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Editorial

Differential equation-driven intelligent control: Integrating AI, Quantum computing, and adaptive strategies for next-generation industrial automation

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Abstract: The increasing intricacy of industrial systems highlights the inadequacies of conventional control theories in the management of high-dimensional nonlinear dynamics, real-time coupling, and multi-scale modelling. This article introduces a transformative paradigm—differential equation-driven intelligent control—that synergizes artificial intelligence (AI), quantum computing, and adaptive strategies to redefine next-generation industrial automation. The following innovations are at the core of this paradigm: Physics-informed neural networks (PINNs) for solving partial differential equations (PDEs), Quantum-enhanced linear algebra for stochastic differential equation (SDE) optimization, and symbolic regression for automated discovery of fractional-order dynamic models. A case study on flexible robotic arm dynamics demonstrates the tunability of hybrid rigid-flexible systems via fractional-order parameters and adaptive Lyapunov-based control. The concept of Equations as a Service (EaaS) is proposed to democratize access to distributed computational solvers, enabling real-time optimization for applications such as drone swarm coordination and carbon-neutral manufacturing. A number of critical challenges are addressed in this text, including the interpretability of AI (for example, through the use of SHAP-based explainability tools), the reliability of hybrid quantum-classical solvers, and ethical governance frameworks. Through interdisciplinary collaboration, the vision for self-evolving factories by 2030 is outlined—where differential equations autonomously refine parameters using real-time sensor data. Examples include smart grids adapting to renewable energy fluctuations at millisecond scales and robotic assembly lines recalibrating dynamics to mitigate material defects. The overarching objective of this paradigm shift, termed EaaS, is to transition differential equations from their traditional role as static descriptors to that of self-optimizing assets. This transition is expected to lay the foundation for resilient, explainable, and sustainable ecosystems in the era of Industry 5.0.

Keywords: differential equation-driven control; physics-informed neural networks (PINNs); quantum variational algorithms; symbolic regression; Equations as a Service (EaaS); explainable AI (XAI); self-evolving algorithm

1. Introduction

The advent of Industry 5.0 necessitates a paradigm shift in industrial automation, driven by the need to manage increasingly complex systems characterized by high-dimensional nonlinear dynamics, real-time coupling, and multi-scale interactions. Conventional control methodologies, such as PID controllers, are inadequate in addressing these challenges due to their reliance on linear approximations and static parameterization. To illustrate this point, consider the example of flexible robotic arms governed by hybrid rigid-flexible dynamics (see Equation (1)). In such cases, traditional models are unable to capture memory effects, fractal damping, or adaptive responses to disturbances such as payload variations or unmodeled vibrations.

At the core of this transition lies differential equation-driven intelligent control, a framework that integrates physics-informed machine learning, quantum computing, and adaptive strategies to bridge the gap between theoretical models and real-world applications. To illustrate this, consider the dynamics of a flexible robotic arm described by:

$$
\begin{aligned}
&m(u)\left\{a\frac{d^2u}{dt^2}+(1-a)\left[p\frac{d^{2\alpha}u}{dt^{2\alpha}}+(1-p)D_t^{2\alpha}u\right]\right\}\\
&+C(u,\frac{du}{dt},\frac{d^{\alpha}u}{dt^{\alpha}})\left\{b\frac{du}{dt}+(1-b)(q\frac{d^{\alpha}u}{dt^{\alpha}}+(1-q)D_t^{\alpha}u)\right\}\\
&+G(u)=\tau(t,t^{\alpha})+\Delta(u,t,,t^{\alpha})
\end{aligned}
\tag{1}
$$

Here, $d^{\alpha}u/dt^{\alpha}$ is the two-scale fractal derivative [1,2] quantifying motion in the fractal space, while the fractional order D_t^{α} governs memory-dependent energy dissipation [3,4]. The fractional order α is relative to the two-scale fractal dimensions [5]. Parameters a and b balance rigidity and flexibility, enabling tunable control from precision welding (a = 1) to soft robotics (a = 0) [6]. Weighting factors p and q model motion property in a fractal space or metamaterials' viscoelasticity. The term $G(u)$ adapts gravitational forces to elastic deformations, Δaggregates uncertainties, which are critical in systems with high-dimensional nonlinearity, and τ is the control input applied to the joints and which can be expressed as:

$$
\tau=-K_1[u(t)-u_d(t)]-K_2\frac{d^{\alpha}}{dt^{\alpha}}[u(t)-u_d(t)]-K_3D_t^{\alpha}[u(t)-u_d(t)] \tag{2}
$$

where $u_d(t)$ is the desired state, K_i (i = 1~3) are constants.

The limitations of classical approaches are not confined to robotics. Industrial systems, including smart grids, drone swarms, and additive manufacturing, necessitate real-time optimization and self-calibration under dynamic conditions. This necessitates innovations such as physics-informed neural networks (PINNs) for solving partial differential equations (PDEs) [7], quantum-enhanced solvers for stochastic optimization [8], and the symbolic regression [9] for automated discovery of fractional-order models. To illustrate this point, we may consider the use of PINNs, which are able to embed PDE constraints directly into neural networks, thus enabling accurate thermal management in a complex system [10]. Similarly, hybrid quantum-classical algorithms have been shown to accelerate matrix inversions for real-time control [11].

This editorial article proposes a synergistic framework within which differential equations evolve from static descriptors to self-optimizing assets. The proposed framework unifies AI-driven modelling, quantum acceleration, and adaptive execution, thereby addressing three critical gaps in the field.

1. Interpretability: The utilization of explainable AI (XAI) tools, such as SHAP values, facilitates the reconstruction of control decisions back to their underlying governing equations.

2. Scalability: The combination of quantum solvers with dimensionality reduction techniques is employed for the purpose of dealing with high-dimensional partial differential equations (PDEs).

3. Ethical governance: The incorporation of fairness and sustainability constraints into automated workflows.

Recent studies have optimized maintenance strategies in industrial settings through differential equation approaches [12], while a cooperative control strategy integrating longitudinal and lateral dynamics for preview-enabled intelligent vehicles was proposed in Ref. [13], demonstrating the universality of differential equations in cross-domain control problems. A case study on flexible robotic arms (Section 3) demonstrates how fractional-order parameters and Lyapunov-based adaptive control enable stability in variable environments. Furthermore, the concept of Equations as a Service (EaaS) (Section 4) democratizes computational power, allowing real-time optimization for applications ranging from traffic flow management to carbon-neutral manufacturing.

This interdisciplinary approach will enable the envisioned self-evolving factories by 2030, where differential equations will autonomously refine parameters using sensor data, enabling millisecond-scale adaptations—from smart grids responding to renewable fluctuations to assembly lines mitigating material defects. This transition not only redefines industrial automation but also establishes the foundations for resilient, explainable, and sustainable ecosystems in the era of Industry 5.0.

2. Technological convergence: AI, quantum, and adaptive control

2.1. AI-driven modeling: From data to physics-informed equations

Physics-informed neural networks (PINNs) are a machine learning framework that embeds partial differential equation (PDE) constraints, thus enabling solutions for complex thermal management and smart manufacturing. Symbolic regression is a process that automates the discovery of equations from sensor data, identifying fractional-order terms and weighting factors that model viscoelasticity in flexible materials.

2.2. Quantum acceleration

Quantum algorithms such as Harrow-Hassidim-Lloyd (HHL) [14] have been shown to accelerate matrix inversions for PDE discretization, thereby enabling real-time control of smart grids and robot swarms. Hybrid quantum-classical solvers combine quantum annealing for global exploration with classical feedback for precision, enhancing robustness in dynamic environments.

2.3. Adaptive execution

Reinforcement learning (RL) [15,16] is a process by which control policies are dynamically aligned with system evolution. To illustrate this, consider the example of self-calibrating 3D printers, which leverage RL to minimize warping defects through real-time thermal adjustments [17]. Edge devices are capable of solving ordinary differential equations (ODEs) in a localized manner, thereby facilitating millisecond responses for high-speed assembly lines. The application of RL in the context of thermal adjustment within MEMS systems has also been demonstrated [18,19].

3. Case study: Adaptive control of flexible robotic arms

It is hypothesized that the dynamics of flexible robotic arms are governed by Equation (1). The parameter a is employed to balance rigidity and flexibility (e.g., a = 1 for precision welding and a = 0 for soft robotics). The parameter b is a measure of fractal damping models in tendon-driven robots operating in variable friction environments. The fractional order has been demonstrated to quantify memory effects for slow energy dissipation in viscoelastic materials and fractal damping effect.

A layered optimization strategy combines metaheuristic algorithms (e.g., genetic algorithms) for global parameter search, physics-informed machine learning for real-time inference, and quantum annealing for rapid convergence under dynamic conditions. Lyapunov-based adaptive controllers ensure stability.

4. Equations as a Service (EaaS): Democratizing computational power

It is to be posited herewith that one might consider the following hypothetical scenario: one is a city planner charged with the optimization of traffic light timings with a view to reducing congestion. The problem involves the solution of complex differential equations that model traffic flow patterns. The team is faced with the challenge of limited computational capabilities, as supercomputers are financially unfeasible and standard laptops are incapable of handling the required calculations. The following is an exposition of how Equations as a Service (EaaS) addresses this challenge:

Firstly, traffic flow equations (e.g. fluid dynamics-inspired models) and parameters (e.g. current traffic volume and road layouts) are uploaded to a cloud-based EaaS platform via a simple interface. The platform then utilizes intelligent workload distribution to ensure optimal performance. Specifically, quantum solvers address large-scale optimization to identify optimal traffic light sequences, GPU clusters simulate real-time traffic scenarios across thousands of virtual vehicles, and classical servers compile results into actionable reports highlighting congestion hotspots and proposed light timings. Thirdly, within minutes, users receive optimized traffic light schedules, predicted to reduce rush-hour delays. A further advantage is that costs are only incurred for the resources used, extremely cheap for both quantum processing and GPU, thus eliminating the need for upfront investments in hardware.

Beyond efficiency, EaaS offers two key advantages. Data security is ensured through blockchain encryption, and collaboration is streamlined by inviting global transportation experts to review and refine models with controlled access. Furthermore, an algorithm marketplace enables users to integrate specialized tools, such as a researcher’s novel AI model for predicting sudden traffic jams, for a nominal fee, thereby enhancing the accuracy of simulations.

Fundamentally, EaaS democratizes computational power by treating it like electricity: users no longer need to own a “power plant” (supercomputer) to solve equations. Instead, users can access the necessary resources on demand, and only pay for the resources they use. This approach is not limited in its application; it can be used for diverse purposes, ranging from the design of eco-friendly buildings to the prediction of weather patterns. The future of EaaS is envisaged as one in which zero-latency control, self-evolving factories and carbon-neutral manufacturing are enabled, thereby transforming equations from static tools into dynamic, accessible assets that drive innovation.

The field of self-evolving learning, a recent development in the area of deep learning technology, has the potential to further enhance such systems by enabling models to adapt autonomously to dynamic environments [20].

5. Challenges and future directions

Notwithstanding the immense potential inherent in the utilization of differential equation-driven intelligent control, there are several challenges that must be addressed if this technology is to realize its full impact. Primarily, the issue of scalability remains a critical hurdle. The resolution of high-dimensional partial differential equations (PDEs) for systems such as drone swarms or multi-robot coordination necessitates AI-driven dimensionality reduction techniques and hybrid quantum-classical solvers to manage computational complexity. To illustrate this point, consider the example of simulating carbon-neutral manufacturing processes, a task that may require real-time optimization across thousands of variables, thereby pushing classical algorithms to their limits. The same applies to smart structures, whose structural behavior is actively controlled to achieve goals such as vibration attenuation, noise reduction, enhanced safety, and improved robustness. This task can be successfully achieved only upon significant model reduction in order to render the problem mathematically tractable [21].

Secondly, interpretability gaps hinder trust in AI-augmented control systems. Explainable AI (XAI) tools, such as SHAP values or attention maps, are required to elucidate the fractional-order terms present in adaptive policies. To illustrate this point, consider a scenario in which a factory's energy optimization model unexpectedly prioritizes renewable energy sources over cost efficiency. In such a case, XAI frameworks must transparently trace this decision back to the governing equations and sustainability constraints embedded in the system.

Thirdly, there is a lag between technological advancements and the development of ethical governance frameworks. It is imperative for EaaS platforms to adopt transparency certifications to audit algorithmic safety, bias, and environmental impact. To illustrate this point, consider a quantum-enhanced solver employed for supply chain optimization, which might unwittingly favor regions offering cheaper labor, thereby giving rise to ethical concerns. It is therefore vital for policymakers and engineers to collaborate in a proactive manner in order to embed fairness and accountability into equation-driven automation. In the forthcoming period up to 2030, our Yango differential equation-driven intelligent control group (**Figure 1**) predicts that the focus will be on the development of self-evolving factories, in which differential equations will autonomously refine their parameters using real-time sensor data. The concept of a smart grid that updates its power distribution model instantaneously based on renewable energy fluctuations is another example of this technological advancement. Similarly, a robotic assembly line that recalibrates its fractional-order dynamics to adapt to material defects is another example of this technological advancement. Achieving this objective necessitates the integration of sustainability constraints, such as carbon-neutral operations, directly into equation-solving workflows. The unification of control theory, quantum computing, and AI ethics is expected to transform equations from static descriptors into adaptive, self-optimizing assets that will drive resilient and equitable industrial ecosystems.

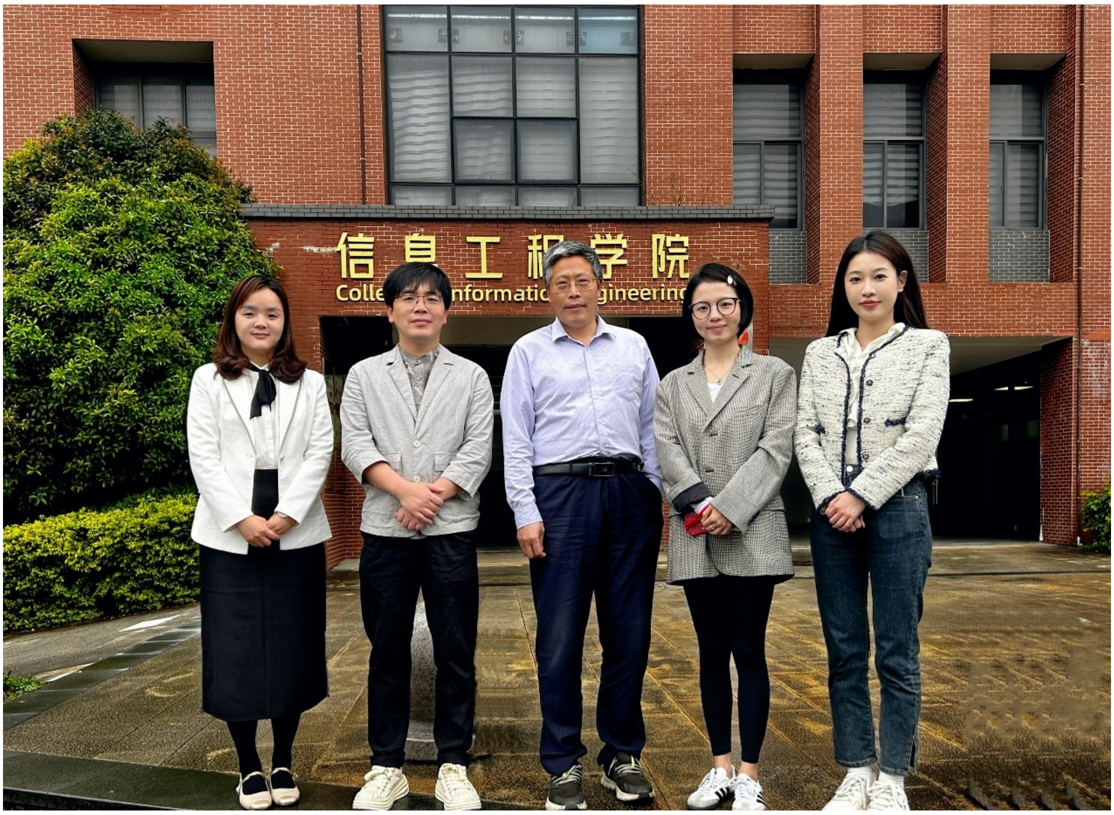

Figure 1. Yango differential equation-driven intelligent control group.

6. Conclusion

The integration of differential equation-driven intelligent control represents a paradigm shift in the domain of industrial automation. The integration of artificial intelligence, quantum computing, and adaptive strategies within this framework facilitates the development of resilient, explainable, and sustainable systems. The democratization of advanced mathematics, a consequence of the aforementioned developments, is set to accelerate innovation across a range of fields, from precision manufacturing to climate modelling. The future of automation is therefore likely to be characterized by the evolution, learning and self-optimization of equations, which has the potential to usher in a new era of Industry 5.0.

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