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A Review on Intelligent Control

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Abstract: Intelligent control significantly boosts operational efficiency and precision while minimizing the need for manual labor. It is capable of functioning effectively in intricate environments and facilitates automated decision-making processes. Additionally, it drives technological advancements and fosters industrial growth. This technology is crucial for enhancing workplace safety, optimizing resource allocation, bolstering global competitiveness, and supporting broader socioeconomic progress. The significance and scope of intelligent control have grown substantially as a result. Intelligent control has been widely applied in fields such as industrial automation, smart home systems, and traffic management. AI contributes by providing smart decision-making capabilities, machine learning facilitates self-optimization, and deep learning improves pattern recognition, all of which collectively boost the performance and adaptability of intelligent control systems. Compared to conventional control methods, intelligent control excels in addressing nonlinear and uncertain challenges. It demonstrates superior adaptability and learning capabilities, operates effectively without requiring precise models, and achieves more efficient control outcomes in complex environments. This paper mainly conducts a review of intelligent control in terms of basic concepts and framework, key technologies, application fields, challenges and development trends.

Keywords: Intelligent Control, Leader-Follower Control, FPID, GANs, MRAC

1. Introduction

Intelligent control systems are a remarkable achievement of contemporary scientific and technological advancement. By leveraging technologies such as artificial intelligence, these systems undergo continuous refinement and enhancement. They have been widely applied in areas like industrial automation, traffic management, and smart home solutions. Through accurate control and analysis, intelligent control systems have significantly boosted production efficiency, ensured safer transportation, and enhanced living standards. Whether in factory production lines or everyday household devices, the presence of intelligent control systems is pervasive, driving society toward greater intelligence and efficiency.

This article serves as an review of intelligent control systems. The second section of the paper presents the core principles and architecture of intelligent control. The third section describes the essential technologies of intelligent control and highlights some control approaches. The fourth section introduces the application domains of the aforesaid control methods. The fifth section elaborates on the challenges and development trends that intelligent control is confronted with.

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2. The core principles and architecture of intelligent control

2.1. The core principles

The essence of developing modeling and control strategies for intelligent control systems [1,2] revolves around effectively managing intricate processes through the application of mathematical frameworks and advanced algorithms. During the modeling phase, it is crucial to conduct an in-depth examination of the system to construct appropriate mathematical representations, such as state-space models and transfer functions, while accounting for characteristics like nonlinearity and time-varying behavior. The accuracy of the model is verified through system identification methods. In terms of control methodologies, techniques like adaptive control and genetic algorithms play a significant role in intelligent control systems. Adaptive control [3] facilitates real-time adjustments of parameters and optimizes control outcomes, ensuring efficient and stable performance across diverse operational scenarios. Genetic algorithms [4], inspired by natural selection and genetic principles, are utilized to refine controller settings, improving the efficiency and adaptability of control strategies. By integrating these approaches, intelligent control systems can more effectively address complex environments and boost overall control effectiveness.

The merger of control theory with artificial intelligence (AI) methodologies represents a significant research direction in contemporary control engineering. This fusion aims to leverage the powerful capabilities of AI technologies to enhance conventional control strategies and address control challenges in systems that are complex, nonlinear, uncertain, and large-scale. Fuzzy control [5], which is based on fuzzy logic, does not require exact mathematical models and is well-suited for managing systems that are difficult to model. Neural network control [6] leverages the learning and approximation capabilities of artificial neural networks to address intricate control challenges, making it particularly well-suited for systems with high nonlinearity. This methodology includes various approaches such as feedforward neural networks, recurrent neural networks, deep learning techniques, among others.

2.2. Architecture of intelligent control

Intelligent control systems can be categorized into multiple layers [7], each responsible for specific functions while working together to achieve control objectives. Figure 1 illustrates the different layers of intelligent control along with their interrelationships. At the sensor layer, data collection occurs; the transmission layer is in charge of relaying this data; the processing layer handles data analysis; decisions are formulated at the decision layer; and actions based on these decisions are carried out by the execution layer. The management layer oversees and enhances the overall system performance, with the ability to modify the operational states and parameters of other layers. To ensure seamless coordination and closed-loop control across the system, continuous information exchange between these layers is essential [8].

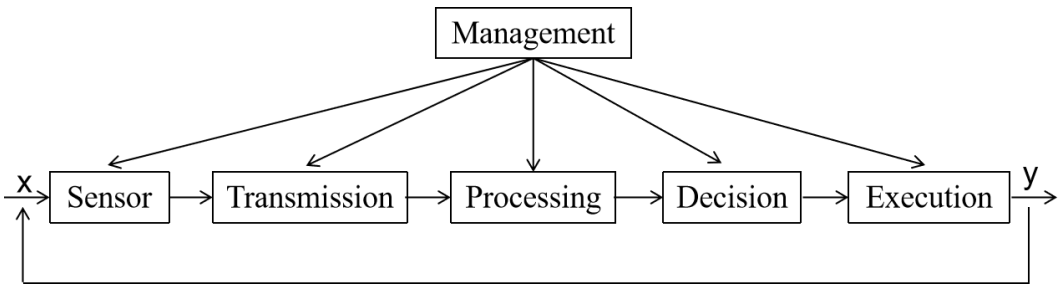

Figure 1: Different layers of intelligent control.

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3. The essential technologies of intelligent control approaches

This part presents the key techniques in intelligent control approaches, encompassing both the overview and classification of the key methods. Subsequently, the principles of some of the specific methods are elaborated.

3.1. Collective intelligence

Collective intelligence refer to a phenomenon observed in nature where collective behaviors emerge within biological groups as a result of interactions, collaborations, and coordination among individuals. This form of intelligence is not inherent to any single member but rather emerges at the group level. Studies into Collective intelligence [9] provide innovative concepts and methodologies for various fields, including artificial intelligence, robotics, network optimization, and data mining.

The categories of Collective intelligence primarily include the following types. Ant colony [10], bee colony [11], bacterial [12], and fish swarm optimization algorithms [13] address optimization challenges by mimicking the respective biological behaviors. The particle swarm optimization algorithm [14] emulates the foraging activities of bird flocks and resolves optimization issues by updating both individual and collective experiences. In swarm robotics [15], complex tasks are primarily accomplished through local interactions among the robots.

The leader-follower control approach is utilized in Unmanned Aerial Vehicle (UAVs) operations [16,17]. In 2021, researchers including Ali Zain Anwar explored the control of leader-follower formations in multi-UAVs. This approach mirrors certain characteristics of natural group behaviors, where one or more entities assume leadership roles while the others function as followers. Tasks are achieved through their coordinated interactions. Consider a formation of N UAVs [18], where the position vector of the i-th UAV is represented by $p_{\mathrm{i}} = [x_{\mathrm{i}}, y_{\mathrm{i}}, z_{\mathrm{i}}]^{\mathrm{T}}$, its velocity vector by $v_{\mathrm{i}} = [v_{\mathrm{xi}}, v_{\mathrm{yi}}, v_{\mathrm{zi}}]^{\mathrm{T}}$. The index of the leader is designated as l, and that of the follower is marked as f. The leading UAV can adhere to a predefined trajectory or track a dynamic target. Its motion can be characterized by the following equations:$\dot{p}_{\mathrm{l}} = v_{\mathrm{l}}, \dot{v}_{\mathrm{l}} = a_{\mathrm{l}}$. Here,$a_{\mathrm{l}}$ represents the acceleration of the leader UAV, which may be determined by path planning algorithms or external control inputs. Each follower UAV's motion is governed by:$\dot{p}_{\mathrm{f}} = v_{\mathrm{f}}, \dot{v}_{\mathrm{f}} = a_{\mathrm{f}}$. In this context,$a_{\mathrm{f}}$ denotes the follower's acceleration, typically influenced by its relative position and velocity with respect to the leader UAV. The follower UAV's acceleration a_{f} is computed using the following control law:

$$a_{\mathrm{f}} = a_{\mathrm{c}} + a_{\mathrm{r}} \tag{1}$$

where $a_{\mathrm{c}}$is the control acceleration aimed at aligning with the leader, and a_{r} is the avoidance acceleration ensuring safe distances within the formation.

The alignment control acceleration a_{c} is given by:

$$a_{\mathrm{c}} = k_{\mathrm{p}}(p_{\mathrm{l}} - p_{\mathrm{f}}) + k_{\mathrm{v}}(v_{\mathrm{l}} - v_{\mathrm{f}}) \tag{2}$$

where k_{p} and k_{v} are positive gain coefficients.

The avoidance acceleration a_{r} is a function that considers the relative positions of other UAVs to prevent collisions:

$$a_{\mathrm{r}} = -k_{\mathrm{d}} \sum_{\mathrm{j}\neq\mathrm{f}} \frac{p_{\mathrm{f}} - p_{\mathrm{j}}}{\left\| p_{\mathrm{f}} - p_{\mathrm{j}} \right\|^{3}} \tag{3}$$

Here, k_{d} is the avoidance gain, and the summation encompasses all other UAVs in the formation.

These equations constitute the core mathematical framework for the leader-follower control strategy in UAV systems. In practical implementations, additional factors must be considered.

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3.2. Control based on fuzzy logic

Fuzzy Logic Control (FLC) is a control methodology that mimics human decision-making processes and is particularly useful for managing complex systems that are difficult to represent using conventional mathematical models [19,20].

The primary categories of fuzzy logic-based control systems are outlined below. Adaptive fuzzy control (AFC) [20] dynamically modifies its rules based on system performance, whereas predictive fuzzy control (PFC) [21] forecasts the system's future behavior. Although both approaches leverage fuzzy logic, they serve distinct application objectives.

Fuzzy Proportional-Integral-Derivative (FPID) [22,23] control combines the advantages of conventional PID control with fuzzy logic, aiming to overcome the challenges faced by traditional PID controllers in managing nonlinear, time-varying, and uncertain systems. In 2021, researchers including Ali Moetasem enhanced and optimized the frequency response in a hybrid microgrid system by employing a fuzzy PID control approach. Taking the two-area hybrid microgrid system mentioned in Figure 2 as an illustration, the fuzzy PID control can enhance the dynamic performance and robustness of the system. The image illustrates the control framework of the power system, segmented into two regions (Region Swing1 and Region Swing2). For both Region 1 and Region 2, the control algorithms employed in the PI controllers and FOPID controllers can be represented as follows:

$$u_1 = k_p e + k_i \int e\,dt + a_0 p^{\alpha} e + a_1 p^{\alpha} \frac{de}{dt} \tag{4}$$

$$u_2 = k_p e + k_i \int e\,dt + a_0 p^{\alpha} e + a_1 p^{\alpha} \frac{de}{dt} \tag{5}$$

Among them, e is the error signal, k_p and k_i are the proportional and integral coefficients respectively, a_0 and a_1 are the coefficients of FOPID, and α is the differential order. This control framework ensures efficient management of various components within the power system by utilizing multiple controllers and energy storage systems, thus maintaining the stability and reliability of the power network.

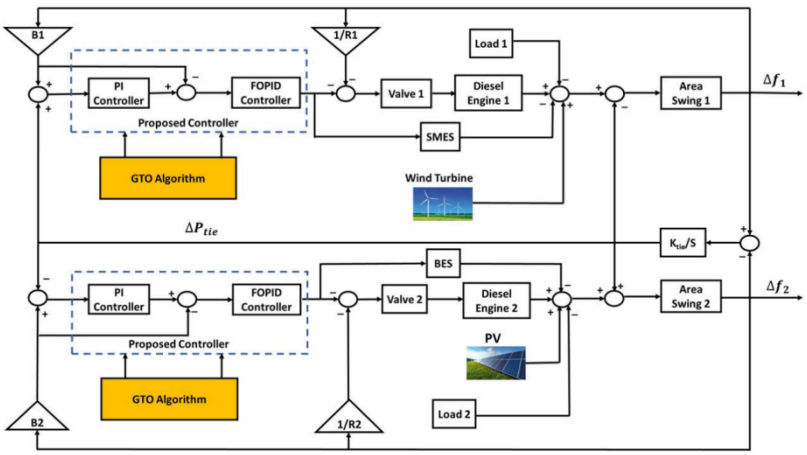

Figure 2: Block diagram representation of the two-area hybrid microgrid system.

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3.3. Deep Learning

Deep Learning [24] represents a specialized area within Machine Learning, where it mimics the structural and functional aspects of human neural networks to achieve automated data feature extraction and model learning.

Deep learning encompasses a wide variety of models, each designed to address specific types of data and tasks. CNNs [25] is particularly adept at processing data that exhibits spatial hierarchical structures, like images and videos. RNNs [26], on the other hand, is proficient in capturing temporal dependencies within sequential data, making it ideal for time series analysis and natural language processing tasks. Meanwhile, GANs [26] comprises two neural networks—a generator and a discriminator—that engage in competitive learning to understand the distributional features of data, enabling tasks related to data generation and transformation.

GANs consist of two key elements: the Generator and the Discriminator. These components engage in an adversarial interaction, competing against each other to produce high-quality synthetic data [27]. In 2021, Jiang Yifan and other scholars investigated the discriminator component within GANs. Within this framework, the generator G utilizes a random noise vector z (commonly derived from the prior distribution $P_z(z)$) as its input to create a synthetic sample $G(z)$, striving to replicate the characteristics of the real data distribution $P_{\text{data}}(x)$. On the other hand, the discriminator D [28] evaluates a given sample x (whether it is real or generator-produced) and outputs a scalar $D(x)$ that signifies the probability of x being drawn from the true data distribution. The training of GAN can be conceptualized as a minimax game, formulated as:

$$\min_G \max_D V(D,G) = E_{x\sim P_{\text{data}}(x)}\left[\log D(x)\right] + E_{z\sim P_z(z)}\left[\log(1-D(G(z)))\right] \tag{6}$$

Here, E denotes the expectation. The first component represents the expected log probability that the discriminator accurately distinguishes real data. The second component represents the expected log probability that the discriminator successfully identifies the synthetic data produced by the generator.

During the training phase, the discriminator D and the generator G undergo alternating updates. When updating D, G remains unchanged, and the focus is on enhancing D's ability to distinguish by maximizing $V(D, G)$. Conversely, when updating G, D stays fixed, and the aim is to improve the realism of the generated samples by minimizing $V(D, G)$. The ultimate objective of the GAN framework is to achieve a Nash equilibrium, where the interaction between D and G optimizes $V(D, G)$. At this equilibrium, the generator G can produce outputs that closely mimic the real data distribution, making them virtually indistinguishable from actual data.

3.4. Neural Network Control

Neural network control involves the development of control systems using artificial neural networks (ANNs). This methodology mimics the operational principles of the human brain by creating models through the analysis of a system's input and output data, thereby enabling decision-making and control actions [24].

In practical applications, neural network control can be classified into several categories. Model Reference Adaptive Control (MRAC)[29], indirect adaptive control [30], fuzzy neural network control, and recurrent neural network control all enhance system adaptability and improve control performance. These methods share the ability to manage uncertainties and nonlinearities. However, they differ in their approaches: MRAC and indirect adaptive control concentrate on parameter adjustments, where MRAC utilizes reference models for adaptation, and indirect adaptive control refines parameters based on error learning. In contrast, fuzzy neural network control and recurrent

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neural network control address complexity by employing fuzzy logic and temporal sequence learning, respectively. Fuzzy neural networks highlight the application of fuzzy rules, while recurrent neural networks excel in dynamic system modeling.

Model Reference Adaptive Control (MRAC) is an intelligent control methodology that dynamically modifies the controller parameters to ensure that the controlled system's output closely follows that of a desired reference model. This approach operates independently of the exact mathematical representation of the controlled system, relying instead on an adaptive mechanism to guarantee performance. In 2021, Wang Yu and other researchers investigated an autonomous nonlinear rotorcraft utilizing MRAC. Figure 3 illustrates the block diagram of Model Reference Adaptive Control (MRAC). The reference input r_{m} is fed into the Adaptive Reference Model. This model takes the reference input r_{m} and produces the desired output signal x_{m}. The desired output x_{m} from the reference model is compared with the actual system output x, yielding the error signal:

$$e = x_{\mathrm{m}} - x \tag{7}$$

Based on the error signal e, the parameters of the adaptive law K_{r} are updated. The error signal e is transformed into the weight space to produce the rate of change of weights $\dot{\widehat{W}}_{\mathrm{r}}$. Using $\dot{\widehat{W}}_{\mathrm{r}}$ as input, the RBFNN processes this information to generate the control adjustment signal Δu. To ensure the input remains within acceptable limits, the saturation function $\mathrm{sat}(\Delta u)$ is applied to Δu. The feedback signal e_{u} is combined with other control signals to form the final feedback control signal. The error signal Δx is projected onto a different weight space to generate $\dot{\widehat{W}}_{\mathrm{r}}$. With $\dot{\widehat{W}}_{\mathrm{r}}$ as input, the second RBFNN refines the control signal further. After passing through a saturation function, the final control signal is generated and utilized in the control system. Stability verification is performed to ensure the robustness of the adaptive control system, typically employing Lyapunov [31] theory for analysis.

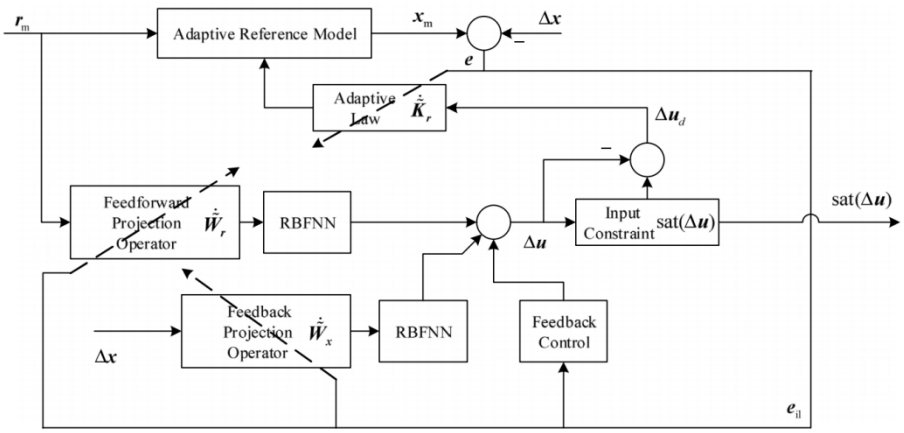

Figure 3: Block diagram for MRAC law.

4. The application domains of intelligent control

In this section, we focus on examining the practical application areas of the previously discussed methods in the field of intelligent control.

4.1. The leader-follower control strategy for the cooperative control of UAVs

The implementation of leader-follower strategies in intelligent control is prevalent across domains including robotic cooperation, multi-agent frameworks, unmanned vehicle formations, and drone

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clusters [16]. During agricultural spraying tasks, a single drone assumes the role of the leader to chart the course [32], while the remaining drones follow in sequence to apply pesticides uniformly, thereby improving operational efficiency. This approach significantly decreases labor expenses and enhances the degree of automation in agriculture.

4.2. Fuzzy Proportional-Integral-Derivative (PID) Control

Fuzzy PID control is widely employed in intelligent control systems for accurate regulation [23], such as managing temperature in smart homes. For example, a fuzzy PID controller can automatically modify the air conditioner's settings by considering both the temperature difference between inside and outside environments and the humidity levels. This ensures a stable indoor temperature and improves living comfort. It also highlights the controller's significant role in promoting energy efficiency and environmental sustainability [33].

4.3. Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) find applications in intelligent control across various domains, including robot vision, autonomous driving perception, and fault detection. For instance, in manufacturing, GANs can be used to simulate the grasping motions of robots, generating a large amount of grasping data for objects of various shapes and sizes [28]. These data are used to train robots, enabling them to learn and perform precise grasping motions, thereby enhancing the operational efficiency and accuracy on automated production lines [34].

4.4. Model Reference Adaptive Control (MRAC)

Model reference adaptive control (MRAC) finds extensive application in intelligent control systems, particularly in areas like autonomous aircraft navigation and robotic arm operation [35]. For example, in unmanned aerial vehicle (UAV) flight control, MRAC can dynamically modify flight settings to maintain stability under varying conditions, such as fluctuating weather patterns or changes in payload. This capability allows UAVs to execute precise missions, including agricultural spraying and topographical mapping, autonomously and without the need for human oversight [36].

5. Challenges and development trends

The primary application challenges of leader-follower control strategies in intelligent control systems involve effectively mitigating communication delays and disturbances, especially in environments with multiple leaders or followers. The future direction focuses on investigating more efficient communication protocols and coordination methods to boost the system's overall performance and robustness [37].

In the context of fuzzy PID control within intelligent control systems [38], the key challenge is accurately designing the fuzzy rule base to accommodate the varying dynamics of different systems. The evolving trend is to integrate advanced AI technologies, such as deep learning, to automate the optimization of fuzzy logic controller parameters, thereby enhancing control precision.

The application of GANs in intelligent control faces challenges related to maintaining stable network training and ensuring reliable control performance. The future direction involves exploring innovative training techniques and network architectures to better adapt to complex, nonlinear control scenarios [39].

Model Reference Adaptive Control (MRAC) confronts the challenge of addressing model uncertainty's impact on control system performance. The emerging trend is to incorporate machine

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learning methodologies to refine model identification accuracy, thus bolstering the system's adaptive capacity and robustness.

6. Summarization and prospection

Intelligent control, a key area in modern technology, has been widely applied across various industries including manufacturing, residential environments, transportation, and beyond. This article offers an in-depth examination of intelligent control, covering fundamental concepts and structures, core technologies, areas of application, challenges, and future directions. Particular emphasis is placed on discussing the leader-follower approach in swarm intelligence, fuzzy PID control mechanisms, generative adversarial networks (GANs) within deep learning, and model reference adaptive control (MRAC) in neural network-based control systems. In the future, intelligent control will combine sophisticated algorithms, IoT, and cloud computing to develop highly autonomous, adaptive, and predictive control systems. These systems will be crucial for industrial automation and will also extend into diverse areas of daily life—including homes, healthcare, and transportation—boosting intelligence levels and driving technological advancements and societal progress.

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