RESEARCH ARTICLE

Primary Thought on the Incorporation of Intelligent Control and U-control (I-U-control)

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Abstract

This study explains the main idea and structure of an integrated What-How intelligent control and universal control (I-U-control) system. The proposed framework consists of two control layers. The bottom layer uses the U-control framework to manage 'How' to control within a universal framework. The top layer uses intelligent control (I-control) to coordinate and guide 'What' to achieve both global and local control goals. This study also reviews the configurations, functions, and integration of these two control layers in analysis, design, and applications.

Keywords: universal(U)-control, data-driven operation, control Lyapunov stability, lyapunov derivative inequality, intelligent (I)-control, goal-oriented control systems (GOCS), What-How intelligent control systems (WH-ICS).

1 Introduction

The universal control (U-control) framework introduces a versatile paradigm in control systems engineering, offering a comprehensive configuration and basic functionality to enhance the conventional approaches. Its key innovation lies in 1) general instant and asymptotic model inversions, 2) complete sliding mode control crossing the full range between model-based and model-free, 3) separated designs of stabilisation and tracking control, which can either fully take advantage of a given model and/or eliminate the need for complex system modelling while maintaining the required control performance. The U-control framework is characterised by its simplicity, total robustness, and model-free architecture, making it well-suited for industrial applications rife with complexity and uncertainty and enhancing the operational flexibility and efficiency through communication between man-machine directly, a supplement to man-model-machine in conventional routines. The new research on the Framework of U-control may refer to [1].

1.1 Framework of Universal (U)-Control

The U-control framework [1] as shown in Figure 1 has been proposed for configuring dynamic control systems with reference to plant model and/or model-free, which is built on several critical anchors, including:

1. **Dynamic Inversion:** Both model-based instantaneous dynamic inversion (IDI) and model-free asymptotic dynamic inversion (ADI).
2. **Model-Free Sliding Mode Control (MFSMC):**

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Ensures robustness without relying on system models. The MFSMC improves traditional Proportional-integral-derivative (PID) control by using full-state feedback sliding mode manifold instead of standard output errors.

3. **Lyapunov Derivative Inequality (LDI):** Provides a theoretical foundation for stability analysis in model-free systems.

4. **Simplicity and Robustness:** The framework is designed to be simple to implement while maintaining high robustness across a wide range of structural system dynamics, such as nonlinear nonaffine, input/output coupling, underactuated, neural type, and so on.

List of symbols and abbreviations.

U-control	Universal-control
I-control	Intelligent I-control
WH-I-control	What-How intelligent control
WH-ICS	What-How intelligent control systems
GOCS	Goal-oriented control systems
ADI	Asymptotic dynamic inversion
IDI	Instantaneous dynamic inversion
MFSMC	Model-Free Sliding Mode Control
LDI	Lyapunov Derivative Inequality
UDI	Universal dynamic inversion
PM	Model-based physical
OM	Online model-based
LQR	Linear quadratic regulation
PP	Pole-placement
NN	Neural networks
TMF	Total model-free
TMFRC	Total model-free robust control
RSF	Robustness sensitivity function
UAV	Unmanned Aerial Vehicles
AI	Artificial intelligence
ML	Machine learning
RL	Reinforcement Learning
DL	Deep learning
HSs	Hybrid systems
GA	Genetic algorithms
PSO	Particle swarm optimisation
ACO	Ant Colony Optimisation
BTP	Burn-through point
VSS	vertical sintering speed
HICS	Hierarchical intelligent control systems
MAS	Multi-agent systems

Generally, there are two key factors in control system design, 1) description of the plant to be controlled, and 2) the controller to change the plant performance by feedback. The phrase U-control comes from the following considerations, which aims to reduce the burden and complexity arising from the need to model the plant in the control system design, U-control has separated the controller design from the plant directly. The universality is explained below.

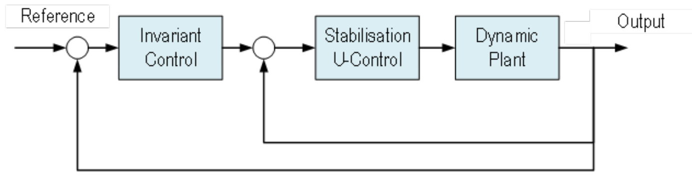

Figure 1. The U-control framework.

1. **Universality of U-control in the aspect of models:** The universality of U-control lies in its feasibility in designing control systems by referring to the plant model or treating the plant as an agnostic box with admissible inputs and attainable outputs. This is formulated as:

$$aD_{mb} + bD_{mf}, a + b = 1 \tag{1}$$

where D_{mb} and D_{mf} denote model-based and model-free approaches respectively, and $b = 1 - a$ denotes the weight of the model-free component. Coefficient $a = 1$ corresponds to fully model-based control, $0 < a < 1$ represents nominal model-based control, where $a = 0$ indicates fully model-free control. The parameter a reflects the degree of trust in the system model's fidelity [1]. The U-control framework, as illustrated in Figure 1, separates the robust stabilization of plant dynamics (inner loop) [1] from the control system performance specification (outer loop) [2]. This separation allows for greater flexibility, simplicity, and robustness in designing and tuning control systems for various applications, such as motion control in various mechatronic systems.

2. **Universal dynamic inversion (UDI):** The generalized universal dynamic inversion features two innovative concepts and algorithms: IDI and ADI. IDI relies on the given model to directly invert the system dynamics by solving the associated equations, which enables the separation of control system performance from the treatment of the associated plant. ADI, in a prototype of closed loop control, drives the system dynamics over time and gradually achieves inversion while the plant is treated as an agnostic dynamic. Furthermore, in fully

actuated multi-input and multi-output (MIMO) systems, MIMOs are often coupled, meaning changes in one input can affect multiple outputs. The general UDI extends dynamic inversion to include decoupling, which ensures that each input primarily affects its corresponding output, minimizing unwanted interactions [3].

3. **Universal design by separating stabilization and tracking:** In control system design, two main methods have been conventionally adopted: (1) model-based physical (PM) design, e.g., linear quadratic regulation (LQR) and pole-placement (PP) control, and (2) data-driven adaptive pointwise online model-based (OM) design, which includes techniques like adaptive control, neural networks (NN) enhanced control, reinforcement learning (RL) control.

   Both approaches involve model-based control, PM is typically derived theoretically or experimentally before the design phase. The OM is determined by a pointwise data fitting model updated in real-time, most of the time employing data iteration for control decisions. U-control covers both model-based designs in a generic procedure, and further supplements total model-free (TMF) control. The TMFRC is introduced to U-control by treating systems as complete uncertainties within a black box, focusing on available inputs and measurable outputs, while eliminating the need for physical and data-driven models as well as data iteration. The U-control method simplifies and enhances the control system design while offering simplicity and robustness in control functionality and parameter tuning. TMFRC employs an MFSMC that ensures robust stability by satisfying the LDI. Unlike the trial-and-error tuning method commonly used with PID controllers, TMFRC ensures consistent performance within system limits. For example, the PID auto-tuning function in Simulink demonstrates this contrast by simplifying the tuning process through three predefined gain combinations.

4. **Expanded analysis of robustness sensitivity function (RSF):** With TMF control proposed, evaluating its robustness becomes a critical consideration. Conventional RSF is a model-based approach for assessing robustness. In the context of U-control, a total RSF has been proposed for the model free U-control systems [1]. However, the total RSF is still required for further justification and formulation in theoretical aspects.

5. **Industrial applications with TMF control:** While keeping the merits of model-based approaches, the MF approach 1) provides a complete model-free control framework, 2) reduces the computational burden, 3) increases system robustness, and 4) may provide a new prototype for co-design of various emerging systems, such as Industrial IoT Systems, Unmanned Aerial Vehicles (UAV), where U-Model-based sliding mode controllers have been designed for quadrotor systems [41, 42]. Unlike traditional design methodologies where the hardware and software are developed independently, the co-design emphasises the joint optimisation of both aspects to improve the performance, efficiency, and adaptability of UAVs for various applications. These are very useful for practical nonlinear dynamic system operations.

1.2 Framework of Intelligent (I)-control

An intelligent system refers to a system that incorporates elements of artificial intelligence (AI) to perform tasks that typically require human cognitive abilities. These tasks include reasoning, learning, problem-solving, decision-making, perceiving the environment, and natural language processing. Powered by cutting-edge technologies, intelligent systems revolutionize traditional models and create new paradigms of human-machine collaboration with high efficiency, precision, and automation.

1.2.1 The predominant characteristics of intelligent systems

The predominant characteristics of intelligent systems include the following:

1. Autonomy: They can operate independently without continuous human intervention.
2. Adaptability: They learn and improve from experiences and adapt to changing environments.
3. Reasoning: They can make logical decisions based on available data and knowledge.
4. Perception: They use sensors or input data to perceive and understand their environment.
5. Interaction: They interact with humans and other systems through natural language, visuals, or other means.

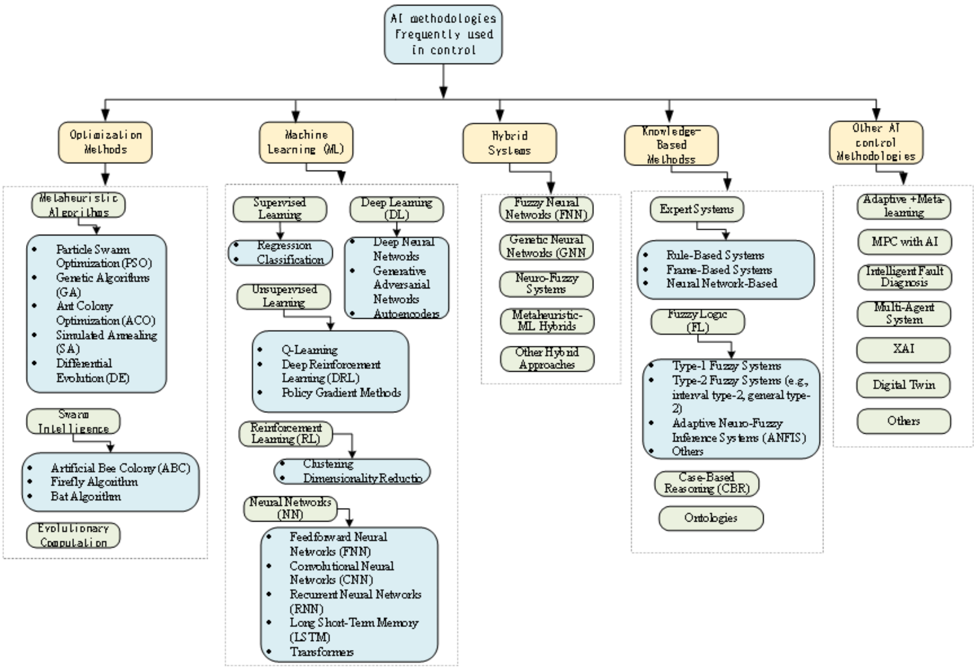

Figure 2. Classification of AI-based control techniques.

1.2.2 *Framework Of I-control*

Regarding the intelligence enhanced control system analysis and design called intelligent control systems, I-control in short in the study. I-control is admitted as an advanced control method that utilises artificial intelligence (AI) techniques to enhance the performance and decision-making capabilities of traditional control systems. These systems are designed to manage dynamic and complex processes where conventional control strategies may fall short [4, 5]. Here a summary of the I-control is presented for the completeness of the study. The major types of intelligent systems widely used come in various forms, including intelligent control for multiagent systems [6] and shared control strategies in collaborative systems [7]. The key techniques frequently used in I-control can be shown as Figure 2, which illustrates an overview of key AI-based algorithms and their associated functionalities. Some of the key topics in intelligent systems include the following. These include more human-like interaction capabilities, greater autonomy and decision-making power, enhanced integration with IoT (Internet of Things) devices, and ethical and secure AI systems that ensure fairness and privacy:

1. Optimisation-Driven Control methods: Metaheuristic methods have emerged as powerful tools in optimizing control systems, providing efficient strategies for achieving optimal system performance [8]. Swarm Intelligence techniques [9] such as Particle swarm optimisation (PSO) and Ant Colony Optimisation (ACO) [10] have been successfully applied in tuning control parameters, optimizing controller gains, and improving system response times. These methods mimic the collective behaviours seen in natural swarms and colonies, allowing for robust optimisation within control systems. Evolutionary Computation methodologies, including Genetic algorithms (GA) [11] and Differential evolution [12], have demonstrated remarkable capability in evolving potential solutions through principles inspired by biological evolution, as illustrated in Figure 2. All the algorithms above effectively explore solution spaces, enhancing and refining candidate solutions to achieve optimal or suboptimal results.

2. Machine learning (ML) Enhanced Control: ML represents a sophisticated paradigm within the field of artificial intelligence, offering a diverse array of techniques to discern patterns and make decisions without being explicitly programmed. (a) Supervised Learning: The method uses annotated data to train models, mainly applied to predictive modelling tasks such as regression analysis and classification tasks. (b) Unsupervised Learning: Clustering methods, unsupervised anomaly detection in industrial control systems [14], and dimensionality

reduction techniques, such as kernel PCA with decentralized frameworks, are used to analyse unlabelled datasets and discover patterns without human supervision [13]. (c) Reinforcement Learning (RL): RL allows agents to learn optimal decision-making policies by interacting with their environment through trial and error. It is widely used in autonomous systems such as robotics control [15, 16], deep reinforcement learning for robotic manipulation with asynchronous off-policy updates [17], continuous control tasks [28], and industrial automation [18, 19], as well as self-driving vehicle technologies and personalised recommendation systems. (d) Deep Learning (DL): DL uses neural networks to extract hierarchical representations for intelligent control. (e) Neural Network (NN) Control: NN Control involves the learning of patterns and approximation of complex nonlinear functions, particularly useful in systems lacking mathematical models or where such models are not practical, including Feedforward Neural Networks, Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, and Transformers. Hybrid intelligent systems further blend these AI technologies, such as neural network-based adaptive sliding mode control for underactuated mechanical systems [20] and neuro-fuzzy approaches optimised by genetic algorithms [21]. Hybrid Control Architectures integrate traditional control methods like PID control with AI technologies, such as replacing classical PIDs with fuzzy controllers in HVAC systems for improved energy efficiency and user comfort [22]. Deep learning approaches have also been applied to fault detection and isolation in industrial processes [25].

3. Knowledge-Driven Control Methods: Knowledge-driven control methods utilize structured knowledge and reasoning techniques, including fuzzy logic controllers for linguistic and rule-based control under uncertainty [23], case-based reasoning for adaptive problem-solving, and industrial applications of fuzzy control for knowledge-driven decision-making [24].

4. Other AI-based control methods: Other AI-based control methods include digital twin-based systems for real-time simulation and predictive control [33], explainable AI for transparent and interpretable decision-making [26], multi-agent systems (MAS) for distributed coordination and collaborative problem-solving in complex environments [27].

2 Integration of intelligent systems with traditional control methods for enhanced performance

2.1 Hybrid AI-Traditional Control Methods

These methods in Figure 2 can be used individually, or combined with traditional control methods (e.g., PID control) to form HSs. The core idea is to leverage AI's self-learning, self-adaptive, and nonlinear processing capabilities to compensate for the limitations of traditional control methods in complex systems. Table 1 summarizes the common integration approaches and their application scenarios.

Hybrid fuzzy decision-making models have also been applied to evaluate the influence of Industry 4.0 technologies on manufacturing strategies [40].

2.2 Hierarchical Structure of Complex Systems

Among methods in Table 1, intelligent control often adopts a layered structure in complex systems to achieve more efficient control and management [29, 30]. The hierarchical methods proposed in the literature are typically divided into 2 layers, 3 layers, or more layers, with the specific number of layers and their distinctions depending on the application scenario and system complexity. Below is a summary of common hierarchical methods and their differences:

1. **2-Layer Structure:**

   The 2-layer structure is the simplest hierarchical method, typically divided into a high layer and a low layer [31].

   (a) The High Layer offers decision-making and optimisation at a strategic level. It is responsible for global optimisation, task planning, and decision-making technologies.

   (b) The low layer generates and executes real-time control signals. It typically uses traditional control methods (e.g., PID control) or fundamental intelligent control techniques (e.g., fuzzy control). These methods suit simpler systems like single-robot control or smart home automation.

2. **3-Layer Structure**

Table 1. Comparison of integration methods.

Integration Method	Advantages	Challenges	Application Scenarios
Direct Replacement	Simplifies design while adapting to nonlinear systems	Requires large amounts of training data, limited real-time performance, poor interpretability	Simple control tasks (e.g., temperature regulation)
Hybrid Control	Balances robustness and precision	High structural complexity and challenging parameter tuning, complex coordination strategy design	Complex industrial processes, robotics
Hierarchical Structure	Strong scalability, suitable for complex tasks	Requires coordination across multiple layers of communication	Large-scale systems (e.g., smart grids)
AI Parameter Tuning	Enhances the performance of traditional controllers	Offline optimisation may not adapt to dynamic changes, online learning may cause instability	Motor control, chemical processes
High-Level Optimisation and Decision -Making	Enables global optimisation and coordination of complex systems	High computational complexity, difficulty in balancing multiple objectives	Smart grids, multi-robot systems, smart cities
Fault Diagnosis and Fault-Tolerance	Improves system safety	Depends on the completeness of fault data, diverse fault modes	Aerospace, industrial robotics
Data-Driven Control	Addresses model uncertainties	High computational overhead, relies on data quality, data privacy issues	High-precision manufacturing, complex dynamic systems
Reinforcement Learning Synergy	Adapts to dynamic environments	Long training times, difficult safety verification and exploration may lead to system failure	Intelligent transportation, game AI
Edge Intelligent Control	Low latency, high real-time performance	Limited computational resources, difficulty in model light weighting	Industrial IoT, autonomous driving
Digital Twins	High-precision modelling and simulation, support predictive maintenance	Requires high-fidelity models, high data synchronization costs	Smart manufacturing, smart cities
Human-Machine Collaborative Control	Combines human expertise with AI computational power	Complex human-machine interaction design, difficulty in building trust	Medical robotics, collaborative robotics
AI-based Adaptive Control	Dynamically adapts to environmental changes	The stability of online learning is difficult to guarantee	Drones, robotics

The 3-layer structure framework is a widely adopted organisational approach. It consists of a high layer, a middle layer, and a low layer. While the higher and lower layers align with the 2-layer structure, the inclusion of the middle layer, referred to as the coordination and control layer, adds a critical element to intelligent systems.

The Middle Layer addresses complex scenarios such as multi-robot coordination and advanced process control, highlighting its ability to enable smooth interactions and improve overall system performance. It is essential for managing intricate collaborations among multiple subsystems in intelligent systems. Figure 3 shows the other configuration of hierarchical intelligent control systems [32], which is structured in general control terminologies and functionalities.

3. **4-Layer or More Layer Structure**

For more complex systems, the literature sometimes proposes 4 or more-layer methods. Below is a typical 4-layer structure [33], Figure 4 shows a representative hierarchical control configuration, analogous to energy management strategies in plug-in hybrid electric vehicles using fuzzy adaptive PID control [33]. In such frameworks, the system resembles a network of interconnected nodes arranged in a tiered framework. Directives and objectives cascade downward from higher-level nodes to subordinate units, while sensory feedback and operational outcomes propagate upward. Lateral communication between peer nodes enables localized coordination.

(a) High Layer is task planning and scheduling layer, it determines the overall strategy and sequence of tasks to be executed, ensuring that the system operates efficiently and meets its objectives.

(b) Sub-High Layer: is responsible for global optimisation and multi-subsystem coordination. The primary goal of this layer is to ensure that all subsystems work harmoniously to achieve the best overall performance.

(c) Middle Layer: Control and Adjustment Layer: It monitors the performance of the subsystems and makes necessary adjustments to ensure that they operate within the desired parameters. This layer acts as a bridge between the high-level planning and the low-level execution.

(d) Low Layer: Execution Layer. It directly interacts with the hardware and software components to carry out the commands received from the higher layers.

Higher layers extend the time horizons for strategic planning and execution cycles, whereas lower layers prioritize localized, real-time operations with immediate response requirements. Lower layers execute context-specific tasks with minimal interference from upper layers, which focus on global coordination and abstract reasoning. For instance, foundational layers rely on reactive, data-driven processes (e.g., sensor-actuator loops), while upper tiers employ abstract models and predictive analytics to coordinate long-term objectives. This architecture aligns well with hierarchical task network methodologies, which systematically decompose complex objectives into manageable actions across levels.

3 Synergistic Integration of U-Control and I-Control

3.1 Motivation for U-I-Control Synergy

From the above discussion, it is evident that U-control excels at providing robust, TMF stabilisation and tracking, ensuring system stability even under uncertainties and disturbances, plus simplicity in the system design and tuning. Primarily, I-control introduces adaptability and learning capabilities, enabling the system to optimise performance in complex, non-stationary environments dynamically. It also leverages high-level decision-making and optimisation, allowing the system to refine control strategies without manual intervention autonomously.

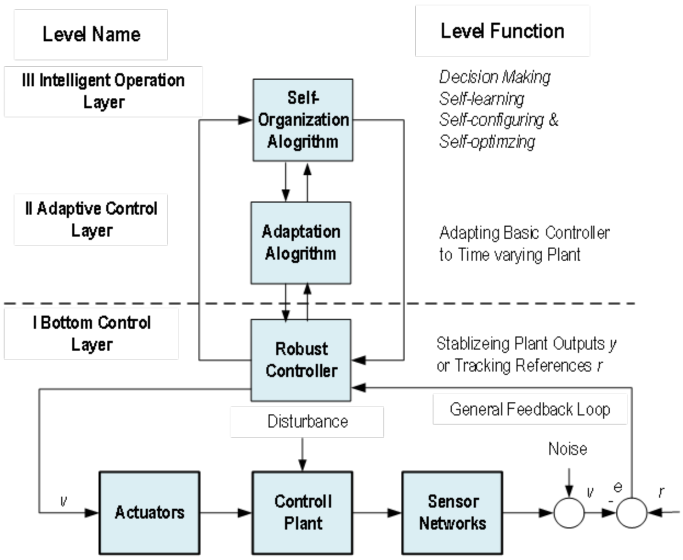

Figure 3. Three layers of intelligent control systems.

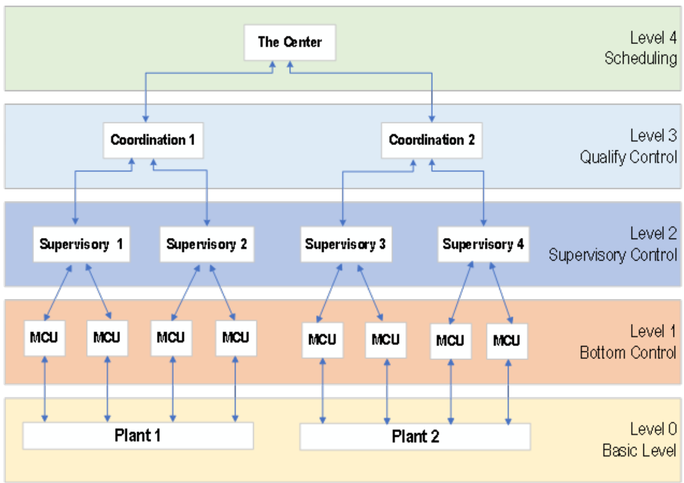

Figure 4. Conventional hierarchical manufacturing control operation [33].

Thus, it is possible to achieve synergistic robust adaptability, simplify control design, and support scalable applications. Industrial and autonomous systems often face challenges such as unmodeled dynamics, fault tolerance, real-time constraints, real-time decision-making, and energy efficiency requirements. The U-I synergy addresses these challenges by combining U-control's real-time robustness with I-Control's optimisation and fault tolerance, as demonstrated in applications like autonomous vehicles (to be explained in Section 4.1) and industrial processes (to be explained in Section 4.2).

3.2 Synergistic Enhancement of I-Control via U-Control

While U-control focuses on achieving stability and simplicity in control systems, its integration with more advanced intelligent approaches like GOCS [34] enhances performance in dynamic environments. GOCS are designed to focus on achieving specific objectives or goals within a system, rather than merely following predefined setpoints or rules. GOCS suggest shifting from instructing a system on how to perform a task to specifying what needs to be achieved, and aim to optimise performance by adjusting actions in real-time, as shown in Figure 5. Combining U-control's strengths with the flexibility and adaptability of GOCS makes it possible to address more complex, dynamic goals in real time.

Based on the I-Control framework, the U-control method can be integrated into two distinct approaches. The first is a hybrid control strategy that combines U-control with underlying control methods. The second is a hierarchical control architecture, where the lower layer directly employs the U-control method as formulated in Figure 1 and Equation (1). In contrast, the upper level utilises I Control-based optimisation for enhanced performance. Focusing on high-level goals and constraints allows the system to adapt to changing environments, while U-control's robustness ensures that it can handle unexpected disturbances or dynamic changes as shown in Figure 5. The high-level goals and constraints from GOCS can be used to define the desired system performance in the outer loop of the U-control framework. The inner loop of U-control can handle the robust stabilization and decoupling of the system, ensuring that the control actions are feasible and robust to uncertainties.

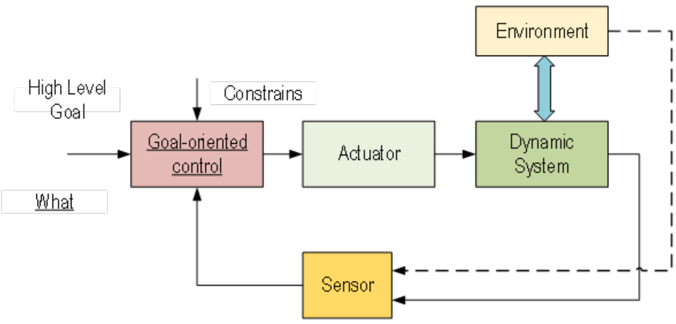

Figure 5. Goal-oriented control system (GOCS).

U-control's integration with GOCS, as illustrated in this framework, is just one possible approach. Table 2 outlines other potential combinations of I-control with U-control. Notably, TMF U-control is considered a priority for integrating with I-control because it offers a simpler and more direct approach to handling uncertainties and nonlinearities in systems without requiring detailed mathematical models. This combination capitalizes on U-control's robustness and AI's adaptability and learning capabilities, leading to more efficient and flexible control in complex dynamic systems.

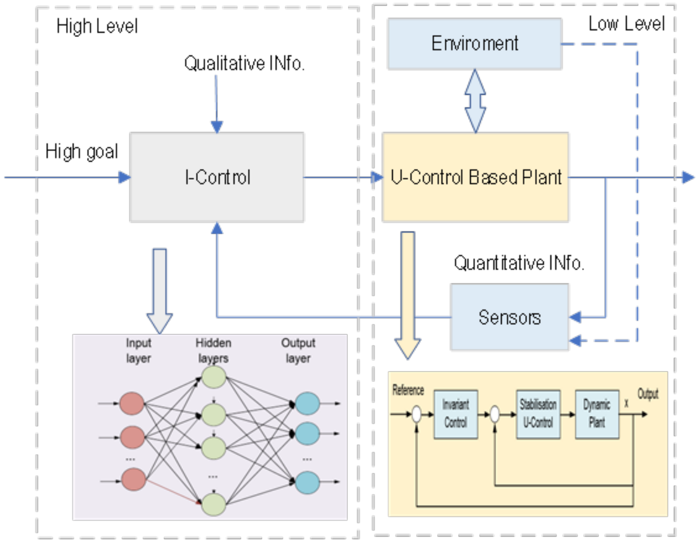

Figure 6. Flowchart for the design of the incorporation of U-control and I-control.

3.3 High-Level Integration Strategies

3.3.1 *Core Integration Architecture*

This section introduces the key strategies for integrating U-control and I-control, outlining how these objectives are achieved through the following five steps:

1. Inner Loop design: The inner loop control is designed using either model-based or TMF control strategies [1]. The primary goal is to make the bottom-layer control loop universal, straightforward in design, robust in tuning, and against internal/external uncertainties. This ensures that the inner loop operates reliably, rapidly and consistently under varying conditions so that the up-layer I-control can confidently treat the U-loop as an ideal functional point or a group of objects while designing the I-control loop.

2. Constraint and Safety Management: To address system constraints and safety requirements, a TMF U-control framework should be developed. This framework ensures that the system can handle operational limits and safety concerns without relying on precise system models, making it adaptable to complex and uncertain environments.

3. Outer Loop design: Optimise the system's performance specifications by employing intelligent control methods (as depicted in

Table 2. Comparative framework for AI integration in model-based and TMF U-control systems.

Direction/Method	Model-based U-control	TMF U-control
Universal Dynamic Inversion	Use precise models for UDI to linearize the system. AI can optimise the inversion process, improving accuracy and robustness.	Use AI (e.g., RL or NN) to achieve TMF universal dynamic inversion, learning the inverse model directly from input-output data, and adapting to system uncertainties.
Parameter Optimisation	AI optimises controller parameters (e.g., PID parameters, PP parameters) based on model performance metrics.	AI optimises parameters of TMF controllers, such as gains in sliding mode control (SMC), using data-driven approaches to adapt to system dynamics.
Fault Diagnosis & Fault-tolerant Control	Combine AI (e.g., DL) for fault detection and diagnosis, using model knowledge to quickly locate faults and adjust control strategies.	Use AI (e.g., reinforcement learning) for TMF fault-tolerant control, learning in real-time to adapt to the system's dynamics under fault conditions.
Data-driven Modelling	AI extracts model features from data to assist in the design of model-based U-control, improving model accuracy and adaptability.	AI learns the system's input-output relationship directly from data, building TMF control strategies without relying on a priori models.
Reinforcement Learning	Combine reinforcement learning to optimise model-based control strategies, using model predictions to optimise control actions.	Reinforcement learning is at the core of TMF U-control, learning through trial and error to optimise control strategies for complex dynamic systems.
Digital Twins	Digital Twins combined with model-based U-control, using AI to optimise model parameters and control strategies, achieving real-time monitoring and optimisation.	Digital Twins combined with TMF U-control; AI adjusts control strategies in real time to adapt to system dynamic changes.
Human + AI Control	Human operators combined with model-based U-control use AI to assist in decision-making and improve control accuracy and efficiency.	Human operators combine with TMF U-control. AI provides real-time suggestions, and operators make the final decision, adapting to complex environments.
Distributed Control	AI optimises distributed model-based U-control strategies, coordinating MAS.	AI optimises distributed model-free U-control strategies, adapting to the dynamic changes in MAS.
Robustness Enhancement	AI analyses model uncertainties to optimise the robustness of model-based U-control.	AI continuously updates TMF control laws from streaming data.
Real-Time Adaptation	AI detects a deviation between the model and real-world and update the model in recalculated optimal control parameters.	AI learns the optimal control strategy and detects a deviation directly from feedback data without relying on models. U-control proactively adapts inputs based on predictions.

Figure 6) and optimise control strategies through adaptive dynamic programming to adapt to system changes dynamically [35]. Additionally, optimise the parameters of the outer-loop controller using intelligent control techniques to achieve rapid system response and stable control. Furthermore, reinforcement learning algorithms are utilised to optimise control strategies through continuous interaction with the environment.

4. Constraints: To deal with constraints and

safety, U-control algorithms must execute deterministically within the inner loop's required time frame and avoid computationally intensive operations (e.g., high-dimensional matrix inversions) in MF implementations. For higher levels, ensure intelligent algorithms (e.g., RL, fuzzy inference) operate within real-time computational limits (e.g., sampling rates). Simplify optimisation problems (e.g., use lightweight NN or rule-based approximations).

5. Validation and Testing: To achieve the above objectives, extensive bench-testing of the TMF U-control framework is essential. This testing should be conducted across a wide range of examples, at least in a simulated environment, to validate the robustness, adaptability, and performance of the proposed control strategies. Such validation ensures that the system is ready for real-world applications and can reliably meet the desired performance specifications.

3.3.2 High-Level Enhancement Strategies

While U-control provides a simplified and direct approach to achieving system stability, its inherent design may occasionally limit the attainment of globally optimal performance. To address this limitation, an AI-driven intelligent controller should be integrated at the supervisory level to dynamically refine the U-control parameters. Specifically, swarm intelligence algorithms—such as PSO and ACO—can be leveraged to explore complex, nonlinear parameter spaces, identifying near-global optima for control variables. By balancing transient response and stability margin, swarm intelligence reduces the inherent risk of over-optimisation in pure model free U-shaped control implementation, such as excessive actuator wear and oscillation behaviour.

1. Human- AI Control and U-control: In the U-control framework, human experience and real-time decision-making mechanisms can be integrated to form a human-machine collaborative division of labour mode: operators are responsible for high-level strategy formulation and abnormal supervision, while the U-control system performs dynamic fine-tuning for low-level control. Using intelligent methods such as fuzzy logic and NN to parse human instructions and convert them into parameter adjustment signals retains the judgment advantage of expert experience in complex scenarios and ensures control accuracy through automation. This collaboration not only enhances the decision-making reliability of the system in uncertain environments but also strengthens operational trust through the "human safety net" mechanism - when the system encounters critical risks, manual intervention can quickly correct them, avoiding the potential risk of loss of control caused by full automation.

2. Digital Twins and U-control: Combine U-control with digital twins technology to create a virtual replica of the physical system. This setup allows real-time testing and refinement of control strategies in a simulated environment before applying them to the system. By mirroring system dynamics, the digital twins act as a safe testing ground, enabling adjustments and validations without risking real-world performance. This integration streamlines control design, reduces development costs, and ensures smoother transitions from simulation to practical implementation.

3. Hybrid Control Architecture: A practical solution is to blend MF U-control with traditional model-driven strategies, guided by adaptive decision-making logic. Under stable conditions—where system dynamics are well understood, and high-fidelity models exist—the controller prioritises model-based methods for precision. However, when facing unmodeled disturbances (e.g., sudden load shifts, or environmental noise), it autonomously switches to the MF U-control framework. This transition is managed through performance-driven criteria: AI algorithms continuously evaluate real-time metrics like error thresholds and stability margins, triggering the optimal control mode.

   By dynamically leveraging the accuracy of model-based approaches and the flexibility of U-control, the HSs maintains robust performance across routine operations and edge cases. For instance, in industrial robotics, this duality ensures smooth transitions between repetitive high-precision tasks and unpredictable scenarios like collision recovery.

3.4 Optimisation Strategies for Bottom-Layer U-Control

Based on existing underlying U-control methods, further optimisation of their design and performance can be achieved in the following directions in the future:

1. The robustness and adaptability of underlying U-control can be further improved, for example, by combining I-control strategies and introducing adaptive sliding mode control algorithms to enhance the ability to suppress unmodeled dynamics and external disturbances.
2. For control performance optimisation, intelligent optimisation methods such as GA and PSO can be used to dynamically adjust U-control parameters, thereby improving system response speed, overshoot, and steady-state accuracy, while enhancing dynamic decoupling capabilities and reducing coupling interference in multivariable systems.
3. It is recommended to integrate cutting-edge technologies to expand application scenarios, such as using digital twins technology to build a simulation platform for the virtual real interaction and to verify the effectiveness of control strategies in real-time; or deploy lightweight U-control algorithm through edge computing to reduce communication delay of distributed system and improve real-time performance.
4. Attention should be paid to the scalability and complexity management of the system, such as developing a modular U-control framework that supports flexible configuration and rapid porting, enabling it to adapt to controlled objects of different sizes and complexities, while simplifying maintenance and upgrade processes.

4 Case studies: practical applications of U-I-control integration

The following gives two possible integration examples of how to realise the I-based U-control, covering UAVs with minimum energy control [37], robotic systems [41], neuro-fuzzy controlled manipulators [21], and industrial process control.

4.1 Example 1: Autonomous Systems Control

Control systems for autonomous systems with energy constraints [31].

4.1.1 Three-level Hybrid Control Architecture:

Given mixed data, one straightforward idea is to discretize all continuous variables, another idea is to use the three- layer hybrid control architecture. The high layer (I-control) processes discrete and qualitative signals (e.g., voice commands, event triggers) and outputs high-layer decision signals (e.g., mode switching, trajectory adjustment). The middle layer converts discrete signals into continuous-compatible formats (e.g., zero-order hold or interpolation) and ensures that discrete signal updates align with the U-control sampling rate. It also employs intelligent methods (e.g., fuzzy logic) to quantify qualitative signals (e.g., "fast response") into continuous signals. The bottom layer (U-control) retains the original continuous or discrete design, with optional discretization. The decision to discretize depends on signal type and closed-loop performance.

High layer (I-control) design: One possible design approach involves using an LQR-based top layer (I-control) in conjunction with a U-control base layer, incorporating a time-varying Q/R design mechanism, while the bottom layer U-control retains the original dynamic inversion structure. This design is well-suited for the automatic control of autonomous systems [31] like model-free adaptive control with rigorous stability analysis [38] and minimum energy control of autonomous aerial systems [37].

1. For model-based U-control, the bottom model can be represented as:

$$\dot{x} = f(x, u, d(t)) \tag{2}$$

where u is the control input, and $d(t)$ is the external disturbance.

For system (2), we propose the following optimisation problem:

$$\begin{aligned} \min J(x,u) = \int_0^\infty \big(& x(t)^T Q(t) x(t) + \\ & u(t)^T R(t) u(t) \big)\, dt \end{aligned} \tag{3}$$

During peak hours, Q should be increased and R decreased to prioritise accuracy. During off-peak hours, Q should be decreased and R increased to prioritise energy efficiency.

2. For MF U-control implementations, design composite energy function:

$$V_{MF} = x^T P x + \sigma^T \Lambda(t) \sigma \tag{4}$$

where P is the solution of the LQR Riccati equation, σ is the U-control sliding surface, Λ is the sliding mode gain matrix.

4.1.2 Incorporating constraints

1. Parameter Update Constraints: Limit Q/R variation rates:

$$\left\|\frac{dQ}{dt}\right\| \leq \gamma\|Q\|, \left\|\frac{dR}{dt}\right\| \leq \gamma\|R\| \tag{5}$$

2. Time-Scale Separation Condition:

$$\tau_{U-control} < \tau_{LQR} \tag{6}$$

   where $\tau_{U-control}$ is the dynamic inversion response time of U-control (e.g., milliseconds to sub-seconds) and τ_{LQR} is the decision update period of LQR (e.g., 1–10 s), ensuring that the inner loop responds much faster than the outer loop.

3. Stability Condition Constraints

$$\dot{\mathrm{V}} \leq -\lambda_{LQR} \parallel x \parallel^2 - \lambda_{U-control} \parallel \sigma \parallel^2 \tag{7}$$

   where the decay rates λ_{LQR} and $\lambda_{U-control}$ must be coordinated.

4. Hierarchical Cost Function Consistency:

$$J_{total} = \int_0^\infty \left(x(t)^T Q(t)x(t) + u(t)^T R(t)u(t)\right) dt \\ \approx J_{U-control}(e, u) \tag{8}$$

   To ensure U-control's output energy complies with real-time LQR weight $R(t)$, we have

$$\parallel u_{U-control} \parallel^2 \leq \frac{R_{\max}}{R(t)} \parallel x \parallel^2 \tag{9}$$

4.1.3 Intelligent Methods for UDI

1. For model-based U-control, the nonlinear system model is in general not exact, and the inversion of the inner loop is difficult to obtain, the inversion process is excessively intricate to be executed in its exact form. A NN can be incorporated into the controller design to provide error compensation.

2. For TMF U-control implementations, adaptive approaches like fuzzy logic, NN, or RL [36] may serve as alternatives to MFSMC in the inner loop, thereby deriving the control law.

4.1.4 Evaluation & Experiments

We propose three metrics to evaluate the results in real production, collectively assessing a method's performance. Experiments should be conducted in Simulink/Matlab, evaluating both control performance and energy efficiency under realistic industrial conditions. For example, step changes in energy prices to emulate real-time electricity markets, sudden load disturbances like a 20% torque overload in motor control, and nonlinear dynamics switching, for example, a UAV transitioning from hover to forward flight. Additionally, benchmark comparisons should be made against pure LQR control with fixed parameters and pure U-control without considering energy efficiency, to provide a more holistic understanding of the method's effectiveness and adaptability in various practical situations.

4.1.5 Extended Applications: From Energy Control to Safety-Critical Driving

Minimum energy control of autonomous aerial vehicles [37] represents a special case of autonomous systems as in Example 1, integrating U-control with HICS for safe autonomous driving, encompassing feasibility and methodology in three areas: autonomous driving, path planning and decision-making, and emergency manoeuvring.

The upper layer focuses on decision-making and RL optimisation, while the lower layer handles execution. U-control addresses the nonlinear vehicle dynamics, such as tyre friction and actuator saturation, ensuring tracking accuracy and safety.

1. Autonomous Driving takes lane deviation error, preceding vehicle distance, traffic flow state as input, desired speed and steering angle as output, RL learns optimal policies to balance fuel efficiency and safe following distance, while U-control ensures robust tracking performance by compensating for real-world nonlinearities. For longitudinal control, throttle and brake commands are generated via U-model inversion. For lateral control, steering accuracy is ensured via the U-control sliding mode surface $\sigma = \dot{e} + \lambda e$, which rejects road disturbances.

2. Path Planning and Decision-Making, RL handles complex traffic scenarios like unprotected left turns and pedestrian crossings, whereas U-control compensates for nonlinearities like understeering on low-friction roads, ensuring that the vehicle

stays on course. Additionally, RL plans optimal evasive paths during critical situations, such as avoiding obstacles, while U-control guarantees stable tracking even when facing model uncertainties, like sudden braking on icy or slippery roads.

3. Emergency Manoeuvring, the strategy focuses on executing rapid and safe manoeuvres when confronted with unexpected situations, with RL handling the decision-making of the best evasive action, while U-control ensures that the vehicle's dynamics are accurately controlled, even under extreme conditions. One challenge is the co-training of RL and U-control, which can be addressed by using offline RL pre-training combined with online U-control fine-tuning to avoid instability. Another challenge is the conflict between multi-objective goals, such as safety and comfort, which can be resolved by embedding control barrier functions in U-control to constrain RL outputs.

4.2 Example 2: Industry Process Control

Using the example of "Hierarchical Intelligent Control of the Sintering Process" [39], we demonstrate the U-I control method. The sintering process is a crucial pre-treatment step in steel production, where low-grade iron ore is agglomerated into high-grade sinter through combustion. The key control parameters in this process are the burn-through point (BTP) and the vertical sintering speed (VSS). BTP is the most important heat state parameter, directly affecting the quality and quantity of the sinter, while VSS is a significant factor influencing BTP. The sintering process is highly complex, nonlinear, time-varying, and has significant time delays, making it difficult to measure BTP online directly. Traditional control methods often fail to meet the control requirements due to these challenges. Hierarchical intelligent control systems (HICS) and U-control are highly complementary in their core principles. The soft-sensing and fuzzy control capabilities of HICS can enhance the model adaptability of U-control, while the dynamic inversion and TMF robustness of U-control can address the limitations of HICS in terms of mechanistic model accuracy. The integration approaches can take the following two possible forms.

4.2.1 U-Control Substitution for HICS Lower-Layer

1. The lower layer applies U-control to replace the PID-based DCS, reformulating strand speed control as a U-model dynamic inversion problem $\dot{y} = f(y) + g(y)u$, where u comes from the upper-layer LQR/fuzzy control.
2. Use MFSMC to handle model-free dynamics (e.g., variations in bed resistance).

4.2.2 Hybrid Architecture (HICS + U-control)

1. Upper Layer (HICS): BTP soft sensing retains the original soft-sensing algorithm. Dynamic adjustment of LQR weights $Q(t), R(t)$ (e.g., prioritize energy savings during high electricity prices).
2. Lower Layer: Model strand speed control as a U-model polynomial $y^{(n)} = \sum_{i=0}^{n} a_i(t)y^{(i)}$ and solve the inverse model in real-time using Newton-Raphson iteration.

There are many challenges to stability and real-time requirements, such as the compatibility between upper-layer LQR and lower-layer U-control Lyapunov functions. U-control should be deployed on real-time controllers interfaced with DCS hardware.

5 Conclusion

This study presents the primary concept and configuration of a What-How intelligent control system, which is established with two layers of control, bottom control and coordination control. This WH-I-control provides a flexible and scalable open framework to integrate data-driven dynamic adaptation and knowledge-guided optimisation for problem-oriented, data-driven system operation. Accordingly, human expertise, scientific, engineering experience, and industrial results are effectively accumulated in the data and knowledge bases with proper classification, qualitative and quantitative assessment, and generalisation.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Quanmin Zhu served as an Associate Editor of the *ICCK Transactions on Sensing, Communication, and Control* at the time of manuscript submission. To ensure the integrity of the peer-review process, Quanmin Zhu was not involved in the editorial handling, peer review, or decision-making process for this manuscript, which was handled independently by another editor. The remaining author declares no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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