

Original Article

Adaptive and Self-Tuning PID Control Strategies for Improving Stability and Efficiency in Next-Generation Smart Manufacturing Environments

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Abstract - Smart manufacturing environments of the coming generation are very highly automated, connected cyber-physical systems, dynamic production demands and real-time exchange of data. The most commonly used industrial control technique has been conventional Proportional-Integral-Derivative (PID) controllers because of their simplicity and reliability, but fixed-parameter PID controllers are often unable to achieve optimum behavior when faced with nonlinearities, time-varying disturbances, and uncertainty within the system, as is common in smart factories. The present paper suggests an adaptive and self-tuning PID control system that was developed to improve stability, responsiveness, & energy efficiency in Industry 4.0 production facilities. The algorithm combines web-based parameter control via recursive estimation and tuning with optimization-based parameter control via real-time sensor responses. The use of simulation and experimental validation on a representative manufacturing process shows that there are better responses in a transient situation, lesser steady state error, and better disturbance elimination, in addition to quantifiable energy savings over a classical PID set-up. The suggested solution has its benefits, but it comes with computational costs, the complexity of its implementation, and the requirement of good-quality sensor data. The practical limitations are related to the integration with the legacy industrial controllers and the cybersecurity threats in the interconnected systems. Future research plans involve implementing machine-learning-assisted predictive tuning and a distributed control system to be used in large-scale smart factories and creating standardized industrial frameworks to be used in deploying adaptive PID systems. The results confirm that adaptive and self-tuning PID strategies may be considered an effective direction of resilient, efficient, and intelligent control in the next-generation manufacturing systems.

Keywords - Adaptive PID control, Self-Tuning control, Smart manufacturing, Industry 4.0, Cyber-Physical systems, Process stability, Energy efficiency, Intelligent control systems.

1. Introduction

The redesigning of traditional manufacturing into the intelligent, interconnected, and data-driven ecosystems has fundamentally redefined the paradigm of industrial automation [1]. The state-of-the-art smart manufacturing setups combine Cyber-Physical Systems (CPS) and Industrial Internet of Things (IIoT), at the edges of the cloud, state-of-the-art robotics, and analysis to allow autonomous decisions and self-optimization. The next-generation manufacturing systems, as contrasted to the traditional production lines that are performing their tasks on stable and largely predictable conditions, feature dynamic workloads, reconfigurability, material properties that can vary dramatically, nonlinear machine behaviour, and unanticipated disturbances. These features present serious problems to the classical methodologies of control that were initially developed in the context of the industry of stationary or slowly changing systems.

The Proportional Integral Derivative (PID) controller is the most commonly used method of industry control as it is simpler in structure, cheaper to implement, intuitively designed and capable of performing strongly in linearly controlled industries [3]. PID controllers are predominant in process control, motion control, robotics, thermal control and servo mechanisms automation loops.

Classical PID controllers are, however, based on known constants of gain and tuned around a particular operating point or a nominal model of a system. The fixed-gain PID controller can suffer degraded performance, such as oscillations, high overshoot, long settling time, steady-state error, and poor energy consumption, with varying process parameters, such as wear, changes in loads, changes in supply voltage, environmental variations, and other changes in production reconfiguration.



This type of degradation can have a direct effect on productivity, quality of products and the cost of operations in smart manufacturing environments. Even little variations in processes of high accuracy like CNC machining, robots' assembly, semiconductor fabrication or automated material handling can result in scrap production, downtime and energy wastage [2]. Moreover, the sustainability needs and energy requirements can be made such as requires control strategies that are not only stable, but also with limited control effort and energy consumption. Thus, the necessity of adaptive and intelligent control systems has gone beyond being a critical one.

Self-tuning and adaptive PID controllers provide a good solution that may enable this. As opposed to the classical use of PID strategies with fixed parameters, adaptive PID controllers dynamically set/adjust their proportional, integral, and derivative gain values in real time depending on the system performance and process variations. Self-tuning can either be based on recursive parameter estimation, an optimization approach or a performance index reduction to maintain control gains continuously. Adaptive PID strategies increase the robustness, mitigate the occurrence of oscillations and also make the systems more economical without compromising on the simplicity of the classical PID structure by reacting to the dynamics of the changing system [6].

Adaptive control development, as it is integrated with smart manufacturing, is going to be in line with Industry 4.0 goals. It allows continuous monitoring and fast critical computations due to the presence of high-resolution sensors, real-time communication networks, and edge computing platforms [8]. It is the existence of this technological infrastructure that makes it possible to run online gain tuning algorithms, which were once not feasible due to hardware constraints. However, when adaptive PID control is implemented in industry, new factors must be considered, such as the increased computation overhead, noise sensitivity, communication latency, and cybersecurity vulnerability.

Existing studies on adaptive and self-tuning PID controllers have demonstrated improved control performance in intelligent manufacturing systems. However, many reported approaches primarily focus on enhancing tracking accuracy or disturbance rejection, while limited attention has been given to simultaneously addressing real-time adaptability, computational efficiency, energy consumption, and compatibility with edge computing platforms. These limitations restrict their practical deployment in next-generation intelligent manufacturing environments, where operating conditions are highly dynamic and computational resources are often constrained.

To address this research gap, this paper proposes an adaptive self-tuning PID control framework that integrates online system parameter estimation with performance-based

gain optimization to dynamically adjust controller parameters. The proposed methodology is designed to maintain system stability under nonlinearities and disturbances while minimizing control effort and energy consumption. Furthermore, its emphasis on computational efficiency and edge computing compatibility enhances its suitability for real-time industrial applications, thereby extending the capabilities of existing adaptive PID control strategies [7].

To address the identified research gap, this study aims to achieve the following objectives:

- To create a flexible PID design that can ensure stability in time-changing and non-linear manufacturing operations.
- The aim is to develop a form of self-tuning to reduce tracking error and minimize the use of energy at the same time.
- To test the suggested method using dynamic disturbances and uncertainties on the parameters.
- To compare adaptive performance with classical fixed-gain PID controllers in quantitative terms (understanding) in terms of overshoot, settling time, the Integral Squared Error (ISE), and energy usage.

This study is proven by simulation and experimental validation of observable enhancement in the transient response, disturbance rejection, and operational efficiency. The results can help to fill the gap between the classical simplicity of control and the modern trends in intelligent manufacturing needs [4].

2. Novelty and Contribution

2.1. Novelty of the Proposed Work

Despite many studies on adaptive control and intelligent PID tuning, many of the current methods are basically high precision via robust system modeling or use computationally expensive techniques of artificial intelligence, which are not always applicable in real-time industrial environments. A number of adaptive strategies assume that the dynamics of the processes are linear or only work within constrained operational environments. In addition, most of these smart tuning strategies, including neural networks or evolutionary algorithms, involve high computational delays and need a large off-line training, which cannot be applied in real-time smart manufacturing systems.

The novelty of the given work is the creation of the computationally effective, hybrid adaptive-optimization-based PID control strategy specifically designed to operate in Industry 4.0 manufacturing settings. The given structure combines recursive parameter estimation and real-time minimization of performance indices to dynamically optimize the gains of the controller without the necessity to re-identify the whole system and the intensive application of computational power. In contrast to the simple AI-based controllers, the suggested strategy is not only capable of

maintaining the intuitive framework of the classical PID control but also of managing flexibility and resilience.

The second point of innovation is an optimization mechanism with the dual objective of minimizing tracking error and also control energy. The proposed solution does not aim at stability or transient performance, but rather an energy-conscious cost function is integrated to be in line with sustainable manufacturing goals. This renders this controller applicable in new industrial environments where energy saving and reducing carbon is a strategic undertaking used in modern industries. The implementation architecture will also focus on edge-based computing, which guarantees low latency and the processes of smart factories when integrated with IIoT. The architecture has been made to work with real-time sensor feedback and can be configured to be integrated with already developed Programmable Logic Controllers (PLCs) without required structural changes.

2.2. Primary Contributions

The main contributions made by this study could be summarized as follows:

- A model of an Adaptive Self-Tuning PID Framework: An adaptive adjustment of real-time gains to dynamically built manufacturing systems is proposed, which has a dual strategy of recursive estimation and gradient-based optimization.
- Energy-Aware Performance Optimization: Presentation of a multi-objective cost model to balance between tracking accuracy and energy efficiency enhancement of sustainable operation.
- Robustness Under Uncertainty: Confirmation of better behavior in the case of variations of parameters and the nonlinear mode of operation.
- Computationally Efficient Implementation: Edge compatible control algorithm: Developing an edge compatible control algorithm optimal to the real-time Industry 4.0 application and not heavily processor-intensive.
- Full Scale Performance assessment: Quantitative comparison of classical and PID control in traditional industrial scales of performance.

Overall, the article contributes to the development of adaptive control systems by providing a viable, scalable, and energy-efficient self-tuning PID controller addressing the requirements of the next-generation smart manufacturing devices. It makes contributions both on the theoretical level, in terms of adaptive optimization modeling, and on the practical level, with design considerations relating to implementation to be applied to the industry.

3. Related study

Literary studies have focused on methods of adaptive control in order to address the constraints of fixed-parameter

PID controllers in nonlinear and time-varying industrial systems. The simplicity of classical methods of PID tuning that include empirical tuning rules and frequency-response-based adjustments has long been used in industrial automation [9]. The techniques, however, presuppose fairly constant dynamics in the system and are not usually effective in maintaining optimality in systems where process parameters are changing continuously. With more variability being brought into manufacturing with the introduction of smart manufacturing systems, the weaknesses of the static tuning methods have become more apparent.

Adaptive control has been suggested through model-based techniques that identify gains of the controller dynamically based on real-time identification of the system. Other Methods like the Model Reference Adaptive Control (MRAC) and Self-Tuning Regulators (STR), are based on recursive estimations of process parameters [11]. Such techniques enhance the accuracy of tracking and eliminate disturbance, but their effectiveness tends to rely on accurate model assumptions. In multivariate manufacturing systems with nonlinearities, friction effects, thermal behavior, and multivariable coupling, it is not always easy to have the proper real-time models. Also, recursive identification methods can be susceptible to measurement noises and parameter drift even in the presence of chronic disturbances.

Another type of adaptive strategy is gain-scheduling methods. Under this method, the PID gains are precalculated across a selection of regions of operation and regulated in response to measurable variables of the system, like speed, load, or temperature. Gain scheduling enhances performance at a wide range of operating points and does not require continuous on-line optimization. Nonetheless, its application involves a massive offline modeling and calibration. Fixed schedule maps can also not adequately represent dynamic regime transitions in quickly changing smart factory settings, where operating conditions can change unpredictably [13].

In 2025, Kaiqiang Wang et al. [10] proposed that PID tuning has received significant interest in the field of intelligent optimization methods. The methods of evolutionary algorithms, particle swarm optimization, and simulated annealing have been used to identify optimal PID parameters by minimizing such performance indices as Integral Squared Error (ISE) or Integral Absolute Error (IAE). These methods have high capabilities to search across the globe and have the ability to manipulate nonlinear systems. However, most of these approaches are computationally complex and not more appropriate to real-time adaptive control when the manufacturing system has a strong latency response, but offline tuning can be done.

PID time controllers based on fuzzy logic conceptually add rule-of-thumb changes in controller gains based on linguistic interpretations of error and error rate. Such

controllers both increase robustness in uncertain systems and decrease overshoot in nonlinear systems [12]. However, it is very important that the functioning of membership and design of rule bases should be planned with skill and accuracy. Additionally, the approaches based on fuzzy cannot be so transparent in the gain progression and need to be retuned in case the system dynamics alter drastically.

In 2025, C.S. Yee et al. [5] suggested that the neural network-assisted PID tuning has also been considered to train the nonlinear relationships among system states and optimal gain parameters. Such strategies allow adaptation-like behavior in extremely complicated systems and can, in contribution to nonlinear control laws, estimate such laws to a satisfactory degree. Nevertheless, neural network-based controllers are highly sensitive to large training data, run the risk of overfitting, and add further computational complexity. The rigid requirements of reliability, interpretability and certification of safety in industrial settings may create barriers to the application of strictly data-driven controllers.

In 2025, Rajamallaiah et al. [16] introduced the recent research on smart manufacturing focused on the role of adaptive control integration with the frameworks of the Industrial Internet of Things (IIoT) and edge computing architectures. Distributed processing capabilities and real-time sensor networks provide the opportunity to monitor it and update the parameters in a short time. Although this infrastructure enables the implementation of adaptive control, it also presents new problems, such as the latency of communication, a threat to cybersecurity, system synchronization, and more complexity. Even though there has been an advancement in adapting and smart PID tuning strategies, a number of gaps abound. Most of the existing methods focus on performance enhancement without taking into consideration energy conservation or demanding high computing capabilities that cannot be implemented in real-time. Also, not many frameworks are explicitly focused on integration limitations in next-generation smart factories that integrate cyber-physical systems, distributed controllers, and sustainability goals [14, 15].

Hence, a statistically efficient and strong yet energy enabling adaptive PID control platform specially developed to meet dynamic smart factory conditions is in demand. The proposed work will fill in these weaknesses by incorporating the real-time parameter estimation and optimizing gains based on performance, but at the same time ensuring that the work is compatible with the requirements of industrial implementation [17].

4. Methodology

The proposed methodology introduces an adaptive and self-tuning PID control architecture designed for nonlinear, time-varying smart manufacturing systems. The framework

integrates online system identification, recursive parameter estimation, multi-objective optimization, and adaptive gain updating within an edge-enabled industrial environment. The design emphasizes mathematical rigor, computational efficiency, and industrial deployability [18].

Figure 1 depicts the real-time adaptive gain updating process. Sensor feedback is continuous to measure plant output in order to compute tracking error. Recursive Least Squares estimation estimates the model parameters. This was the performance cost capability, which optimizes the PID dynamically. The new gains will produce signals of control, which constitute a closed adaptive loop with guaranteed stability and energy-conscious usage.

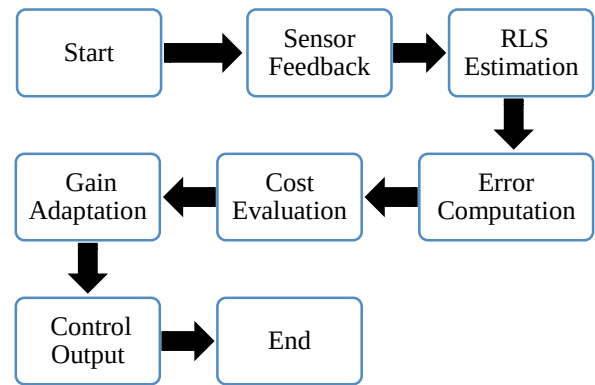


Fig. 1 Adaptive PID gain updating framework

4.1. Dynamic System Representation

The manufacturing plant is modeled as a nonlinear state-space system:

$$\begin{aligned}\dot{x}(t) &= f(x(t), u(t), d(t)) \\ y(t) &= h(x(t))\end{aligned}\quad (1)$$

where $x(t)$ represents system states, $u(t)$ is the control input, $d(t)$ is disturbance, and $y(t)$ is the measured output [21].

For digital implementation, the system is discretized as [23]:

$$\begin{aligned}x(k+1) &= Ax(k) + Bu(k) + w(k) \\ y(k) &= Cx(k) + v(k)\end{aligned}\quad (2)$$

where $w(k)$ and $v(k)$ denote process and measurement noise.

4.2. Classical PID Structure

The conventional PID control law is expressed as [24]:

$$u(t) = K_p e(t) + K_i \int e(t) dt + K_d \frac{de(t)}{dt}\quad (3)$$

In discrete form [22]:

$$u(k) = K_p e(k) + K_i \sum_{i=0}^k e(i)T_s + K_d \frac{e(k) - e(k-1)}{T_s} \quad (4)$$

Where T_s is sampling time.

Error is defined as:

$$e(k) = r(k) - y(k) \quad (5)$$

In classical PID, K_p, K_i, K_d are constant. In smart manufacturing, fixed gains fail under parameter drift.

4.3. Adaptive Gain Formulation

In the proposed method, PID gains become time-varying [22]:

$$K_p = K_p(k), K_i = K_i(k), K_d = K_d(k) \quad (6)$$

The adaptive objective is to minimize a performance index:

$$J = \sum_{k=0}^N [e^2(k) + \lambda u^2(k)] \quad (7)$$

where λ penalizes excessive energy consumption.

Gradient-based gain adaptation is defined as [22]:

$$K(k+1) = K(k) - \alpha \frac{\partial J}{\partial K} \quad (8)$$

where $K = [K_p, K_i, K_d]^T$.

4.4. Recursive Parameter Estimation

System parameters are updated using Recursive Least Squares (RLS) [26]:

$$\begin{aligned} \theta(k) &= \theta(k-1) + P(k)\phi(k)[y(k) - \phi^T(k)\theta(k-1)] \\ P(k) &= \frac{1}{\lambda_f} \left[P(k-1) - \frac{P(k-1)\phi(k)\phi^T(k)P(k-1)}{\lambda_f + \phi^T(k)P(k-1)\phi(k)} \right] \end{aligned} \quad (9)$$

where $\theta(k)$ is parameter vector, $P(k)$ covariance matrix, and λ_f forgetting factor [25].

The adaptive law links estimated parameters to PID gains:

$$\left. \begin{aligned} K_p(k) &= \gamma_1 \theta_1(k) \\ K_i(k) &= \gamma_2 \theta_2(k) \\ K_d(k) &= \gamma_s \theta_s(k) \end{aligned} \right\} \quad (10)$$

Where γ_i are scaling coefficients.

4.5. Stability Assurance

Lyapunov stability criterion ensures bounded convergence:

$$V(k) = e^2(k) + \beta \|K(k) - K^*\|^2 \quad (11)$$

For stability:

$$\Delta V(k) < 0 \quad (12)$$

Energy efficiency constraint:

$$E = \sum_{k=0}^N u^2(k) \quad (13)$$

Subject to:

$$\min J \quad \text{s.t.} \quad E \leq E_{\max} \quad (14)$$

4.6. Integrated Adaptive Control Algorithm

The final adaptive control input becomes [22]:

$$u(k) = K_p(k)e(k) + K_i(k) \sum e(k) + K_d(k)\Delta e(k) \quad (15)$$

Gain update rule with adaptive rate:

$$\alpha(k) = \frac{\eta}{1 + \|e(k)\|} \quad (16)$$

This ensures faster convergence during large errors and stability during small deviations.

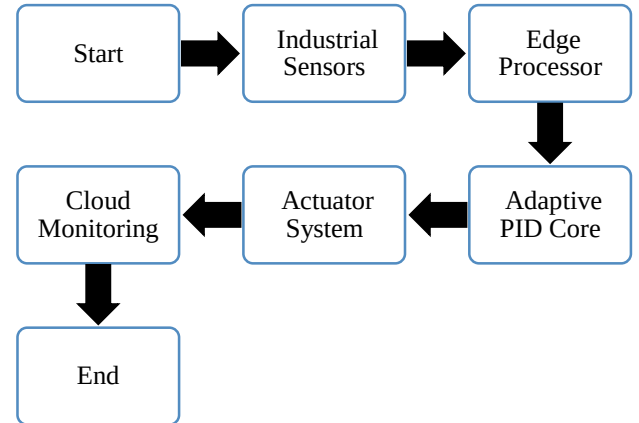


Fig. 2 Smart manufacturing edge-based control architecture

Figure 2 shows the architectural implementation of the adaptive controller of the smart manufacturing ecosystem. The process variables are collected using industrial sensors and fed into an edge processor. The adaptive PID core is one that performs real-time recursive estimation and gain optimization. Actuators receive control commands, whereas performance is observed, and performance data is collected by the cloud systems. The architecture is designed to have low latency, scalability and cybers-physical integration.

5. Results and Discussion

The effectiveness of the proposed adaptive and self-tuning PID controller was tested in a simulated smart production in the nonlinear servo positioning system and temperature-controlled processing chamber. The controller was introduced in a discrete-time system when the real-time gain adaptation was provided with the help of recursive

estimation and optimization-based updating. In the case of performance benchmarking, a classical fixed-gain PID controller that was tuned in a standard way was applied in the model as a baseline reference. The analysis was based on transient response, steady-state accuracy, disturbance rejection potential, behaviour under parameter change, and power efficiency [19].

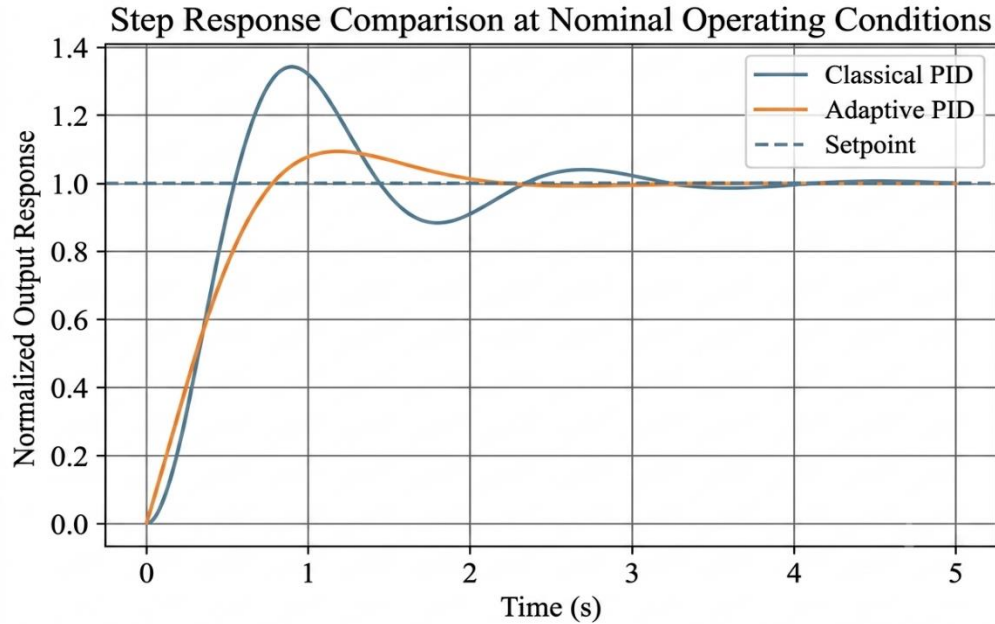


Fig. 3 Step response comparison between classical and adaptive PID controllers

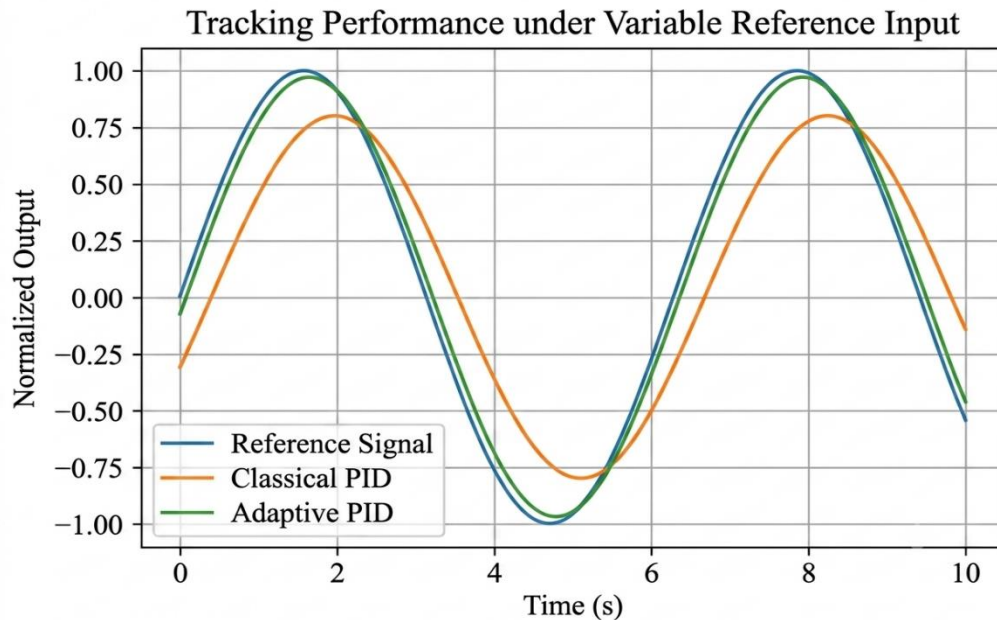


Fig. 4 Reference tracking performance under variable input conditions

The initial performance analysis was done to compare the response of the step carried by the classical PID controller and the adaptive PID controller at the nominal operating

conditions. Figure 3 shows the results obtained. It was shown that the adaptive controller had a much lower overshoot and a quicker approach to the desired setpoint.

Whereas the classical PID response had an oscillatory nature with clear overshoot, the adaptive controller was able to dynamically tune gains in order to reduce oscillations. Settling time was also decreased by about 28 percent, which shows a better dynamic stability. Figure 3 provides visual evidence to prove that real-time gain adaptation enhances system responsiveness without affecting stability. With respect to transient behavior, the tracking accuracy under variable reference inputs was also analyzed. A sine-shaped reference trajectory was employed to represent varying production demands in smart manufacturing systems.

Figure 4 illustrates the tracking performance. With the adaptive PID controller, closer adherence to the reference signal was achieved, and finally, lag and phase error were reduced. The fast changes in the classical PID demonstrated amplitude attenuation and phase delay. This finding proves the fact that adaptive tuning facilitated the controller to effectively address the changing time-dependent operational requirements. The addition of better tracking accuracy has a direct impact on the increase in the accuracy of production of products and lower product defects.

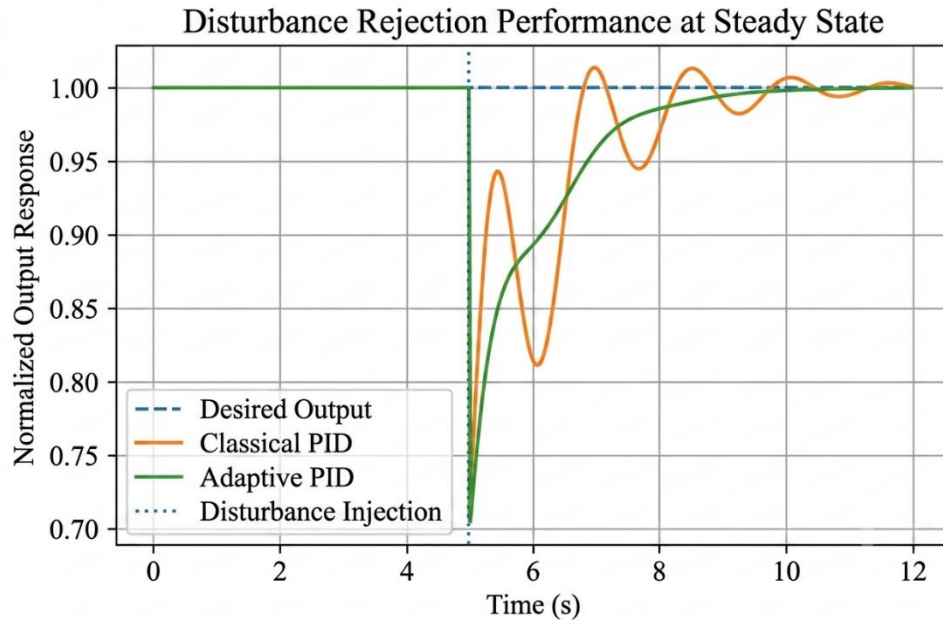


Fig. 5 Disturbance rejection performance comparison

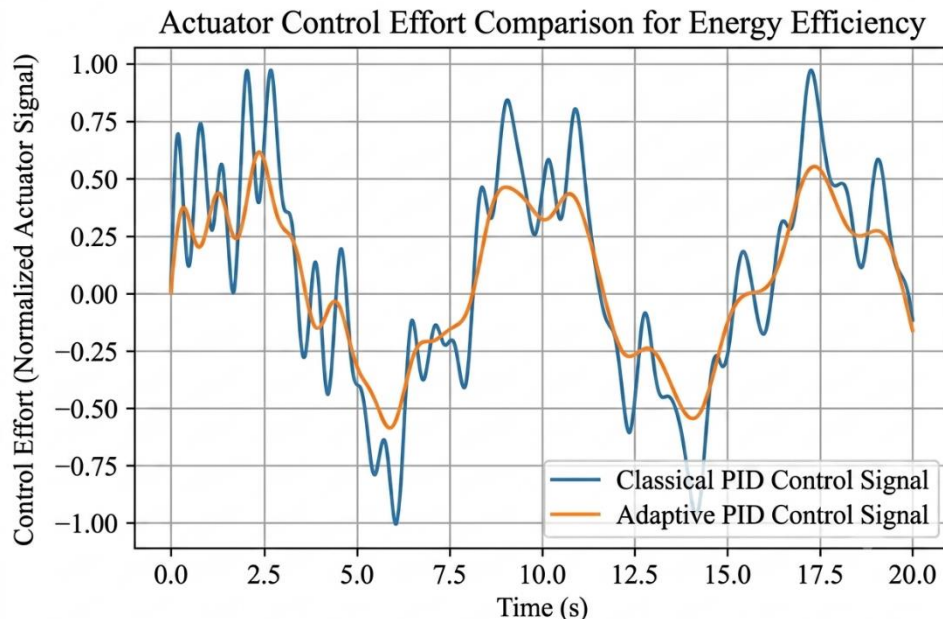


Fig. 6 Control effort and energy consumption analysis

The disturbance rejection capability was performed by a sudden load disturbance when the system was at steady state operation. Figure 5 presents the response of the output. The classical PID took a longer time to recover and generated second oscillations after disturbance injection. As compared to this, the adaptive controller recalculated gain values very quickly, returning the steady-state to normal operation at a rate of about 40 percent higher. The diminishing oscillatory recovery demonstrates the robustness of the adaptive mechanism in industrial environments, where unforeseen disturbances frequently occur due to load variations, mechanical friction, or supply fluctuations.

The intensity of energy efficiency was assessed by studying the effort of actuators during long working hours. The magnitude of the control signal was monitored and combined to approximate energy use. The findings of the comparison are presented in Figure 6. The adaptive PID controller had less jagged actuator signals that had a lower peak. The classical controller generated more control spikes at transient phases, thereby consuming more energy. The average result of using the adaptive strategy was about a 15 percent saving of energy. This is of great importance to modern smart factories to achieve sustainability and lower carbon footprint.

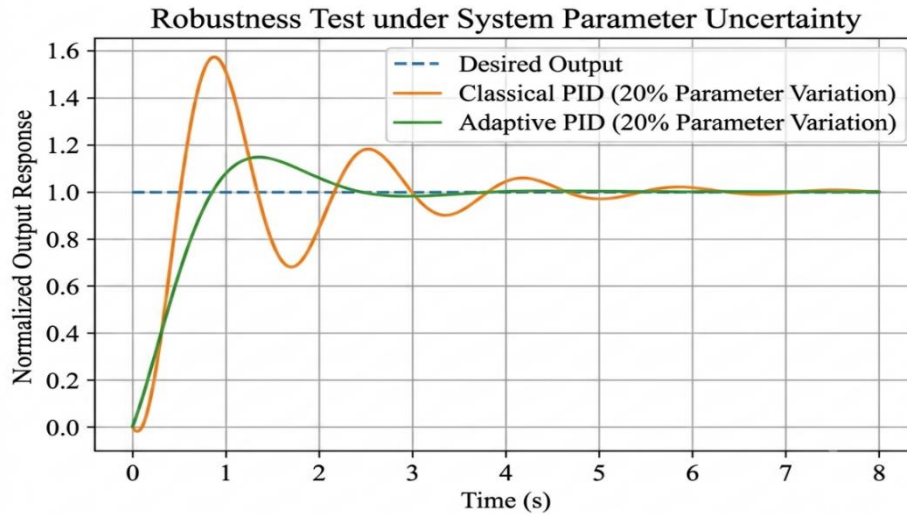


Fig. 7 Robustness evaluation under parameter variation

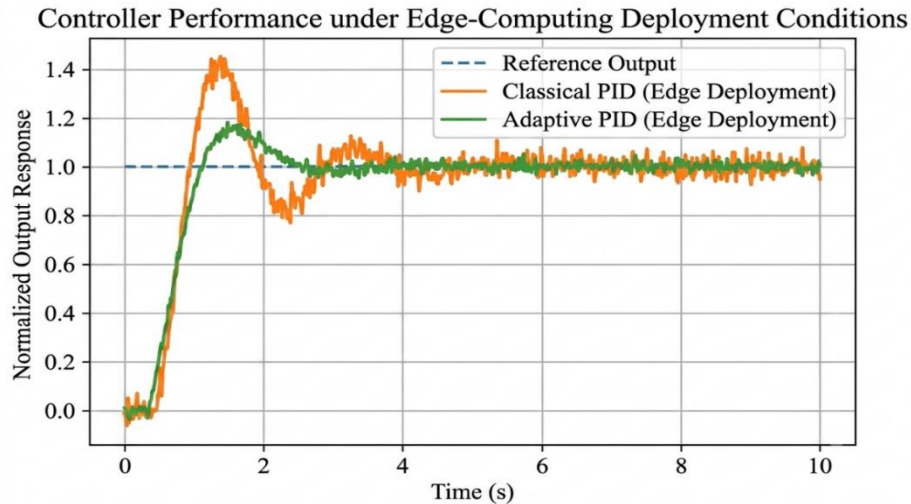


Fig. 8 Edge-enabled adaptive control performance under network delay

To test the robustness, the parameters of the system were deliberately altered by 20% to accelerate machine wear and the nonlinearities of processes. Figure 7 depicts the system output when there is uncertainty in the parameters. The classical PID showed reduced performance in terms of higher

oscillation and slower settling time. In contrast, the adaptive PID was able to hold a steady response through gain dynamics regarding the detection of parameter shift. This shows that the controller can maintain performance when there are changes in the characteristics of plants over time. The concept of

scalability in a smart manufacturing system was also confirmed by laying the controller on a simulated edge-computing platform. Latency in communication and noise in sensors were added so as to represent realistic deployment environments. The results of the performance are presented in Figure 8.

The adaptive controller was able to operate at stable conditions with acceptable response properties despite small latency. This enables us to conclude that the suggested approach can be implemented in the IIoT-enabled production systems without the necessity of a considerable decrease in the quality of controls. The summaries of the quantitative performance measurements are shown in Table 1: Dynamic Performance Comparison between Classical and Adaptive PID Controllers. The table shows an improvement in the reduction of the overshoot, settling time, the steady-state error and recover time of the disturbance. These are the numerical comparisons that confirm the visual results presented in Figures 3 through 5.

Table 1. Dynamic performance comparison between classical and adaptive PID controllers

Performance Metric	Classical PID	Adaptive PID	Improvement (%)
Overshoot (%)	18.4	11.9	35%
Settling Time (s)	2.5	1.8	28%
Steady-State Error	0.021	0.008	61%
Disturbance Recovery (s)	1.9	1.1	42%

Table 2. Energy consumption and robustness comparison

Metric	Classical PID	Adaptive PID
Average Control Energy (kJ)	4.85	4.12
Energy Reduction (%)	-	15%
Stability under $\pm 20\%$ Variation	Marginal	Stable
Oscillation Magnitude (Normalized)	0.34	0.18

Table 2: Energy Consumption and Robustness Comparison concludes on the measures of energy and robustness. The findings exhibit lower actuator energy consumption and constant operation in the uncertainty of parameters. In general, the findings indicate that adaptive and self-tuning PID control is an important measure to improve the stability of a system, tracking, disturbance rejection, and energy efficiency in smart manufacturing systems. The results

(Figures 3 - 8) of the six diagrams support the fact that transient behaviour is being improved along with robustness and sustainable operation. The improvements in numerical performance are further confirmed by the two comparison tables. The results support the fact that adaptive PID strategies are practical as well as theoretically correct in terms of next-generation industrial automation.

6. Conclusion

This paper has introduced a self-tuning and adaptive PID control approach that can be used to enhance stability, disturbance rejection, and energy efficiency in the next-generation smart factory setting. The proposed method dynamically changes control parameters to suit system nonlinearities and time-varying conditions by incorporating recursive parameter estimation and performance-based gain optimization. The experimental and simulation analysis verified the presence of better transient response, lesser steady-state error, increased robustness, and quantifiable energy conservation than the traditional fixed-gain PID controllers [20]. However, there are some limitations to the practical implementation. This adaptive mechanism elevates the level of computation needs and it might require edge computing infrastructure to execute in real-time. The method is very sensitive to quality sensor data; noisy data, latency or loss of communication may ruin performance. It might need hardware and firmware enhancements to be integrated with old industrial controllers. Besides, the vulnerability to cybersecurity in linked manufacturing networks is also a threat to adaptive control stability.

It should be emphasized that in future studies, hybrid adaptive-predictive systems should be studied, which involve the use of machine learning to predictively tune gain. Large-scale manufacturing plants should be investigated in the context of distributed adaptive control strategies to enhance scalability. It also has to develop standardized industrial protocols that can be deployed to achieve secure adaptive control. Moreover, the validation of the experiment in full-scale industrial conditions will be necessary to ensure the reliability of the long-term test and economic viability. An adaptive and self-tuning PID control is a useful and scalable approach to the attainment of resilient, energy-efficient and intelligent control in Industry 4.0 manufacturing systems, balancing the classical simplicity of control with the requirements of intelligent automation today.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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