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Reinforcement Learning-Optimized Data-Driven Fractional-Order Sliding Mode Observer for Sensor Fault Detection

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Abstract

This paper addresses the problem of model-free control and sensor fault detection for discrete-time nonlinear systems by proposing an intelligent proportional–integral–derivative controller in conjunction with a fractional-order sliding mode observer. The proposed method eliminates the need for an explicit mathematical model and relies solely on input and output signals. By integrating sliding mode observation with fractional calculus, the proposed fault detection scheme benefits from enhanced memory characteristics and increased degrees of freedom in the observer design. This integration enables an effective trade-off between detection accuracy and convergence speed, thereby improving the overall performance of the fault detection mechanism. Enhancing the fault detection mechanism significantly reduces false alarm rates, thereby improving operational reliability and yielding tangible benefits in terms of economic efficiency. To intelligently tune the controller and observer parameters, a Reinforcement Learning–based optimization strategy is employed. This learning mechanism enables the adaptive tuning of controller and observer design parameters to achieve enhanced tracking accuracy while simultaneously improving the precision of residual generation for reliable fault detection within the system. The stability of the resulting closed-loop system is rigorously established using Lyapunov theory. The effectiveness and superiority of the proposed approach are validated through comprehensive simulation studies conducted on a data-driven, model-free nonlinear discrete-time system. The simulation results demonstrate significant improvements in tracking performance, robustness, and fault estimation accuracy compared to conventional approaches.

Keywords: Data-Driven Fault Detection; Sensor Fault; Fractional-Order Sliding Mode Observer; Reinforcement Learning; Discrete-Time System.

1. Introduction

In modern industrial environments, an enormous volume of process data is continuously generated, collected, and archived through advanced sensing, communication, and storage infrastructures. These data implicitly encapsulate rich information about system states, operational conditions, and underlying process dynamics. However, in many practical applications, deriving accurate first-principles models remains prohibitively complex due to nonlinearities, uncertainties, time-varying behaviors, and unmodeled disturbances. Consequently, a fundamental challenge facing the control community is how to systematically exploit the abundance of available data and the knowledge extracted from it to develop efficient control and optimization strategies in the absence of precise mathematical models. In this context, the advancement of data-driven control methodologies has emerged not merely as an alternative paradigm but as an inevitable and transformative direction for the evolution of modern control theory, carrying profound theoretical importance and substantial practical impact across industrial domains [1]. Model-Free Adaptive Control (MFAC) represents a rigorous and mature data-driven framework that achieves adaptive regulation using only input–output measurements, entirely bypassing explicit model dependence. By inherently addressing nonlinearities, time-varying structures, and robustness challenges within a unified formulation, MFAC has evolved into a theoretically solid and industrially validated paradigm in modern control. Beyond control design, the data-driven paradigm has also profoundly influenced the field of fault detection and diagnosis [2].

Over the past two decades, fault detection and fault diagnosis have advanced significantly, driven by increasing demands for reliability, economic efficiency, and environmental sustainability in modern industrial systems [3]. Data-driven fault detection has become a cornerstone of modern control and monitoring systems, offering the capability to extract critical operational insights directly from measured process data without relying on explicit mathematical models. Its significance lies in enabling early and accurate identification of anomalies, enhancing system reliability, reducing downtime, and mitigating economic and environmental risks. By leveraging large-scale data and advanced sensing, data-driven approaches offer adaptive, scalable, and robust monitoring solutions that can handle complex nonlinearities, time-varying behaviors, and unmodeled disturbances inherent in industrial processes. This paradigm shift is transforming traditional fault diagnosis, laying the foundation for intelligent and predictive maintenance strategies in increasingly automated and interconnected systems [4]. Data-driven fault detection methods can generally be categorized into three main groups: statistical and multivariate analysis (MVA) approaches [5], machine learning (ML)–based methods [6], and hybrid strategies [7]. Statistical and MVA techniques identify faults by detecting deviations from established normal operating patterns through residual evaluation or latent variable modeling. In contrast, ML-based methods focus on learning complex nonlinear relationships directly from process data to classify, predict, or estimate fault conditions, making them particularly suitable for nonlinear and time-varying systems. Hybrid approaches integrate the strengths of both paradigms by combining data-driven modeling with residual generation or physical insights, thereby enhancing robustness, adaptability, and interpretability in practical applications.

Among the existing approaches, sliding mode observers (SMO) have attracted considerable attention due to their inherent robustness against matched uncertainties and noise [8, 9]. Owing to this strong robustness property, SMO-based schemes have been extensively employed for fault detection in systems [10]. For instance, in [11] a data-driven SMO was developed for sensor fault detection in model-free systems, where the observer parameters were tuned using the ant colony optimization (ACO) algorithm. Although the proposed scheme demonstrated satisfactory performance, the absence of advanced artificial intelligence–based learning mechanisms limits its adaptability and generalization capability under complex and highly dynamic operating conditions. Furthermore, SMO–based extensions have also been employed for sensor fault detection [12] and actuator fault diagnosis [13], yielding valuable and practically significant results. Nevertheless, the persistent occurrence of false alarms—primarily arising from the inherent trade-off between detection accuracy and response rapidity—remains a fundamental challenge in observer-based fault diagnosis frameworks.

Fractional calculus, owing to its distinctive properties such as inherent memory effect, increased degrees of freedom in system design, and enhanced structural flexibility, provides a powerful framework for improving the performance of control and fault detection systems. These attributes enable a more favorable trade-off between detection speed and accuracy, while its long-term memory characteristic facilitates a more faithful preservation and representation of the dynamic behavior of the detection system over time [14]. The effectiveness and versatility of fractional calculus have been convincingly demonstrated through its successful integration into modeling frameworks [15], controller design methodologies [16], and observer development strategies [17, 18], thereby highlighting its substantial potential for enhancing the performance and flexibility of the proposed method.

The primary motivation of this study is twofold: first, to design a control strategy that guarantees desirable system performance, stability, and response quality; and second, to develop a sensor fault detection mechanism aimed at mitigating false alarms and enhancing system reliability. To this end, a proportional–integral–derivative (PID)-based controller is designed and implemented, providing a structurally simple yet effective framework for performance regulation. In parallel, a fractional-order SMO is proposed for sensor fault detection to improve diagnostic accuracy and reduce the incidence of false alarms. To achieve precise and efficient parameter tuning, Reinforcement Learning (RL) is employed to optimize both the controller gains and the parameters of the proposed fault detection scheme. This integrated approach enables simultaneous enhancement of control performance and fault diagnosis capability within an adaptive, data-driven framework. In summary, the principal contributions and technical novelties of this work can be summarized as follows:

- The proposed method for sensor fault detection has been enhanced.
- Introduces a fractional-order observer to improve fault detection accuracy and reduce false alarms.
- RL is employed to intelligently tune PID gains and fractional-order sliding mode observer (FOSMO) parameters for precise and efficient model-free adjustment.

The article is organized as follows: Section 2 describes the data-driven modeling framework and its details. In Section 3, the theoretical foundations of discrete fractional calculus are explained, while Section 4 introduces the discrete fault detection threshold. Section 5 presents the proposed methodology; Section 6 shows the simulation results along with analysis and discussion; and finally, Section 7 concludes the study by summarizing the key findings and suggesting potential directions for future research.

2. Modeling Based on Data-Driven

In this section, a class of single-input single-output (SISO) nonlinear discrete-time systems is considered. The system dynamics are assumed to be governed by an unknown nonlinear mapping between the input and output signals. Due to the lack of precise analytical knowledge of the system structure and parameters, a data-driven modeling framework is adopted. Specifically, the system behavior is characterized solely using measured input–output data, without relying on prior physical or first-principles models.

The considered nonlinear discrete-time system is represented using the Compact Form Dynamic Linearization (CFDL) framework, which is formulated as follows [1]:

$$\mathrm{Z(k+1)} = \mathrm{g}\big(\mathrm{Z(k)}, \dots, \mathrm{Z(k} - \tau_{\mathrm{Z}}), \mathrm{I(k)}, \dots, I(\mathrm{k} - \tau_{\mathrm{I}}), \mathrm{f(k)}\big) \tag{1}$$

at the time index k, $Z(k)$, $I(k)$ and $f(k)$ denote the system output, control input, and sensor fault signal, respectively. The parameters τ_Z and τ_I represent unknown positive integers, while $g(\cdot)$ denotes an unknown nonlinear function.

Assumption 1. The sensor fault signal is bounded within known limits; that is, its magnitude is confined to a predefined and known range.

Assumption 2. The partial derivatives of the nonlinear function $g(\cdot)$ with respect to all its input arguments, including the sensor fault signal, exist and are continuous over the domain of interest.

Assumption 3. System (1) fulfills a generalized Lipschitz condition for all discrete-time instants k, with at most a finite number of exceptional points; that is:

$$|\mathrm{Z}(\mathrm{k}_1+1) - \mathrm{Z}(\mathrm{k}_2+1)| \le \kappa |I(\mathrm{k}_1) - I(\mathrm{k}_2)|$$

where κ denotes a positive constant, $\mathrm{I}(k_1) \neq \mathrm{I}(k_2)$ for distinct time instants $k_1, k_2 \geq 0$ and $k_1 \neq k_2$.

Remark 1. Assumption 1 considers sensor faults that are bounded, which aligns with practical scenarios and has been commonly adopted in [19, 20]. Assumption 2 constitutes a conventional and widely accepted condition in the analysis and control of nonlinear systems. Assumption 3, based on the principle of energy conservation, describes the output behavior under bounded-input–bounded-output conditions and has been validated in numerous industrial applications [21, 22].

Lemma 1. System (1) is obtained under the fulfillment of Assumptions 1–3, with $\Delta I(k) \neq 0$, such that:

$$\Delta \mathrm{Z(k+1)} = \Omega_{\mathrm{c}}(\mathrm{k}) \Delta I(\mathrm{k}) + \mathrm{f(k)} \tag{2}$$

where $\Omega_c(k)$ referred to as the Pseudo-partial derivative (PPD), is a bounded matrix for all k, and represents an unknown parameter vector. Lemma 1 has been rigorously proven in [1].

Since the PPD function is unknown, its estimation is required for the design of the proposed method. The PPD function is thus approximated as follows [1]:

$$\hat{\Omega}_{\mathrm{c}}(\mathrm{k}) = \hat{\Omega}_{\mathrm{c}}(\mathrm{k}-1) + \frac{\xi \Delta I(\mathrm{k}-1)}{\lambda + \Delta I(\mathrm{k}-1)^2}\big[\Delta \mathrm{Z(k)} - \hat{\Omega}_{\mathrm{c}}(\mathrm{k}-1)\Delta I(\mathrm{k}-1)\big] \tag{3}$$

where $\lambda > 0$ denotes the weighting factor, and $0 <$

$\xi \leq 2$ represents the step factor. A detailed and rigorous proof of (3) is provided in [1].

3. Discrete-Time Fractional Calculus Theory

Fractional calculus can be regarded as a generalized extension of classical integer-order calculus, in which the orders of differentiation and integration are not restricted to integer values but are allowed to take arbitrary real or even complex values. Among the various formulations of fractional operators, three definitions are predominantly employed in the literature: the Riemann–Liouville definition, the Caputo definition, and the Grünwald–Letnikov (GL) definition [23]. Each formulation offers distinct analytical and computational properties. GL formulation provides a natural discrete representation that is well-suited for numerical implementation. The discrete fractional difference operator based on the GL formulation is defined as follows [24]:

$$^{\mathrm{GL}}\Delta_0^{\alpha} y(k) = \frac{1}{\mathcal{N}^{\alpha}} \sum_{j=0}^{k} (-1)^j \binom{\alpha}{j} y(k-j) \tag{4}$$

where $y(k)$ denotes a discrete-time function, $\alpha \epsilon (0,1]$ represents the fractional order of the operator, and the term $\mathcal{N}$ denotes the sampling interval.

Due to its intrinsic memory property and additional degrees of freedom, fractional calculus offers enhanced flexibility in representing complex dynamics. As a result, discrete fractional formulations significantly improve modeling accuracy as well as controller and observer design in Complex systems.

4. Fault Detection Threshold

The residual signal, defined as the difference between the measured output and the estimated output, is evaluated using a predefined assessment function. In fault detection systems, this evaluation function is commonly referred to as the fault detection threshold, as it establishes the decision boundary for distinguishing normal operating conditions from faulty behavior [25, 26]. In the fault detection process, a fault is declared whenever the residual signal exceeds the predefined fault detection threshold. Conversely, if the residual remains within the prescribed threshold bounds, the system is considered to be operating under normal conditions. The discrete-time threshold is formulated as follows:

$$t(k+1) = (1-\beta)t(k) + \beta t(\infty) \tag{5}$$

$$0 < t(\infty) < t(0) \tag{6}$$

where, $0 < t < 1$ determines the convergence speed, while $t(0)$ specifies the initial condition of $t(k)$. The ultimate value of convergence is then defined as follows:

$$\lim_{k\to\infty} t(k) = t(\infty) \tag{7}$$

let the residual signal be represented by $r(k)$, accordingly, the corresponding convergence region can be defined as follows:

$$-t(k) < r(k) < t(k) \tag{8}$$

if (8) holds at $k = 0$, then it is satisfied for all subsequent k.

5. Proposed Method

This section presents the detailed development of the proposed methodology. First, a PID controller is designed to ensure accurate reference tracking and satisfactory closed-loop performance of the system. Next, a fault detection scheme based on a FOSMO is introduced. The stability of the overall proposed approach is then rigorously analyzed and proven. Finally, an RL–based optimization algorithm is developed to tune the parameters of both the controller and the proposed observer. A schematic overview of the entire methodology is depicted in Fig. 1.

5-1. Proposed PID Controller

PID control is widely regarded as one of the simplest yet most effective strategies for addressing a broad range of practical control tasks. In this framework, the control input $I(k)$ is generated from the error signal $e_1(t)$ through the combined action of proportional, integral, and derivative terms. Each component contributes to improving the transient response, eliminating steady-state error, and enhancing system stability.

The tracking error employed in the design of the proposed controller is defined as follows:

$$e_1(k) = Z(k) - Z_r(k) \tag{9}$$

where $Z(k)$ denotes the system output and $Z_r(k)$ represents the reference signal. Accordingly, the PID control law is expressed as follows:

$$I(k) = \mathcal{K}_p e_1(k) + \mathcal{K}_i \sum_{k=1} e_1(k) + \mathcal{K}_d \Delta e_1(k) \tag{10}$$

where $\mathcal{K}_p$, $\mathcal{K}_i$, and $\mathcal{K}_d$ correspond to the proportional, integral, and derivative parameters of the PID controller, respectively; these parameters are optimized through a RL–based tuning procedure. The variation of the control signal is considered as $\Delta I(k) = I(k) - I(k-1)$.

5-1. Proposed FOSMO Fault Detector

In this section, the design and implementation details of the FOSMO-based fault detection framework are presented. The estimation error of the system output is defined as follows:

$$e_2(k) = \hat{Z}(k) - Z(k) \quad (11)$$

where $Z(k)$ denotes the measured actual output of the system, whereas $\hat{Z}(k)$ represents its estimated value. The sliding surface is designed as a fractional-order function using the GL formulation, and is proposed by:

$$\mathcal{S}(k) = \beta_1 e_2(k) + \beta_2 \Delta^{\alpha} e_2(k-1) \quad (12)$$

where, β_1 and β_2 denote the observer design coefficients positive constant values, which are tuned using a RL–based optimization algorithm. The switching law is expressed as follows:

$$\Delta\mathcal{S}(k) = -\beta_{\mathcal{S}} \mathrm{sign}(\mathcal{S}(k)) \quad (13)$$

where, $\beta_{\mathcal{S}}$ denote the observer design coefficients positive constant values, which are tuned using a RL–based optimization algorithm. The Difference of the sliding surface is defined as follows:

$$\Delta\mathcal{S}(k) = \mathcal{S}(k+1) - \mathcal{S}(k) \quad (14)$$

by combining (13) and (14), the following expression is obtained:

$$-\beta_{\mathcal{S}} \mathrm{sign}(\mathcal{S}(k)) = \beta_1 e_2(k+1) + \beta_2 \Delta^{\alpha} e_2(k) - \mathcal{S}(k) \quad (15)$$

by substituting (11) into (15) and simplifying, the following expression is obtained:

$$\hat{Z}(k+1) = Z(k+1) + \frac{1}{\beta_1}\left[-\beta_{\mathcal{S}} \mathrm{sign}(\mathcal{S}(k)) + \mathcal{S}(k) - \beta_2 \Delta^{\alpha} e_2(k)\right] \quad (16)$$

Substituting (2) into (16) yields:

$$\hat{Z}(k+1) = Z(k) + \hat{\Omega}_c(k)\Delta I(k) + \frac{1}{\beta_1}\left[-\beta_{\mathcal{S}} \mathrm{sign}(\mathcal{S}(k)) + \beta_2 \Delta^{\alpha} e_2(k)\right] \quad (17)$$

to enhance the estimation precision, the output variable is written in terms of its estimated value, yielding:

$$\hat{Z}(k+1) = \hat{Z}(k) + \hat{\Omega}_c(k)\Delta I(k) + \frac{1}{\beta_1}\left[-\beta_{\mathcal{S}} \mathrm{sign}(\mathcal{S}(k)) + \beta_2 \Delta^{\alpha} e_2(k)\right] \quad (18)$$

Based on the estimated output signal, the residual, serving as an indicator of sensor fault occurrence in the system, is computed as follows:

$$r(k+1) = Z(k+1) - \hat{Z}(k+1) \quad (19)$$

if $r(k+1) > t(k+1)$, the system is considered faulty; otherwise, if $r(k+1) > t(k+1)$, the system is deemed fault-free. Next, the stability of the proposed observer is analyzed.

Proof of Stability: For this purpose, the following positive definite Lyapunov candidate function is introduced:

$$\mathcal{V}(k) = \frac{1}{2}\mathcal{S}(k)^2 \quad (20)$$

taking the fractional-order difference of both sides of (20) yields:

$$\Delta\mathcal{V}(k) = \mathcal{S}(k)\Delta\mathcal{S}(k) \quad (21)$$

by applying (13) to (21), the following is obtained:

$$\Delta\mathcal{V}(k) = \mathcal{S}(k)\left[-\beta_{\mathcal{S}} \mathrm{sign}(\mathcal{S}(k))\right] \quad (22)$$

simplifying (22) leads to:

$$\Delta\mathcal{V}(k) = -\beta_{\mathcal{S}}\left|(\mathcal{S}(k))\right| \leq 0 \quad (23)$$

Given that the first difference of the Lyapunov function is negative semi-definite, the proposed observer guarantees Lyapunov stability.

5-3. RL Optimization Algorithm

RL is a branch of ML concerned with deriving optimal policies for sequential decision-making in complex and uncertain environments.

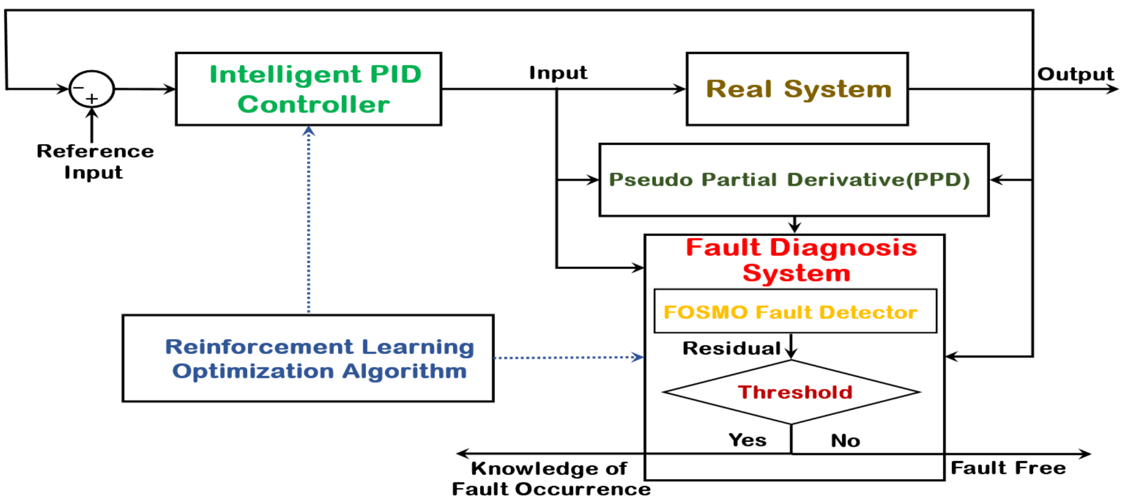

Fig. 1. Schematic overview of the proposed method.

Rather than relying on explicit supervision, RL improves performance through interactions with the environment, using feedback from previous actions to guide future behavior. This paradigm is conceptually rooted in the trial-and-error learning processes observed in humans and animals. Within the RL framework, the decision-making entity is called the “agent”, while the external system with which it interacts is termed the “environment”. The agent influences the environment by selecting actions, although the underlying dynamics governing the environment remain unchanged. At any instant, the environment is characterized by a “state”, and the agent chooses actions based on this state along with evaluative feedback signals [27].

Learning in RL is driven by rewards and penalties that assess the quality of the agent’s decisions. Favorable actions yield positive reinforcement, whereas unfavorable ones result in negative feedback. Using this evaluative information gathered across different states and actions, RL algorithms iteratively refine the agent’s policy. The primary objective is to obtain a policy that maximizes the expected cumulative return over time. Typically, this return is defined as an aggregation of immediate reinforcement signals specified by the designer. Through continuous interaction with the environment, the agent progressively approximates an optimal strategy guided solely by these reward-based signals.

In this work, the RL toolbox of MATLAB was employed to tune the adjustable parameter. The agent was implemented using the Deep Deterministic Policy Gradient (DDPG) algorithm. Key design settings include 128 neurons in the hidden layer, a discount factor of 0.9, a learning rate of 0.02, and a maximum of 200 training episodes. These hyperparameters were selected empirically through iterative experimentation.

In this analysis, the main hyperparameters were varied within reasonable ranges (e.g., learning rate: 0.01–0.03, discount factor: 0.85–0.95), while the remaining settings were kept unchanged. The results in Table 1 demonstrate that the proposed method maintains stable learning behavior and satisfactory performance across these ranges, indicating that the algorithm is not overly sensitive to the selected hyperparameter values. Furthermore, it should be emphasized that these parameters do not act as fixed operating points. Instead, the reinforcement learning agent continuously adapts its policy online and produces time-varying control actions that are optimized with respect to the current system conditions.

Table 1. Sensitivity analysis results with respect to key hyperparameters.

Hyperparameters	Value	RMSE	IAE
	0.01	0.0277	0.1961
Learning Rate	0.02	0.0213	0.1747
	0.03	0.0224	0.1874
	0.85	0.0341	0.2451
Discount Factor	0.9	0.0307	0.2231
	0.95	0.0371	0.2578
	90	0.0412	0.5014
Number of Neurons	128	0.0413	0.5024
	166	0.0416	0.5035

6. Simulation Results and Discussion

To rigorously assess the efficacy and robustness of the proposed methodologies, this section presents a comprehensive simulation-based evaluation structured in two distinct parts. The first part examines the performance characteristics of the proposed PID controller, focusing on its tracking capability and overall control quality. The second part investigates the effectiveness of the FOSMO-based fault detection scheme in accurately identifying system faults. Collectively, these studies provide a thorough validation of both the control strategy and the fault diagnosis framework under representative operating conditions.

The practical system studied in this work is model-free and characterized solely based on measured data, as outlined below [28]:

$$\mathrm{Z(k+1)} = \frac{\mathrm{Z(k)}}{\mathrm{Z(k-1)^2+1}} + 0.8\mathrm{I(k)} + 0.3\mathrm{I(k-1)} + \mathrm{f(k)} \tag{24}$$

where $Z(k)$denotes the system output, $I(k)$ represents the system input, and $f(k)$ corresponds to the sensor fault affecting the system.

The reference signal is defined as follows:

$$\mathrm{Z_r(k)} = 0.4\sin\left(\frac{\mathrm{k}\pi}{35}\right) + 0.3\cos\left(\frac{\mathrm{k}\pi}{25}\right) \tag{25}$$

The threshold value is determined using the method presented in [25], which is based on the maximum residual norm under normal system operation while considering uncertainties and noise. The following threshold was set for the fault detection mechanism during the simulation study:

$$\mathcal{t}(\mathrm{k}) = 0.05 + 0.03\sin\left(-0.15\pi + \frac{\mathrm{k}\pi}{20}\right) + \exp(-0.1\mathrm{k}) \tag{26}$$

6-1. Controller Assessment

This section evaluates the proposed PID controller’s performance when the system operates without any sensor faults ($f(k) = 0$). The PID controller parameters obtained through RL tuning are $\mathcal{K}_p = 0.94$, $\mathcal{K}_i = 0.57$, and $\mathcal{K}_d = 0.41$. The system is initialized with $Z(0) = 0.1$, and, $I(0) = 0$.

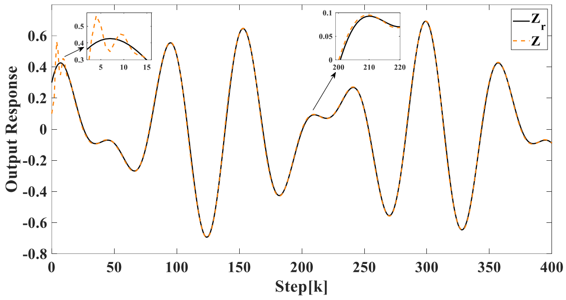

Fig. 2. Tracking performance of the proposed PID controller with respect to the reference signal.

Fig. 2. illustrates the performance of the data-driven system in tracking a time-varying reference signal. As observed, the system response Z closely follows the reference signal Z_r with high accuracy, demonstrating the capability of the PID controller to eliminate steady-state error in the presence of oscillatory dynamics. Although a slight transient overshoot is observed during the initial steps ($k < 20$), the system rapidly converges and maintains stable tracking performance throughout all steps.

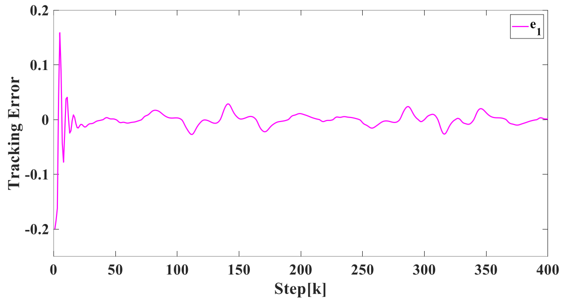

Fig. 3. Reference tracking error performance of the proposed PID controller.

Fig. 3. illustrates the small tracking error achieved and highlights the effectiveness of the PID controller in maintaining high accuracy. Following a brief transient interval ($k < 25$) characterized by a maximum deviation of about 0.18, the error quickly converges to zero. The remaining oscillations during the tracking process are bounded within a tight range $[-0.03, 0.03]$, demonstrating strong stability and robustness against time-varying reference dynamics. This near-zero error level verifies the proper tuning of the PID parameters.

Fig. 4. presents the control input profile, which exhibits a smooth and non-oscillatory behavior, thereby safeguarding actuator health. The PID controller produces a bounded control effort within $[-0.4, 0.4]$, enabling the tracking error to settle within a tight tolerance of ±0.03 following a brief transient interval. The fast error convergence to near zero and the coherence of the control signal with the reference dynamics indicate properly tuned gains and asymptotic stability under rapid variations. Overall, these results demonstrate the effectiveness of the proposed control structure in attaining high tracking accuracy with low control energy.

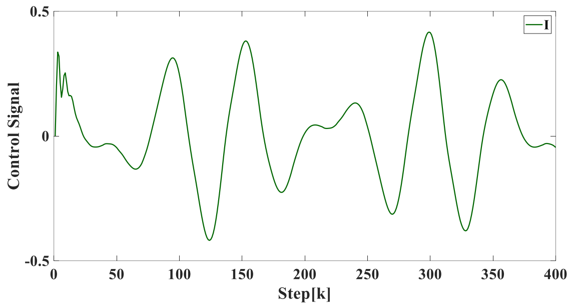

Fig. 4. Control effort applied to the system using the proposed PID controller.

6-2. Fault Detector Assessment

The following evaluates the FOSMO-based detection mechanism in the presence of sensor faults, which are considered as outlined below:

$$f(k) = 0.2 + 0.01\sin(Z(k)\pi) \quad (27)$$

The parameters of the FOSMO are RL-tuned to $\beta_1 = 0.84$, $\beta_2 = 0.37$, and $\beta_s = 0.007$. The FOSMO is initialized with $\hat{Z}(0) = 0$, and $\widehat{\Omega}_c(0) = 0.25$.

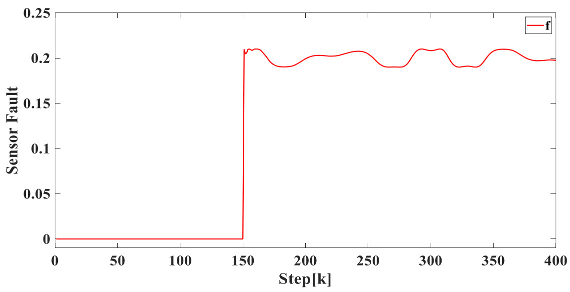

Fig. 5. Applied fault signal used for evaluation.

According to Fig. 5., a time-varying sensor fault is introduced into the system at $k = 150$ to assess the effectiveness of the proposed FOSMO observer relative to the standard SMO. This setup enables a direct comparison of their fault detection capabilities under dynamic fault conditions.

Fig. 6. presents a comparative evaluation between the proposed FOSMO-based fault detection scheme and the classical SMO. The results show that the proposed approach remains free of false alarms before the onset of the sensor fault, while the SMO and Luenberger produce

erroneous alarms caused by chattering effects. From an industrial perspective, such false positives can lead to considerable economic costs. When the sensor fault is introduced at $k = 150$, both observers correctly identify the fault and signal abnormal system conditions.

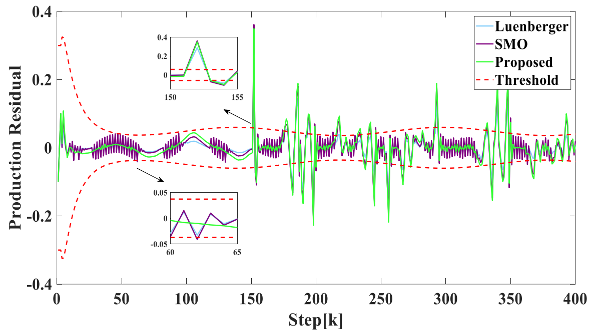

Fig. 6. Residual-based fault detection performance of SMO and the FOSMO proposed.

Table 2. Mean Squared Error (MSE) comparison of the developed methods.

PID	Luenberger	SMO	FOSMO
4.5612e-4	0.0035	0.0033	0.0029

6-3. Discussion

The simulation results demonstrate that the RL-tuned PID controller achieves high tracking accuracy with zero steady-state error and smooth control input. In the fault detection part, the proposed FOSMO outperforms the conventional method in suppressing false alarms, achieving a reduction in the false alarm rate. Before fault injection, the other method produced erroneous alarms due to chattering, whereas the FOSMO remained completely silent. Compared with existing methods, the main novelty lies in the combination of fractional-order design with RL-based parameter tuning, which eliminates manual trial-and-error. This model-free approach for discrete-time nonlinear systems and sensor fault detection offers a clear advantage over previous works. The RL-based optimization inherently involves higher computational complexity compared to classical methods such as Genetic Algorithm (GA) or Particle Swarm Optimization **(**PSO). This is primarily due to the neural network updates and the direct, dynamic interaction of the agent with the environment. However, for complex and time-varying nonlinear systems, this additional computational burden is justified by the superior adaptability and accuracy of RL, as demonstrated in our results. The offline training time (185 seconds) is a one-time cost, while the online execution remains fast enough for real-time implementation (0.37 ms per step).

7. Conclusion

Sensor fault detection in a nonlinear, data-driven system was successfully implemented using the proposed discrete FOSMO. The fractional-order design of the sliding surface endowed the proposed observer with enhanced memory and adaptability, resulting in more accurate residual generation. The residual signal, defined as the difference between the estimated output and the measured output, demonstrated a 14% improvement in fault detection performance compared to the conventional SMO method and a 20% improvement compared to the Luenberger method, as shown in Table 2. The obtained results demonstrate that the proposed FOSMO method effectively prevents false alarms relative to other methods, leading to improved system reliability and efficiency. Furthermore, RL-based optimization was employed to systematically tune the observer parameters, ensuring a fair comparison and highlighting the robustness and effectiveness of the proposed method. However, the proposed method has several limitations. First, the current study assumes ideal noise-free or low-noise conditions; the performance of the proposed method in the presence of significant measurement noise has not been investigated. Second, the method has been validated only through numerical simulations and has not yet been tested in real laboratory environments or on experimental hardware platforms. Therefore, future work will focus on: (i) evaluating the method under noisy conditions, (ii) conducting experimental validation using laboratory setups.

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