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Recent advances on advanced control strategies for valves with deadband and nonlinear gain

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Abstract

This review synthesizes and critically evaluates the recent literature on advanced control strategies for industrial valves subject to severe nonlinearities, including deadband, stiction, and nonlinear gain. We trace the evolution from established model-based robust and adaptive methods, such as Sliding Mode Control (SMC) and Adaptive Robust Control (ARC), to the increasingly prevalent optimization-based and intelligent paradigms, including Model Predictive Control (MPC) and Reinforcement Learning (RL). Key themes analyzed include the trade-offs between model fidelity and controller complexity, the shift from direct nonlinearity compensation to observer-based disturbance rejection, and the emergence of hybrid control architectures. Through a comparative analysis, we distill the performance trade-offs inherent in different strategies concerning tracking accuracy, disturbance rejection, and actuator preservation. We identify critical research gaps, including the need for verifiable and safe learning-based controllers, the development of physics-informed AI, and the exploration of valve-controller co-design. The review concludes that while no single strategy is universally superior, the field is advancing towards a sophisticated toolbox of specialized, often hybrid, solutions, with significant future potential in data-driven and learning-based methods that are rigorously integrated with established control theory.

Keywords: Control Valve; Deadband; Nonlinear control; Nonlinear gain; Hybrid control strategies; Intelligent control; Adaptive Robust control; Sliding mode control; Reinforcement Learning; Fuzzy logic control; Observer based control; Extended state observer; Stiction

1. Introduction

1.1. The Industrial Significance of High-Performance Valve Control

Control valves are the final control elements that form the backbone of industrial automation, acting as the primary actuators in a vast majority of process control loops. Their ubiquity is underscored by market data indicating that pneumatic control valves alone constitute over 60% of actuators in industrial applications [1]. The performance of these devices is not a peripheral concern; it is directly and inextricably linked to fundamental business and operational outcomes, including product quality, energy efficiency, process safety, and overall economic viability. As industrial processes become more complex and operating envelopes more stringent, the demand for high-performance, reliable, and adaptive valve control has intensified, positioning it as a critical and active area of research in control systems engineering [2].

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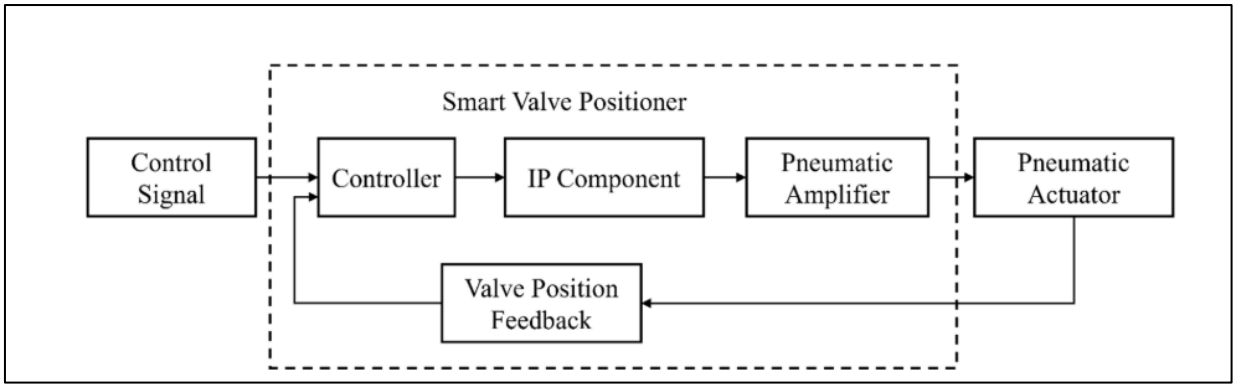


Figure 1 Structural diagram of the smart valve positioner system.

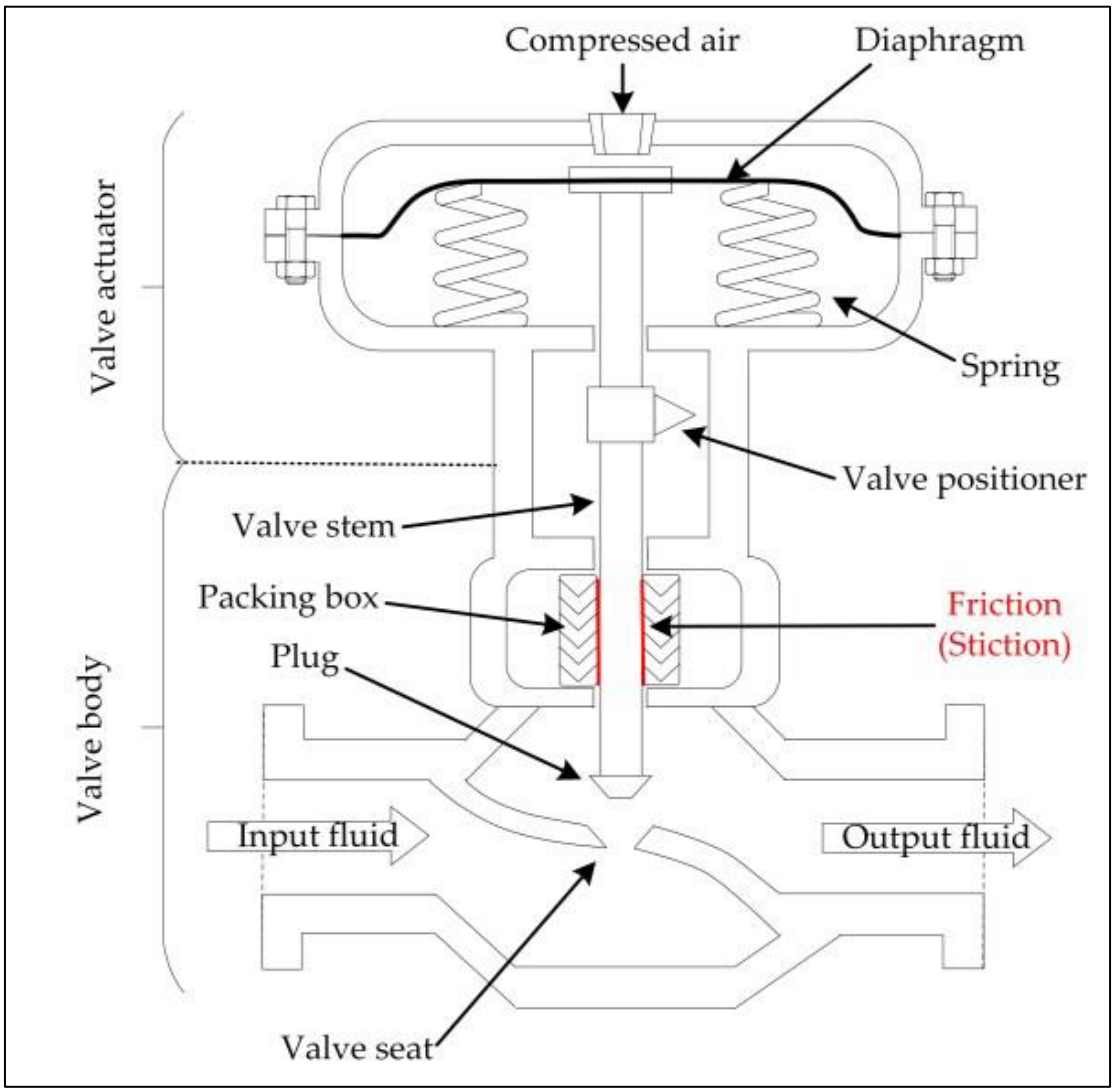


Figure 2 The structure diagram of the valve.

1.2. The Challenge of Inherent Nonlinearities: Stiction, Deadband, and Gain Variation

The primary obstacle to achieving high-performance valve control lies in the inherent, and often severe, nonlinearities present in their mechanical and fluid-dynamic behavior. These are not minor imperfections that we can overlook;

instead, they are frequently the dominant source of performance degradation, leading to control loop oscillations, process variability, and instability [4]. The most commonly cited nonlinearities in the literature include stiction, deadband, hysteresis, backlash, and saturation.

Among these, stiction a portmanteau of static friction is arguably the most pernicious and widely studied phenomenon. It manifests as a "stick-slip" behavior where the valve stem remains stationary despite changes in the control signal until the applied force overcomes a static friction threshold. This results in a sudden, abrupt jump in position [5]. This nonlinear dynamic is a notorious cause of limit cycles in control loops, which not only degrades process control but also accelerates mechanical wear on the valve. A significant challenge is that stiction-induced oscillations can be easily misdiagnosed as poor controller tuning, leading to ineffective corrective actions.

Deadband represents a region of control signal input for which there is no corresponding valve movement. This insensitivity forces the controller, particularly one with integral action, to accumulate error before any corrective action is taken, resulting in tracking offsets and a sluggish response [5]

Furthermore, nonlinear gain signifies that the relationship between the control signal input and the resulting fluid flow through the valve is not constant across the operating range. This variability poses a significant challenge for linear controllers, such as the ubiquitous Proportional-Integral-Derivative (PID) controller, whose performance is predicated on the assumption of process linearity [1]

Compounding these challenges is the fact that these nonlinearities are not static; they evolve. They can change dynamically in response to operating conditions (e.g., pressure, temperature), fluid properties, and the progressive wear and aging of the valve components. This time-varying nature makes their management a persistent and complex problem that demands advanced control solutions [1]

1.3. Scope and Structure of the Review

This review presents a systematic and critical analysis of peer-reviewed literature published between 2020 and 2025, focusing on advanced control methodologies specifically designed to address the challenges of valve deadband, stiction, and nonlinear gain. Foundational research from prior periods is referenced where necessary to provide essential context for recent innovations.

The structure of this review follows the logical progression of control system design and analysis. Section 2 examines the critical first step: the modeling of valve nonlinearities, comparing physics-based and data-driven approaches. Sections 3, 4, and 5 delve into the three predominant classes of advanced control strategies that have been the focus of recent research: model-based robust and adaptive control, optimization-based control with a focus on Model Predictive Control (MPC), and the rapidly ascending paradigm of intelligent and learning-based control. Section 6 presents a comparative synthesis of these strategies, examining their inherent trade-offs and exploring divergent philosophical approaches to the problem. Finally, Section 7 identifies key unresolved challenges and proposes concrete directions for future research. This structure intends to provide a coherent narrative that not only summarizes the state-of-the-art but also illuminates the evolutionary trends and future trajectory of this vital field.

2. Modelling of Valve Nonlinearities

An accurate model of valve nonlinearities is the cornerstone of effective detection, quantification, and compensation [6]. The choice of modeling approach is a critical decision that directly influences the design and efficacy of the control strategy. The literature broadly categorizes these models into two families: those based on physical principles and those driven by empirical data.

2.1. Physics-Based and Semi-Physical Models

Physics-based models aim to capture the underlying mechanical and frictional phenomena that give rise to nonlinear behavior. Prominent examples that are frequently cited as benchmarks include the Karnopp model, the dynamic LuGre model, and the Generalized Maxwell Slip (GMS) model [6]. These models offer high fidelity and can provide deep insight into the valve's behavior. However, their practical application in control design is often hindered by their complexity. They typically involve a large number of physical parameters (e.g., stiffness, damping coefficients, and friction parameters) that are difficult to identify accurately from standard process operational data, limiting their utility for online, adaptive control schemes [6].

2.2. Data-Driven and Phenomenological Models

In response to the practical limitations of physical models, data-driven and phenomenological models have gained significant traction. These models focus on reproducing the observed input-output behavior of the valve rather than its internal physics, offering a simpler parameterization that is more amenable to system identification from operational data[6]

Seminal models in this category include the multi-parameter models by Choudhury et al. and Kano et al., as well as the binary-tree structure proposed by The et al..[6] A notable advancement was the revised binary-tree model by Li et al. (2015), which was specifically designed to overcome the limitations of its predecessors in handling instantaneous reverse motion commands. This revised model demonstrated superior accuracy and robustness when validated against the full suite of standard ISA control valve tests.[6]

Another widely used structure is the Hammerstein-Wiener model, which conveniently separates a static nonlinear block from linear dynamic blocks. This separation is beneficial for system identification and for integration into control frameworks, such as Model Predictive Control, where the nonlinear and dynamic aspects of the process can be handled distinctly [7].

2.3. A Critical Comparison of Modeling Approaches for Control Design

The selection of a valve model is not an independent exercise but is deeply intertwined with the intended control strategy. There is no single "best" model; instead, the literature demonstrates a clear trend towards selecting a model that is "fit-for-purpose" for a specific control objective. This interdependence is a crucial aspect of modern control design for nonlinear valves.

For instance, a control strategy that relies on direct inversion of the nonlinearity, such as a stiction-inversion MPC formulation, necessitates a model that is not only accurate but also mathematically invertible [7]. A complex physical model like Lure, while potentially more accurate in its description, may be computationally prohibitive or analytically intractable to invest in real-time. In this context, a simpler, data-driven model that captures the essential behavior and has a readily available inverse becomes the more practical and effective choice.

Conversely, a robust control strategy, such as Sliding Mode Control (SMC), is designed from the ground up to be insensitive to a defined class of model uncertainties and external disturbances [8]. Such a controller may not require a high-fidelity model of the stiction. Instead, it may only need reliable bounds on the magnitude of the friction forces. For this purpose, a less precise but physically representative model that provides these bounds would be entirely sufficient.

The work of Khandekar and Agashe (2025) reinforces the critical need for effective modeling by demonstrating, through both simulation and experimental validation on a pneumatic valve integrated with a Distributed Control System (DCS), the profound performance degradation caused by stiction and deadband. Their conclusion that a mechanism for online detection and diagnosis of these nonlinearities is essential for improving control performance directly highlights the need for models that are not only accurate but also simple enough to be used in real-time monitoring and fault detection algorithms running on industrial platforms [9].

3. Developments in Model-Based Control Strategies

Model-based control remains a cornerstone of the effort to manage valve nonlinearities. Within this domain, research has focused on refining robust and adaptive techniques to deliver high performance despite the presence of significant model uncertainty and external disturbances. A notable trend is the increasing use of advanced observers to estimate and reject nonlinear effects, representing a philosophical shift in the control design approach.

3.1. Sliding Mode Control (SMC): Advances in Robustness and Chattering Suppression

SMC is a nonlinear control technique renowned for its inherent robustness to a class of uncertainties known as matched uncertainties, which includes many forms of friction and external disturbances [10]. This property makes SMC a natural and powerful choice for controlling valves with poorly characterized or time-varying nonlinearities.

Recent advancements have focused on addressing SMC's primary practical drawback: the high-frequency switching of the control signal, known as chattering, which can excite unmodeled dynamics and lead to excessive wear on the actuator. One practical approach is the use of a variable boundary layer around the sliding surface. Within this layer, the discontinuous control law is replaced by a continuous approximation, smoothing the control signal at the cost of a small

tracking error. A 2023 PhD thesis demonstrated the successful application of a variable boundary layer SMC to an electrohydraulic servo valve, where it outperformed a baseline linear controller in both dynamic response and robustness [8].

Another sophisticated approach is the design of dual-mode or hybrid SMCs. These controllers employ a state-dependent gain structure, using a high-gain control law when the system state is far from the desired trajectory to ensure fast convergence, and switching to a lower-gain law when the state is near the sliding surface to minimize chattering and improve steady-state accuracy [11]. Furthermore, the literature shows a trend towards integrating SMC into broader hybrid architectures. For example, fuzzy logic systems are being used to intelligently tune the SMC switching gains online to reduce chattering [12], and learning-based algorithms are being combined with SMC to leverage the strengths of both paradigms, as seen in LAMDA-SMC topologies [13].

3.2. Adaptive and High-Gain Control: Tackling Parametric and Structural Uncertainties

When system parameters are unknown or vary significantly during operation, adaptive control strategies become essential [14]. The period under review has seen the development of highly sophisticated adaptive schemes that go beyond simple parameter estimation.

A key area of innovation is in adaptive gain design. Palli et al. (2020) proposed a novel adaptive gain selection technique for a high-order sliding mode observer (HSMO) used to estimate the state of a hydraulic actuator. In their A+HSMO method, the rate of adaptation for the observer gain is made proportional to the magnitude of the estimation error itself. This state-dependent adaptation law offers the dual benefit of enabling rapid convergence when errors are significant (e.g., during transients) while limiting excessive gain growth and sensitivity to measurement noise when errors are minor (e.g., at steady state). This approach proved superior to both manually tuned and classic fixed-rate adaptive observers in experimental tests [15]

Related work by Won et al. focuses on nonlinear gain design within the controller itself. They developed a nonlinear controller coupled with a high-gain extended state observer (HGESO) for an electro-hydraulic system. A pivotal innovation in their work is the design of the nonlinear controller gain as a function of the disturbance estimation error provided by the observer. This clever design avoids the common problem of requiring excessively high observer gains to achieve good disturbance estimation, which often leads to amplification of sensor noise and system instability [16]. These studies exemplify a move towards more intelligent, state-aware adaptation laws that enhance both performance and robustness.

3.3. Observer-Based Control: The Role of ESO and HSMO in Disturbance Rejection

Perhaps the most significant evolutionary trend in model-based control for nonlinear valves is the philosophical shift from direct compensation to observer-based rejection. Early approaches often focused on creating a detailed model of a specific nonlinearity, such as stiction, and then designing a compensator to explicitly cancel its effect (e.g., by adding corrective pulses to the control signal) [17]. This approach can be practical but is inherently brittle; if the model is inaccurate or the valve characteristics change, the compensation fails.

The observer-based paradigm takes a different, more robust stance. It assumes that it is impractical or impossible to model all the system's nonlinearities and uncertainties perfectly. Instead, it lumps these effects—including stiction, deadband, unmodeled dynamics, parameter variations, and external load disturbances—into a single "total disturbance" or "lumped uncertainty." The control problem is then reformulated into two parts: first, design an advanced observer to estimate the total disturbance in real-time accurately, and second, design a controller that uses this estimate to cancel the disturbance's effect on the system actively.

The Extended State Observer (ESO) is the quintessential tool for this approach. An ESO augments the standard state-space model of the system with an additional state representing the lumped disturbance, and then uses system input and output measurements to estimate both the original system states and this new disturbance state [1]. This simplifies the controller design immensely, as the controller can be designed for a nominal, linear system, with the disturbance estimate being fed back for cancellation.

The power of this approach is compellingly demonstrated by Deng et al. (2021) in their work on an output feedback backstepping controller for a hydraulic actuator. They used an ESO to estimate not only the lumped uncertainty (including valve dynamics) but also unmeasurable states, such as velocity, allowing them to design a high-performance controller that requires only position feedback the most commonly available measurement in practice. The ESO provides the necessary information to make the system robust to complex nonlinearities, eliminating the need to model

or measure them explicitly. This methodology was shown to be highly effective in comparative experiments [18]. This shift towards robust rejection via advanced observers like ESO and HSMO represents a significant advancement in the practical and resilient control of nonlinear valve systems.

4. The Paradigm of Optimization-Based Control: Model Predictive Control (MPC)

Model Predictive Control (MPC) has emerged as a dominant paradigm for advanced process control, and its application to nonlinear valves is a significant area of research. MPC's core principle of using a dynamic model to predict future process behavior and optimize control actions over a finite horizon makes it uniquely suited to this problem. Its native ability to handle multivariable systems, process constraints (e.g., limits on valve position and rate of change), and nonlinear dynamics directly in the problem formulation provides a robust framework for high-performance control.

4.1. Stiction-Aware and Stiction-Embedding MPC Formulations

A significant research thrust is currently dedicated to making MPC "stiction-aware" to mitigate the performance degradation caused by friction. A foundational comparative study by Bacci di Capaci et al. (2018) analyzed three distinct MPC formulations: a stiction-unaware controller (which treats stiction as an unmodeled disturbance), a stiction-inversion controller (which attempts to cancel stiction using an inverse model), and a stiction-embedding controller [7].

The stiction-embedding approach, which involves augmenting the MPC's predictive model with an explicit dynamic model of the stiction, has proven to be particularly effective. By incorporating stiction dynamics into its predictions, the MPC can anticipate the stick-slip behavior and compute a control sequence that proactively mitigates it, resulting in significantly improved setpoint tracking and reduced oscillations. However, this study also noted a critical trade-off: the improved performance of the stiction-embedding MPC came at the cost of reduced robustness to model mismatch compared to the other formulations [7]

Building on this, Durand (2018) further refined the stiction-embedding MPC framework by incorporating explicit constraints on the rate of change of the input. This addition serves the dual purpose of preventing the controller from requesting physically unrealistic actuator movements and reducing the overall wear and tear on the valve, while simultaneously guaranteeing closed-loop stability for the nonlinear process [4].

4.2. Robust and Economic MPC for Constrained Nonlinear Valve Systems

Given that the models used in MPC are never perfect, ensuring robustness to model mismatch and external disturbances is paramount. The literature explores several robust MPC strategies, including min-max MPC (which optimizes against the worst-case disturbance), constraint tightening (which adds a safety margin to state constraints), and tube MPC (which uses a feedback controller to keep the actual state within a "tube" around a nominal trajectory).

A key challenge is the computational complexity and difficulty in designing the terminal ingredients (terminal cost and terminal constraint set) required to guarantee stability in nonlinear robust MPC. Addressing this, a 2025 study introduces a robust contraction-based MPC formulation. This innovative approach ensures recursive feasibility and stability without requiring an explicit terminal constraint. By utilizing a straightforward quadratic terminal cost function, the design of robust MPC becomes more tractable and applicable to a broader range of nonlinear systems, including those with complex valve dynamics [19].

The concept of Economic MPC (EMPC) is also relevant, particularly in large-scale industrial processes. Unlike traditional MPC, which tracks setpoints, EMPC optimizes a more general economic objective function (e.g., maximizing profit or minimizing energy consumption). However, the successful application of EMPC relies heavily on the availability of an accurate, high-fidelity nonlinear process model [4].

4.3. Innovations in Computational Efficiency for Real-Time Implementation

The primary barrier to the widespread industrial adoption of nonlinear MPC (NMPC) is its high computational demand, which can make real-time implementation challenging. Consequently, a substantial body of research is focused on developing computationally efficient NMPC algorithms.

One powerful technique is the use of online trajectory linearization. At each sampling instant, the nonlinear process model is linearized around a predicted future trajectory, thereby converting the challenging nonlinear optimization problem into a sequence of simpler quadratic programming (QP) problems that can be solved efficiently online [20].

An exceptionally sophisticated trend is the pragmatic fusion of artificial intelligence techniques with the MPC framework to solve specific numerical challenges. For example, some MPC cost functions, such as those based on the L1-norm (which often yields better control quality than the standard L2-norm), are non-differentiable, making optimization challenging. Recent work has demonstrated the use of a neural network, not as a black-box controller, but as a smooth, differentiable approximator for the non-differentiable absolute value function within the cost function. This surgical insertion of an AI component transforms the problem into a smooth, nonlinear optimization that is easier to solve, all while retaining the rigorous structure of prediction, constraints, and optimality that defines MPC [7]. This "glass-box" approach, which leverages the approximation power of NNs to solve a specific sub-problem within a classical framework, represents a highly effective and nuanced integration of AI and control theory.

Another innovative approach, proposed by Engell et al. (2021) for mechatronic systems like control valves, is a derivative-free MPC. This method drastically reduces the degrees of freedom by using adaptive input domain discretization and an extreme move-blocking strategy, simplifying the online optimization to a mere exhaustive search over a minimal, finite set of possible control sequences, which guarantees a deterministic and bounded upper computation time, making it highly suitable for real-time applications with limited computational resources [21].

5. The Rise of Intelligent and Learning-Based Control

Alongside advancements in model-based and optimization-based control, we have witnessed a significant rise in the application of intelligent and learning-based methods. These approaches, often inspired by artificial intelligence and machine learning, offer powerful ways to handle severe nonlinearities and uncertainties, particularly in cases where deriving an accurate first-principles model is intractable.

5.1. Fuzzy Logic Systems for Nonlinear Compensation and Gain Scheduling

Fuzzy Logic Control (FLC) is a well-established intelligent control technique that excels at managing complex, nonlinear systems by using linguistic rules and fuzzy set theory, thereby avoiding the need for a precise mathematical model [10].

A prevalent application in the context of valve control is Fuzzy Gain Scheduling. In this scheme, a conventional PID controller is augmented with a fuzzy inference system that dynamically tunes the proportional (Kp), integral (Ki), and derivative (Kd) gains in real-time. The fuzzy system uses inputs like the error and the rate of change of error to adjust the gains according to a set of heuristic rules (e.g., "IF error is significant AND changing quickly, THEN increase Kp") allowing the controller to be aggressive during significant setpoint changes but gentle near the steady state, effectively adapting to the process's nonlinear behavior and outperforming traditional fixed-gain PID controllers in experimental comparisons [22].

The literature also exhibits a strong trend toward creating hybrid systems that integrate fuzzy logic with other control methodologies. Shan et al. (2021) developed a modified fuzzy-PID-Smith predictive compensator for a challenging pH control process characterized by nonlinearity and significant time delay. In their design, a standard Smith predictor is used to handle the time delay. However, a fuzzy-PID controller is added to the predictive loop to actively compensate for mismatches between the theoretical model and the actual process. This hybrid approach demonstrated superior dynamic performance and robustness compared to either a standalone fuzzy-PID or a standard Smith controller [23]. Similarly, Morales et al. (2022) combined Takagi-Sugeno (T-S) fuzzy models with SMC. The T-S model represents the global nonlinear system as a weighted combination of local linear models, allowing the SMC to have variable gains that are smoothly interpolated and adapted to the current operating region of the process [13].

5.2. Reinforcement Learning for Optimal Valve Control: A Comparative Analysis with PID

Reinforcement Learning (RL) represents a paradigm shift from conventional control design. Instead of being programmed with an explicit control law, an RL agent learns an optimal control policy by directly interacting with its environment (the process) and receiving feedback in the form of numerical rewards or penalties [24].

A pivotal 2020 study by Siraskar provided a direct, experimental comparison between a state-of-the-art RL controller (trained using the Deep Deterministic Policy Gradient, or DDPG, algorithm) and a well-tuned PID controller for a nonlinear valve system. The results of this comparison are nuanced and highly instructive. The RL controller demonstrated markedly superior performance in terms of tracking speed and accuracy, achieving a lower error concerning the reference signal. However, the PID controller proved to be better at rejecting external disturbances and, critically, produced a smoother control signal. This smoother action implies less aggressive movement of the valve stem, which directly correlates with reduced mechanical wear and a longer operational life for the valve. This finding is of

profound practical importance, as it highlights a fundamental performance trade-off between aggressive optimality and long-term actuator health, tempering the hype around RL as a universal replacement for classical control.

The study also shed light on the significant practical challenges of applying RL. Training an effective RL agent is a complex and time-consuming process that involves carefully tuning numerous hyperparameters. To address this, the paper introduced the concept of "Graded Learning," a simplified, application-oriented adaptation of curriculum learning. In this approach, the RL agent is first trained on a simplified version of the control task and then progressively exposed to more complex scenarios.

5.3. Hybrid Intelligent Systems: Integrating Neural Networks and Fuzzy Logic with Conventional Control

The most sophisticated trend in intelligent control is the development of hybrid systems that strategically combine AI/ML techniques with conventional control frameworks to create a symbiotic relationship that leverages the strengths of each. These architectures are not about replacing classical control but augmenting it. The classical controller provides a robust, stable foundation with formal guarantees, while the intelligent component adds a layer of adaptation, learning, or nonlinear compensation.

Morales et al. (2022) exemplify this with two hybrid topologies for a pH neutralization process: LAMDA-SMC and Takagi-Sugeno-SMC [13]. The LAMDA-SMC, which uses a learning algorithm (LAMDA) to modulate the parameters of the sliding-mode control law intelligently, was found to be a particularly robust and balanced solution, capable of excellent reference tracking and disturbance rejection. In this hybrid, the SMC provides the core robustness, while the LAMDA algorithm provides the adaptive intelligence.

In another example, Gabirondo-López et al. (2024) designed a cascade control architecture for a complex industrial heating process. The inner loop uses a standard industrial PID to control the furnace heater (the fast dynamics). In contrast, the outer loop uses a model-free "intelligent proportional" (iP) controller to manage the sample temperature (the slow dynamics). This hybrid structure enables the easy upgrade of existing PID-controlled systems and has proven to be remarkably robust in controlling unknown and variable thermal plants without requiring retuning [25]. These examples demonstrate that the future of intelligent control likely lies in these synergistic combinations, where the adaptive flexibility of AI enhances the proven reliability of classical methods.

6. Comparative Analysis and Synthesis

The diverse array of strategies presented in the literature necessitates a structured comparison to distill their relative merits and drawbacks. No single controller is universally superior; the optimal choice depends on the specific application, performance priorities, and practical constraints. This section provides a comparative synthesis, focusing on key performance trade-offs and divergent design philosophies.

Table 1 presents a concise, high-level comparison of the central control paradigms discussed in this review, summarizing their core principles, strengths, challenges, and typical approaches to addressing valve nonlinearities.

Table 1 Comparative Analysis of Advanced Control Strategies for Nonlinear Valves

Control Paradigm	Core Principle	Strengths	Challenges/Weaknesses	Typical Handling of non-linearities	Key References
Sliding Mode Control (SMC)	Drive system state to a predefined sliding surface and maintain it there.	High robustness to matched uncertainty and disturbances; finite-time convergence.	The chattering phenomenon can cause actuator wear; it requires knowledge of uncertainty bounds.	Treated as a bounded disturbance that is rejected by the discontinuous control law.	[8]
Adaptive Control	Online estimation and adjustment of controller	Explicitly handles time-varying parameters;	Requires persistent excitation for convergence; can be sensitive to	Compensated for via parameter adaptation in	[16]

	parameters to handle system uncertainties.	can improve performance as it "learns" the system.	unmodeled dynamics and noise.	the control law or observer.	
Model Predictive Control (MPC)	Finite-horizon optimization of a process model to compute control actions while respecting constraints.	Explicit constraint handling; optimal performance; natural for multivariable systems.	High computational cost for nonlinear models; performance is highly dependent on model accuracy.	Embedded in the predictive model for explicit compensation, or treated as a disturbance in robust formulations.	[19]
Fuzzy Logic Control (FLC)	Inference based on a set of linguistic "IF-THEN" rules derived from expert knowledge.	Handles complex non-linearities without a mathematical model; robust to imprecise inputs.	Rule-base design can be complex and heuristic; "curse of dimensionality" with many inputs.	Managed implicitly by the fuzzy rule base and membership functions.	[23]
Reinforcement Learning (RL)	Learning an optimal control policy by maximizing a cumulative reward signal through trial-and-error interaction.	Model-free; can discover highly optimal and non-intuitive strategies.	Sample inefficiency; lack of formal stability/safety guarantees; complex hyperparameter tuning.	Learned implicitly as part of the optimal policy/value function that navigates the state space.	[24]

6.1. Performance Trade-offs: Tracking vs. Disturbance Rejection vs. Actuator Wear

A recurring theme throughout the literature is the existence of fundamental trade-offs between competing performance objectives. The pursuit of aggressive, high-speed tracking performance often comes at the expense of other critical metrics. The comparative study of RL and PID by Siraskar (2020) is the canonical example: the RL controller's superior tracking speed was achieved through a more aggressive control policy, which in turn led to poorer disturbance rejection and a less smooth control signal compared to the PID controller. The implication that the PID controller would provide a longer life for the valve is a crucial practical consideration that we cannot ignore it [24].

This trade-off is not unique to RL. High-gain controllers, while effective at reducing tracking errors, are known to amplify sensor noise, which can degrade performance and potentially destabilize the system [16]. Similarly, MPC formulations that are tuned for swift response may calculate control actions that involve rapid and frequent changes in direction, increasing mechanical wear on the valve stem and packing. The work by Durand (2018) to explicitly add input rate-of-change constraints to the MPC problem is a direct acknowledgment and mitigation of this issue [4]. A comprehensive control strategy must therefore balance these competing objectives, and the choice of controller often reflects a prioritization of one objective over another.

6.2. Model-Based vs. Model-Free Approaches: A Discussion on Efficacy and Practicality

The literature presents an apparent dichotomy between model-based strategies (like MPC and backstepping) and model-free or model-light strategies (like FLC and RL). Model-based approaches can achieve highly optimized performance, but this performance is contingent on the availability of an accurate process model. The engineering effort required to develop, identify, and validate such a model can be substantial.

Model-free approaches, in contrast, promise to alleviate this modeling burden. They can learn effective control policies from data alone, making them potentially more robust to unmodeled effects and easier to deploy. However, this comes with its own set of challenges. Model-free methods can be data-hungry and sample-inefficient, their tuning process can

be opaque and heuristic (e.g., designing fuzzy rules or reward functions), and they often lack the formal guarantees of stability and safety associated with model-based methods. The emergence of hybrid controllers, such as the "intelligent proportional" controller that uses a simple, continuously updated "ultra local model," represents an interesting middle ground, seeking to reduce the modeling burden while retaining some of the structure and predictability of model-based control [25]

6.3. Conflicting Viewpoints on Compensation vs. Robust Control

As identified in Section 3.3, there are two distinct philosophical approaches to dealing with valve nonlinearities. The first is the compensation approach. This philosophy aims to develop an accurate model of the nonlinearity (e.g., stiction) and then design a specific mechanism to counteract or invert its effect. Examples include the stiction-inversion MPC formulation [23] and the "knocker" method, which adds small, targeted pulses to the control signal to "unstick" the valve [17]. When the model is accurate, this approach can be highly effective at eliminating the nonlinearity's impact. However, its performance is critically dependent on model fidelity and can degrade significantly if the valve's characteristics change.

The second is the robust control approach. This philosophy concedes that perfect modeling is impractical and instead aims to design a closed-loop system that is inherently insensitive to the effects of the nonlinearity, which is treated as a form of bounded uncertainty or disturbance. Classic SMC [8] and, more prominently, the observer-based disturbance rejection schemes using ESOs [18] are prime examples of this approach. These methods are generally more resilient to modeling errors and the time-varying nature of real-world valves. However, they may not eliminate the effects of nonlinearity as a perfect compensator might. The clear trend in the recent literature is a gravitation towards robust, observer-based approaches, as their practicality and resilience are better suited to the demands of industrial environments.

7. Identified Literature Gaps and Future Research Directions

Despite significant progress, controlling nonlinear valves remains a challenging field with several open questions and promising avenues for future research. This review identifies three key areas that warrant focused investigation: the development of verifiable and safe learning-based controllers, the creation of hybrid physics-informed AI models, and the exploration of valve-controller co-design.

7.1. Key Unresolved Challenges in Nonlinear Valve Control

Several persistent challenges continue to motivate research. The real-time implementation of computationally intensive algorithms, such as NMPC, remains a hurdle, especially for fast processes or systems with limited onboard computing power [20]. The difficulty of obtaining accurate, reliable models from noisy industrial data continues to be a bottleneck for many model-based techniques [6]. Finally, ensuring robust and consistent performance across a wide range of operating conditions, and as valve characteristics degrade over time, is a critical challenge that drives the search for more adaptive and resilient control strategies [24].

7.2. Future Outlook I: Towards Verifiable and Safe Learning-Based Control

A significant gap in the current literature on learning-based control (especially RL and NN-based approaches) is the general lack of formal safety, stability, and performance guarantees [24]. Unlike classical control methods, which are built upon a rigorous mathematical foundation like Lyapunov stability theory, the behavior of a trained RL agent can be challenging to predict, particularly in states not encountered during training. This "black-box" nature is a significant barrier to their adoption in safety-critical industrial applications.

A crucial direction for future research is therefore the integration of formal verification and validation techniques into the learning control pipeline. This is a multi-faceted challenge that could involve:

Developing RL algorithms with built-in safety constraints, such as constrained policy optimization methods that ensure the learned policy does not violate predefined safety limits.

Combining RL with formal methods from computer science, using techniques like reachability analysis to mathematically prove that the RL-controlled closed-loop system cannot enter unsafe regions of the state space.

Designing "shielded" or "guardian" architectures, where a verifiable safety controller monitors the output of the RL agent and intervenes only if the proposed action is deemed unsafe.

Progress in this area is essential to building trust and enabling the responsible deployment of advanced learning controllers in real-world industrial settings.

7.3. Future Outlook II: Hybrid Physics-Informed AI for Enhanced Generalization

Purely data-driven methods, such as RL and deep learning, can be potent but often suffer from two key weaknesses: they are sample-inefficient, requiring vast amounts of interaction data to learn, and they may fail to generalize to operating conditions outside their training distribution because they typically ignore the wealth of existing physical knowledge about the system they are controlling.

An auspicious future direction is the development of hybrid, physics-informed AI. This paradigm aims to integrate established physical principles directly into the structure or training process of the AI model. For valve control, this could take several forms

- **Physics-Informed Neural Networks (PINNs):** Designing neural network architectures whose loss functions include terms that penalize violations of known physical laws (e.g., simplified differential equations governing fluid flow or mechanical friction).
- **Model-Based RL:** Using a simplified physical model to generate simulated data for pre-training an RL agent, drastically reducing the amount of real-world interaction needed.
- **Residual Physics:** Training an AI model to learn only the "residual," or the difference between a simplified physical model and the real system's behavior.

By grounding the learning process in physical reality, these hybrid approaches have the potential to create controllers that learn much faster, generalize better to new scenarios, and are more interpretable than their purely data-driven counterparts.

7.4. Future Outlook III: Co-Design of Valve Hardware and Control Algorithms

The vast majority of the control literature treats the physical plant—the valve itself—as a fixed and given component for which a controller must be designed [2]. This traditional, sequential design process decouples the mechanical and control engineering domains, potentially leaving significant performance gains on the table.

A transformative future direction is the exploration of simultaneous co-design, where the valve's mechanical properties and its control algorithm are optimized together as an integrated system. Advanced, adaptive control might enable the use of mechanically simpler and therefore cheaper valve designs while still achieving high performance. Conversely, novel mechanical designs, perhaps utilizing innovative materials or alternative actuation principles, could be created specifically to be more compatible with modern control techniques. Research into the complex thermal-fluid-structure coupling that occurs within valves [26] and the impact of dynamic valve timing on overall system efficiency 6 provides a scientific foundation for this holistic design philosophy. This integrated approach represents a paradigm shift from simply controlling a given valve to designing the optimal valve-controller system for a given task.

8. Conclusion

The research landscape has evolved from a focus on isolated techniques to a more integrated and hybridized approach, reflecting the complexity of the underlying problem. This review has traced several key evolutionary trends. There has been a discernible shift in philosophy from direct nonlinearity compensation towards more practical and resilient observer-based disturbance rejection methodologies, with the Extended State Observer emerging as a potent tool. The application of optimization-based control, particularly Model Predictive Control, has become increasingly sophisticated, with significant innovations focused on enhancing computational efficiency and robustness to make it more viable for industrial deployment.

Concurrently, the rise of intelligent and learning-based control has introduced a new frontier. While fuzzy logic continues to provide a robust framework for handling uncertainty without precise models, Reinforcement Learning has demonstrated the potential for achieving superior tracking performance. However, this has also brought to light critical trade-offs between optimality, disturbance rejection, and long-term actuator health, underscoring that no single strategy is a panacea. The most promising developments are arguably in hybrid systems, which synergistically combine the formal guarantees of classical control with the adaptive flexibility of AI.

Looking forward, the future of the field appears to lie not in a "winner-takes-all" competition between paradigms, but in their intelligent synthesis. The key challenges ahead will be to imbue learning-based systems with verifiable safety and stability, to enhance the efficiency and generalization of AI by informing it with physical knowledge, and to break down the traditional barriers between mechanical and control design. The continued pursuit of these research directions will be essential for developing the next generation of high-performance, robust, and reliable valve control systems required by future industries.

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