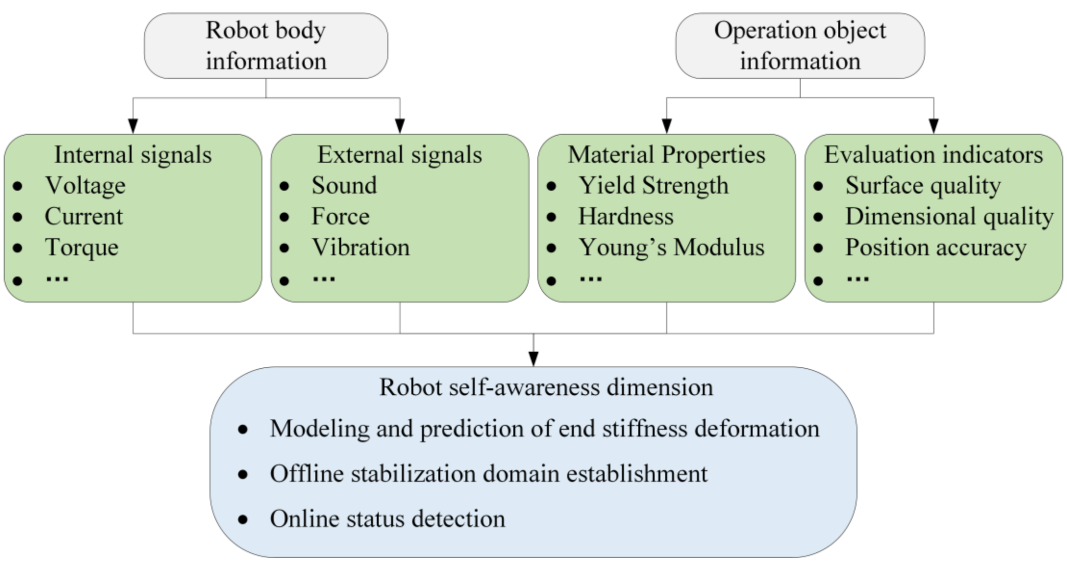

Fig. 2. Robotic operation of self-aware information flow and research dimensions.

This article has been accepted for publication in a future proceedings of this conference, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/ICMCR64890.2025.10962807, 2025 3rd International Conference on Mechatronics, Control and Robotics (ICMCR)

However, the main difficulty of this issue is the continuous variation of the robot's spatial dynamics parameters. As shown in Fig. 2, online monitoring recognizes the status of the robot by collecting internal signals (such as current, joint torque, etc.) and external signals (such as vibration acceleration, end force, sound, etc.), which are susceptible to changes in signal characteristics due to changes in posture. It is crucial to obtain parametric characterization of robot spatial dynamics and operation object information to improve the self-awareness of robot operation.

III. Physics-informed neural networks

As shown in Fig. 3, the PINNs integrate the advantages of both data-driven models and physics models, which could enhance neural network interpretability and lack of data. Its superiority over traditional data-driven models and physical methods is mainly in the following aspects.

A. Data generation

Traditional data-driven learning methods need to rely on a great deal of labeled information for training. They are unsuitable for cross-work situations where data do not satisfy the same distribution. Physical information-based models can generate datasets for data model training and reduce the distributional differences between simulation data and actual operating conditions. This model can minimize the error effects on self-awareness due to differences in data distribution across different industrial robots and robot postures.

Models	Experimental data	Physical theory	Characteristics
Physics-based models	X	√	• Higher solution accuracy • Modeling and solving difficulties
Data learning models	√	X	• Strong feature extraction capability • High data volume requirements
Physics-informed models	√	√	• Less labeled data volume required • Highly interpretable

Fig. 3. Characterization between different models and methods for robot self-awareness applications.

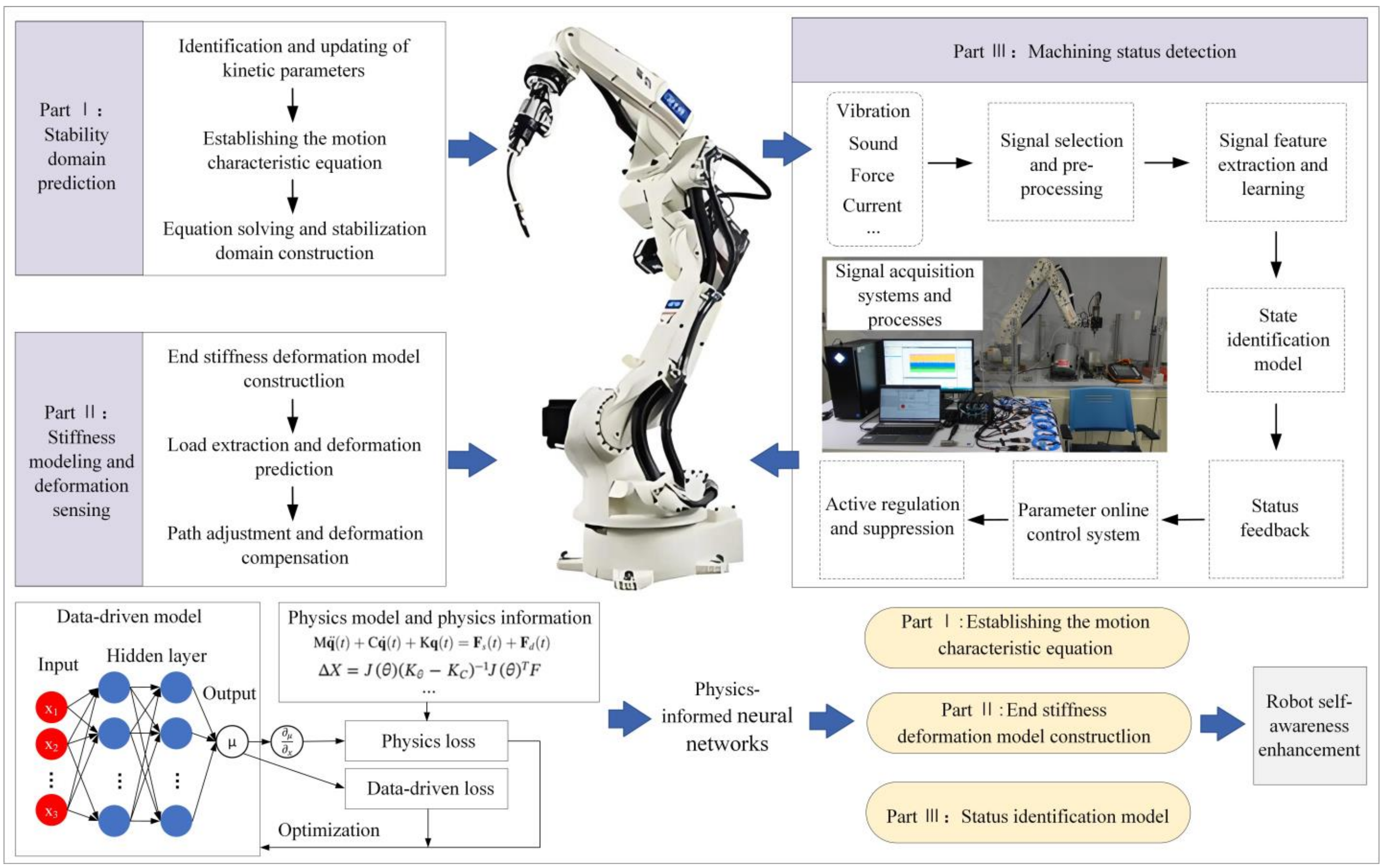

Fig. 4. The proposed framework for robot self-aware machining based on PINNs.

B. Physical constraint

Traditional data-driven machine learning approaches are interpretable and may produce results that exceed physical meaning and limitations. In the PINNs, physical knowledge is used as a regularization term to constrain the space for solutions for machine learning. The solution of the partial differential equation is represented as a neural network, and the partial differential equation and its initial and boundary conditions are constructed as part of the loss function of the neural network, thus constraining the solution space of the parameters of the neural network. Automatic differentiation techniques are used to differentiate the input coordinates and model parameters of the

This article has been accepted for publication in a future proceedings of this conference, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/ICMCR64890.2025.10962807, 2025 3rd International Conference on Mechatronics, Control and Robotics (ICMCR)

neural network so that the neural network adheres to any symmetry, invariance, or conservation principle.

C. *Equation solving*

The PINNs are a new class of general-purpose functional approximators capable of encoding any of the fundamental laws of physics that govern a given dataset and can be described by partial differential equations. Two different algorithms are designed: continuous-time models and discrete-time models. The first type of model forms a new family of data-efficient spatio-temporal function approximators. The latter type allows the use of arbitrarily accurate implicit Runge-Kutta time-stepping schemes with infinite stages.

IV. THE FRAMEWORK FOR ROBOT SELF-AWARENESS

It is feasible and potentially valuable to use the fusion of physics and data to enhance the self-aware operation of robots. The framework for robot self-awareness is shown in Fig. 4, and PINNs could be mainly applied to solve real industrial robotics problems in the following aspects.

A. *Stability domain prediction*

The stabilization domain must be established for parameter guidance before robot machining. Stability domain establishment requires obtaining the robot modal parameters to solve the motion characteristic equations, but the modal parameters are nonlinearly varying for different robots and different postures. It is time-consuming and difficult to obtain the modal parameters of the robot under different poses. It is necessary to establish the nonlinear time-delay equation and solve it, so as to establish the three-dimensional stability domain diagram of the robot machining. The learning model incorporating physical information can be used to establish an algorithm for updating the modal parameters of the robot, and its solving algorithm for differential equations can be used to establish the stability domain map.

B. *Stiffness modeling and deformation sensing*

Robots have low joint and end-effector stiffness especially in open series articulated structures. Besides, the dynamic and static stiffness of the robot changes with the change of spatial poses and with a nonlinear characteristics. The deformation of the robot's end-effector under high loads and speed is an essential factor affecting operational accuracy. To improve the accuracy of robot end-effector positioning and machining accuracy, it is necessary to sense the end-effector deformation of the robot under various loads and then compensate for the error in its positioning. It is necessary to establish the relationship between the deformation of each joint of the robot and the deformation of the end-effector through stiffness modeling, so as to obtain the deformation of the end-effector under different loads and spatial variation poses. A physical fusion data learning model approach can be used to model the robot end stiffness and establish the deformation compensation mechanism under different working loads.

C. *Status detection*

Robotic machining processes are subject to variable loads and changes in dynamic parameters, causing unavoidable instabilities. The instability phenomenon may lead to surface deterioration of components, tool wear, and even damage to the robot's structural framework. Therefore, it is necessary to monitor the machining status of the robot online and make timely adjustments to the machining parameters and operating status. To improve the feasibility and practicality of the method, the status detection process requires the model to have strong physical interpretability and rely less on labeled data. Adoption of data-driven and fusion of physical knowledge to build a state recognition model for robots, which can improve robots' self-awareness and self-adjustment ability.

V. CONCLUSION

This paper presents a PINN-based methodology and framework to enhance robot self-awareness machining ability. Enhancing the self-aware operation of robots can be achieved through offline stabilization domain establishment, end-stiffness deformation prediction, and online recognition of states in which PINNs are introduced. This method and framework can improve the self-awareness ability of the robot during operation while increasing the interpretability of the algorithm and reducing the dependence on a great deal of labeling information. This method and framework will help robots be applied in high-load and high-speed machining scenarios, such as the machining (e.g., milling and grinding) of large components. Based on this framework, further research would focus on an autonomous approach to obtain the PINN-based models of robotic machining systems.

REFERENCES

[1] Makulavičius. M, Petkevičius. S, Rožėnė. J, Dzedzickis. A, Bučinskas. V, “Industrial Robots in Mechanical Machining: Perspectives and Limitations,” Robotics, vol. 12 , November 2023.

[2] Ji. W, Wang. L, “Industrial robotic machining: a review,” The International Journal of Advanced Manufacturing Technology, vol. 103, pp. 1239-1255, April 2019.

[3] Wang. W, Guo. Q, Yang. Z, Jiang. Y, Xu, J, “A state-of-the-art review on robotic milling of complex parts with high efficiency and precision,” Robotics and Computer-Integrated Manufacturing, vol. 79, February 2023.

[4] Tao. B, Zhao. X, Ding. H, “Mobile-robotic machining for large complex components: A review study,” Science China Technological Sciences, vol. 62, pp. 1388-1400, June 2019.

[5] Wu. J, Tang. X, Xin. S, Wang. C, Peng. F, Yan. R, “Research on the directionality of end dynamic compliance dominated by milling robot body structure and milling vibration suppression,” Robotics and Computer-Integrated Manufacturing, vol. 85, February 2024.

[6] Liu. Z, Deng. Z, Yi. L, Ge. J, Yang. Peng, “A review of research on robot machining chatter,” The International Journal of Advanced Manufacturing Technology, vol. 135, pp. 49-79, September 2024.

[7] Raissi. M, Perdikaris. P, Karniadakis. GE, “Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations” Journal of Computational Physics, vol. 378, pp. 686-707, February 2019.

[8] Greis. NP, Nogueira. ML, Bhattacharya. S, C. Spooner, T. Spooner, “Stability modeling for chatter avoidance in self-aware machining: an application of physics-guided machine learning,” Journal of Intelligent Manufacturing, vol. 34, pp. 387-413, November 2022.

[9] Li G, Zheng H, Jiang R, Xu. S, Sun. L, “Physics-informed interpretable machine learning method for DOC monitoring in peripheral milling,” The International Journal of Advanced Manufacturing Technology, vol. 132, PP. 179-191, March 2024.

[10] Chen G, Li Y, Liu X, Yang. B, “Physics-informed Bayesian inference for milling stability analysis,” International Journal of Machine Tools and Manufacture, vol. 167, August 2021.