ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Volume 12, Issue 12, December 2025

GA and NSGA-Based PID Controllers for Improved Wastewater Treatment Performance: A Comparative Study

[1] Reshma K V, [2] Dr. A. Vimala Juliet, [3] Dr. Anusha Chacko

[1] Department of Electronics and Instrumentation Engineering, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu, India.
[1] Department of Electronics and Instrumentation Engineering, Vimal Jyothi Engineering College, Chemperi, Kannur, Kerala, India.
[2] Department of Electronics and Instrumentation Engineering, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu, India.
[3] Department of Electronics and Communication Engineering, Vimal Jyothi Engineering College, Chemperi, Kannur, Kerala, India
Corresponding Author Email ID: [1] rk1554@srmist.edu.in, [2] vimalaja@srmist.edu.in, [3] anushachacko@vjec.ac.in

Abstract*— Wastewater treatment plants (WWTPs) require particular and dependable control strategies to ensure effluent quality at the same time as minimizing operational fees. conventional proportional–integral–derivative (PID) controllers frequently face demanding situations in coping with the nonlinear and dynamic nature of treatment strategies. To deal with this, optimization-primarily based tuning strategies which consist of Genetic algorithm (GA) and Non-dominated Sorting Genetic algorithm (NSGA-II) have been accomplished to decorate PID controller typical overall performance. This observe offers a comparative evaluation of GA and NSGA-II optimized PID controllers for WWTP programs. The evaluation is finished using manipulate loop responses and normal overall performance indices, particularly Integral of Absolute Error (IAE), Integral of Squared Error (ISE), and Integral of Time-weighted Absolute Error (ITAE). Simulation consequences show that at the identical time as every GA and decorate effluent awareness prediction and system stability compared to standard PID tuning, NSGA-II presents superior alternate-offs in phrases of multi-goal normal average performance. These results demonstrate the potential of multi-goal evolutionary algorithms for more intelligent and environmentally friendly wastewater treatment manipulation.

Index Terms*— Genetic Algorithm (GA), IAE, ISE, ITAE, NSGA-II, Multi-objective Optimization, PID, Wastewater Treatment Plants (WWTPs).

I. INTRODUCTION

Wastewater treatment plants are very important for keeping the environment safe because they make sure that effluents are handled correctly according to strict rules. Rapid urbanization, unpredictable industrial discharge, and strict environmental rules make it even more important to find ways to control effluent quality while using less energy and lowering operating costs. In practice, the most widely used control strategies in WWTP operations is the PID controller due to its simplicity, ease of implementation, and reliability.

Over 95 percent of industrial control loops are thought to be managed by PID controllers due to their widespread use. Traditional PID tuning techniques are widely used but they frequently fail to address the nonlinear time-varying and interloop-coupled dynamics present in biological treatment processes. The use of evolutionary optimization methods to increase controller efficiency has been spurred by these constraints.

Because they can search globally in complex solution spaces Genetic Algorithms (GA) are particularly well-liked. Deifalla and Gasmelseed (2024) for example used GA techniques to optimize temperature control in a saponification reactor. By minimizing the ITAE index M. H they achieved significant reductions in overshoot and settling time. He. Deifalla and others. [1]. Furthermore, to improve control performance in various systems Y general GA based PID tuning frameworks have been successfully applied.Y Ma et al. [2]. However GAs emphasis on single-objective optimization restricts its capacity to handle several frequently incompatible performance criteria that are essential to WWTP operations such as control stability energy efficiency and effluent quality.

To deal with these challenges, NSGA-II, a multi-objective evolutionary set of rules, has gained traction. Its core strengths elitism, crowding distance, and Pareto-primarily based sorting allow it to yield a various front of most reliable alternate-off solutions K. Deb et al. [3]. NSGA II has been carried out in environmental control contexts, along with multi-goal optimization for anaerobic digestion systems, balancing parameters like effluent first-class and biogas production in wastewater treatment M. Huang et al. [4].

This study examines PID tuning specific to WWTP control based on GA and NSGA-II. Well-known indices including IAE, ISE and ITAE are used to statistically assess

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Volume 12, Issue 12, December 2025

performance. This demonstrates how NSGA-II excels at identifying multi-objective balanced overall performance in comparison to single-goal GA tuning.

II. LITERATURE REVIEW

There is growing pressure on wastewater treatment plants (WWTPs) to comply with stringent effluent discharge regulations while reducing energy and operating expenses. Due to their simplicity traditional PID controllers continue to be widely used however in highly nonlinear and time-varying biological processes their conventional tuning techniques perform poorly. This has inspired researchers to investigate sophisticated optimization methods for supervisory control and PID tuning in WWTPs.

M. H. H. Deifalla et al. [1] used GA-based PID optimization in chemical reactors and showed notable gains in disturbance rejection. Y. Ma et al. [2] examined MATLAB-based GA-PID tuning techniques and confirmed their resilience in a variety of industrial processes.

Liao et al. [5] demonstrated the efficacy of Pareto-based methods by presenting a multi-objective optimization framework for WWTPs that takes into account greenhouse gas (GHG) emissions, operating cost index (OCI) and effluent quality index (EQI). Chen & Co. et al. [6] created a hybrid XGBoost–NSGA-II model for COD prediction and energy optimization demonstrating the advantages of fusing multi-objective search with machine learning.

Liu et al. [7] improved wastewater process control by combining NSGA-II–TOPSIS for decision support with SVM–Bayesian optimization for feature extraction increasing decision robustness and accuracy. Q. et al. [8] presented an NSGA-II-optimized online gain-scheduled PID controller that successfully adjusted to nonstationary influent conditions. Wang & Co. [9] examined wastewater digital twin frameworks and found that NSGA-II is a key optimization engine in the supervisory and soft-sensor layers for real-time control.

Additionally, research has highlighted controller performance indices significance. For dynamic systems Mousakazemi et al. [10] compared error-integral criteria like IAE, ISE, ITAE and ITSE demonstrating how each index highlights distinct facets of error minimization. Mahfoud et al. [11] provided insights into index-driven optimization of PID tuning by demonstrating how the choice of error index greatly affects system overshoot settling time and oscillatory behaviour.

Regarding genetic algorithms (GA) Hu et al. [12] used GA to optimize multi-PID structures for nonlinear control systems reporting better transient performance but also limitations in managing several competing objectives at once. Yang et al. [13] extended multi-objective PID tuning to power system automatic generation control (AGC) demonstrating that better dynamic stability results from optimizing ITAE, ITSE and control effort collectively. Huang et al. [14] demonstrated how hybrid evolutionary approaches can balance resource recovery and effluent quality by integrating GA-ANN with NSGA-II for anaerobic digestion optimization.

These contributions demonstrate that while GA-based tuning frameworks provide notable improvements in single-objective optimization they remain limited in situations where trade-offs across multiple indices are critical. On the other hand by generating Pareto-optimal solutions that balance operational stability energy efficiency and effluent quality NSGA-II and its variations consistently outperform GA. The current study directly compares GA- and NSGA-II-based PID tuning in WWTP control loops using IAE ISE and ITAE indices to offer a thorough evaluation of controller performance.

III. PROPOSED METHODOLOGY

Wastewater treatment plants (WWTPs) are complex dynamic systems in which multiple chemical and biological processes occur simultaneously under various influent conditions. To guarantee effluent quality while lowering energy and operating costs advanced control strategies that go beyond conventional PID tuning are required. The Benchmark Simulation Model No.1 is used in this investigation, which provides a consistent framework for evaluating control strategies in WWTPs to assess and improve controller performance in such environments.

As illustrated in Fig. 1, the biochemical reactor in BSM1 is composed of five continuous stirred-tank units arranged in series. The first two units are anoxic reactors where denitrification occurs, using nitrate as an electron acceptor in the absence of oxygen. The last three units are aerobic reactors, in which aeration supports carbon oxidation and nitrification, thereby reducing ammonia concentrations in the wastewater. Influent wastewater, represented by Q_i, enters the first unit, while an internal recycle flow Q_{int} transfers nitrate-rich liquid from the aerobic section back to the anoxic tanks to support the denitrification process. Effluent leaving the reactor flows to the secondary clarifier, which is divided into multiple sedimentation layers. Clarified effluent Q_e is discharged from the upper layer, while return sludge Q_r and waste sludge Q_w are drawn from the lower layers to maintain biomass concentrations and sludge age within the system.

Two crucial loops are part of the BSM1 frameworks control strategy. First the oxygen concentration in the fifth aerobic reactor $S_{o,5}$ is controlled by the dissolved oxygen (DO) control loop, a PID controller is used to regulate it. Nitrification efficiency and energy consumption are directly impacted by the manipulated variable, aeration rate which is represented by the oxygen transfer coefficient $K_{La,5}$. The second is the nitrate control loop in which the internal recycle flow Q_{int} is adjusted to maintain the nitrate concentration in the second anoxic reactor $S_{NO,2}$. With one loop concentrating on nitrate removal and the other on organic and ammonia

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Volume 12, Issue 12, December 2025

oxidation these loops together constitute the crucial feedback mechanisms needed to stabilize effluent quality.

Both the GA and NSGA-II are used in this study to fine-tune the PID controllers connected to these loops. IAE, ISE and ITAE are examples of error indices that are minimized when GA is used as a single-objective optimizer. NSGA-II on the other hand is implemented as a multi-objective optimizer that simultaneously takes into account all three indices producing a Pareto front of optimal solutions from which trade-offs between error performance and stability can be examined. The study assesses the relative benefits of single-objective and multi-objective evolutionary strategies for improving PID control performance for WWTPs by utilizing both optimization techniques.

The BSM1 framework simulates a number of situations that affect performance evaluation. For every controller setup, the IAE, ISE, and ITAE error indices are calculated. These indices give us numbers that show how stable something is over a long period of time and how accurate tracking errors are. By looking at these indices in relation to process robustness and improving effluent quality, the methodology makes it possible to fully assess how GA- and NSGA-II-based PID controllers react to the nonlinear and disturbance-prone dynamics of wastewater treatment.

The proposed method integrates two essential feedback control loops: a practical benchmark process model and advanced evolutionary algorithms for PID tuning. While the comparison of GA and NSGA-II demonstrates the advantages of multi-objective optimization in providing more intelligent and sustainable process control using BSM1 ensures that the analysis is based on actual wastewater treatment processes.

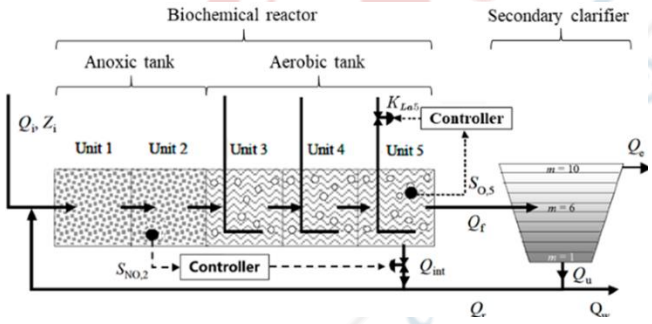


Figure 1. Process flow diagram of BSM1

A. PID Controller Design

One popular feedback control method in industrial and process control systems is a PID controller. Its main goal is to reduce the error between a desired setpoint and the process variable by modifying the input for control. This is accomplished by the PID controller using three different components: derivative, integral and proportional actions. A faster response is provided by the proportional term which produces a control signal proportionate to the current error however oscillations may result from an excessive proportional gain and a slow response from an insufficient gain. A high integral gain may result in overshoot and instability because of windup but the integral term effectively eliminates steady-state error by accounting for the accumulated error over time. Although it is susceptible to measurement noise the derivative term responds to the rate at which the error changes providing anticipatory action that enhances stability and lessens overshoot.

The goal of PID controller is to minimize the error between a desired setpoint(r(t)) and the process variable (y(t)), by adjusting the control input (u(t)).

The control law is: $u(t)= K_p\, e(t)+ K_i \int_0^t e(T)\, d_T + K_d \frac{de(t)}{dt}$

Where:

- e(t) = r(t)−y(t) = error signal
- K_p = proportional gain
- K_i = integral gain
- K_d = derivative gain

B. Genetic Algorithm (GA): Overview

Natural selection and Darwins theory of evolution serve as the inspiration for a population-based stochastic optimization method known as a GA. GA is appropriate for nonlinear complex and multi-modal optimization problems since it does not require derivative information in contrast to traditional gradient-based optimization techniques. The algorithm works with a population of potential solutions which are frequently depicted as chromosomes and undergo processes that are similar to those involved in biological reproduction. A fitness function that represents the optimization goal is used to assess the quality of each chromosomes encoded potential solutions. Fitter individuals are more likely to be selected for reproduction which is the first step in the evolutionary cycle. Subsequently crossover also known as recombination creates offspring with combined features by exchanging genetic material between parent chromosomes. Mutation randomly modifies specific genes to preserve diversity and prevent premature convergence guaranteeing exploration of the solution space. Until a termination criterion like maximum generations or convergence of fitness is met this iterative process keeps going.

C. Need for GA in PID Tuning for WWTPs

In wastewater treatment plants (WWTPs) it is challenging to maintain effluent quality within stringent regulatory limits while simultaneously optimizing the use of energy and chemicals due to highly nonlinear dynamics time delays and frequent disturbances. Because they rely on linear dynamics which can result in subpar or unstable performance traditional PID tuning techniques like Ziegler-Nichols are not effective in this situation. Because it seeks near-optimal PID (K_p, K_i and K_d) that simultaneously balance several performance indices genetic algorithm-based tuning is a dependable choice. Plant nonlinearities and performance

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Volume 12, Issue 12, December 2025

objectives such as IAE, ITAE overshoot and settling time can be directly addressed by the GA method. Because it's crucial to achieve both operational efficiency and effluent quality compliance GA is particularly useful for optimizing WWTP process control.

D. GA-Based WWTP PID Tuning Procedure

Several systematic steps are involved in the GA-based PID tuning process.

1. Define Objective Function (Fitness Function):

Developing a performance index that represents the intended control objectives is the first step. This could involve cutting energy use minimizing error indices like IAE, ISE or ITAE and minimizing effluent quality infractions in WWTP applications.

2. Initialize Population:

Each chromosome in the randomly generated population of chromosomes encodes a potential set of PID ($K_{p,}$ $K_{i,}$ K_d). Each parameters range is predetermined using simulation limitations or process knowledge.

3. Evaluate Fitness:

The established fitness function is used to assess each chromosome. WWTP simulations (e.g. BSM1) the encoded PID gains are applied and the controller's robustness against disturbances settling time and effluent quality indices are measured.

4. Selection:

For reproduction a subset of chromosomes with higher fitness is selected. Better-performing solutions are more likely to spread thanks to common selection strategies like rank-based selection roulette wheel selection and tournament selection

5. Crossover (Recombination):

Crossover is the process by which pairs of specific chromosomes exchange genetic information to create offspring. This step combines characteristics of successful solutions to explore new areas of the search space.

6. Mutation:

Mutation randomly modifies some of the offsprings genes to preserve diversity and avoid stagnation. Avoiding local minima which are frequent in highly nonlinear WWTP dynamics makes this step especially crucial.

7. Replace and Form New Population:

The new generation is made up of the progeny and some of the most fit members of the previous population. This guarantees that while new candidates are constantly investigated strong solutions are maintained.

8. Check Termination Criteria:

Until a stopping condition is satisfied such as reaching a maximum number of iterations or attaining a negligible improvement in fitness values the process is repeated for multiple generations.

9. Select Optimal PID Parameters:

In order to control the WWTP the best-performing chromosome from the last generation is chosen as the ideal PID parameter set. Compared to traditional tuning these parameters guarantee better handling of nonlinearities decreased oscillations and enhanced effluent quality. PID tuning using genetic algorithms offers a strong and adaptable method for controlling wastewater treatment plants as efficiently as possible. In complicated, nonlinear, and limited settings where traditional tuning methods don't work, GA can use evolutionary principles to find the best parameters for the whole system. The strict tuning process, which starts with defining a fitness function and ends with choosing the best gains, makes sure that the final PID controller meets effluent quality standards while also making the system more stable and efficient. Because of this, GA could be used to come up with smart control schemes for modern WWTPs.

E. NSGA II-based Optimization

The NSGA and its improved version, NSGA-II, are popular evolutionary algorithms for solving multi-objective optimization problems (MOPs). Multi-objective optimization requires the simultaneous optimization of two or more competing objectives, rather than concentrating on maximizing or minimizing a single performance measure. Some common examples are trying to get the most done while spending the least amount of money or trying to get the most done while making the control system stronger. NSGA is especially good at giving decision-makers the power to make choices based on practical limits or personal preferences because it gives them a set of trade-off solutions, or the Pareto-optimal front, instead of just one.

A popular evolutionary optimization method for multi-objective optimization problems involving the simultaneous optimization of two or more competing objectives is the NSGA and its enhanced version NSGA-II. Multi-objective optimization looks for a set of solutions that represent the best trade-offs between conflicting goals as opposed to single-objective optimization which looks for the best solution. A mathematical expression for a multi-objective optimization problem is $F(x)= [f_1(x), f_2(x), \ldots\ldots f_m(x)]$, which is the minimization or maximization of a set of functions. confined by equality and inequality restrictions. Every potential solution is assessed according to a number of objective functions including minimizing settling time and overshoot in control systems while adhering to system limitations like stability requirements or actuator limits.

Pareto dominance is a fundamental idea in NSGA-based optimization. If a solution is strictly better in at least one goal and no worse in all it is said to dominate the other. The

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Volume 12, Issue 12, December 2025

Pareto-optimal set is made up of all solutions that are not dominated by any other the Pareto front is the mapping of these solutions in the objective space. When achieving one goal necessitates sacrificing another the Pareto front offers a variety of trade-off solutions. In PID tuning for example lowering overshoot may result in longer settling times and vice versa. NSGA gives decision-makers a variety of workable options to select from based on practical preferences or system requirements by displaying the Pareto front.

In the first step of the NSGA optimization process a population of potential solutions is created and assessed for each of the objectives. Non-dominated sorting is used to rank the solutions into various fronts with the best trade-off solutions being found in the first front. NSGA-II establishes a crowding distance metric that incentivizes solutions to disperse uniformly along the Pareto front in order to preserve diversity along the front. Then to evolve new populations standard genetic algorithm operators like crossover mutation and selection are used. A well-distributed collection of Pareto-optimal solutions is produced after this process is repeated over a number of generations until convergence.

Because real-world problems often involve physical limitations safety margins or design restrictions handling constraints is an essential component of NSGA-based optimization. In order to manage constraints NSGA employs techniques like constraint-dominance which Favors the infeasible solution with the least amount of violation penalty functions which lower the fitness of solutions that violate constraints and feasibility preference which always ranks feasible solutions above infeasible ones. By using this method NSGA guarantees that the solutions it produces are both optimal and feasible.

In conclusion NSGA-based optimization is a reliable and effective approach to multi-objective problem solving. It gives you a Pareto front of solutions that don't dominate each other and follow the rules while also finding the best balance between competing goals. It is a useful tool for tuning engineering design control systems and making decisions because it can keep things different, stop things from converging too quickly, and adapt to real-world conditions.

F. Multi-Objective Functions in WWTP Control

In the context of WWTP control, particularly for tuning controllers (e.g., PID or advanced controllers), time-domain error indices such as IAE, ISE, and ITAE are commonly used as objective functions:

IAE (Integral of Absolute Error): $\int_0^T |e(t)|\, dt$

Measures total error over time. It penalizes sustained small errors but may tolerate short, high-amplitude errors.

ISE (Integral of Squared Error): $\int_0^T e^2\,(t) dt$

Penalizes larger errors more severely, leading to aggressive error reduction. However, it may result in higher control effort.

ITAE (Integral of Time-weighted Absolute Error): $\int_0^T t|e(t)|\, dt$

Penalizes errors at later stages more than at the beginning, promoting fast settling and minimizing long-term deviation.

In a WWTP scenario, the error e(t) could represent the difference between the measured effluent concentration (e.g., ammonium or nitrate) and the desired setpoint. Minimizing these indices ensures better effluent quality and compliance with environmental regulations.

Thus, a multi-objective optimization problem can be formulated as:

Minimize F(x)=[IAE(x), ISE(x), ITAE(x)]

Where x = [K_p, K_i, K_d]

G. NSGA Optimization Workflow for WWTP

These steps comprise the NSGA-based optimization for advanced control or PID tuning in WWTP.

1. **Initialization:** The first step is to create a population of potential controller parameters (K_p, K_i, K_d) that fall within known ranges.
2. **Evaluation of Fit:** Run a WWTP simulation for each potential solution (e. g. A. compute IAE ISE and ITAE from the effluent concentration tracking error (using the BSM1 benchmark model).
3. **Non-dominated Sorting:** The parameter sets in the first Pareto front are independent of each other across all objectives.
4. **Crowding Distance Assignment:** Crowding distance prevents solutions from concentrating in a small area and guarantees diversity within each front.
5. **Select Crossover Mutation:** By combining effective solutions and introducing variations evolve the population.
6. **Convergence:** To achieve a stable Pareto front of trade-off PID parameters repeat for several generations.

The application of NSGA-based optimization to WWTP controller tuning enables the methodical management of several competing goals including ITAE, ISE and IAE. By creating a Pareto front of optimal trade-offs rather than a single solution NSGA gives engineers the freedom to select options based on process priorities such as longer-term stability faster settling or fewer oscillations. By taking operational constraints into account NSGA guarantees that optimized controllers are not only robust practically feasible and compliant with regulations but also theoretically optimal.

IV. RESULTS AND DISCUSSION

The proposed frameworks were made using MATLAB R2023b, which was chosen because it has full support for numerical computation, control system design, and machine learning. We used MATLAB Simulink to model and simulate how the WWTP changes over time, which lets us control it in real time with adjustable solvers and sampling intervals.

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Volume 12, Issue 12, December 2025

Table 1 shows the performance of the NSGA-II-based PID controllers and the Classic PID, GA-PID under three different weather conditions: stormy, rainy and dry. The different influent flow and load disturbances that these conditions show have a direct impact on the control dynamics and effluent stability of wastewater treatment plants (WWTP). The results show that in all cases PID controllers based on Genetic Algorithms (GA) and Non-dominated Sorting Genetic Algorithms II (NSGA-II) perform better than the traditional PID controller. The adaptive optimization of the controller gains which improves transient response and disturbance rejection while preserving acceptable effluent quality is the cause of this improvement.

The Classic PID controller has the worst error indices under all weather conditions because it is unable to handle nonlinear and time-varying process characteristics due to its fixed gain settings. The GA-PID controller on the other hand performs noticeably better than the Classic PID with integral error indices dropping by about 13–19%. This improvement can be attributed to GAs ability to use a global search to find near-optimal PID gain values. As a result the system responds more quickly and with less overshoot. On the other hand the NSGA-II-based controller consistently outperforms GA-PID by about 6–10% and Classic PID by 21–25%. The enhanced results of NSGA-II show how successful multi-objective optimization can be. It simultaneously lessens conflicting goals like IAE, ISE and ITAE improving control performance and making it more stable and balanced.

In dry weather the organic load and influent flow remain relatively constant and the process only slightly varies. Here the classic PID controller maintains performance at a reasonable level but it still exhibits a discernible steady-state error and settles more slowly. The GA-PID reduces IAE ISE and ITAE by roughly 13.5%, 16.7% and 19.1% respectively. This indicates that there are fewer oscillations and the system is more stable. The indices decline by roughly 20.8%, 23.9% and 25.1% for the NSGA-II controller which performs even better. Even when the process changes slightly the NSGA-II-tuned PID ensures that setpoints are tracked faster and that transient response is smoother.

Rain causes flow surges and dilution which significantly alter the influent. The process becomes more nonlinear as a result. Because it has more errors and takes longer to settle the Classic PID performs poorly in this situation. The GA-PID controller reduces overshoot by an average of 12–18% and enhances the transient response. However, with a 20–25% improvement over the Classic PID and a 6–9% improvement over the GA-PID the NSGA-II-based controller is still superior at controlling things. This demonstrates that NSGA-IIs capacity to balance speed and stability while optimizing multiple objectives makes it more resilient to shifting influent conditions that arise during rainy seasons.

Storms significantly alter influent flow and load which leads to serious issues and puts the control systems resilience to the test. The highest IAE and ITAE values indicate that the Classic PID is having a lot of problems. Although the GA-PID controller improves things somewhat (by 13–19%) it still exhibits some minor oscillations and requires more time to recover. In contrast the NSGA-II controller is incredibly robust. When compared to the Classic PID and the GA-PID it can increase ITAE by up to 25% and roughly 6% respectively. This demonstrates that in dynamic and uncertain operating environments NSGA-II is superior at maintaining control stability and ensuring that effluent quality remains high.

Table 1: Control Performance indices

Structure	Dry Weather			Rainy Weather			Stormy Weather		
	IAE	ISE	ITAE	IAE	ISE	ITAE	IAE	ISE	ITAE
Classic PID	112.8	258.1	842.6	129.7	295.4	970.3	157.9	342.1	1212.8
GA-PID	97.6	214.9	681.2	113.8	246.7	798.5	137.2	288.6	978.3
NSGA-II PID	89.34	196.4	631.4	103.2	222.8	747.2	124.1	261.5	917.6
Improvement (%) Classic PID vs (GA-PID)	13.5%	16.7%	19.1%	12.3%	16.4%	17.7%	13.1%	15.6%	19.3%
Improvement (%) Classic PID vs (NSGA-II PID)	20.8%	23.9%	25.1%	20.4%	24.6%	22.9%	21.4%	23.5%	24.3%
Improvement (%) NSGA-II PID vs GA PID	8.5%	8.6%	7.3%	9.3%	9.7%	6.4%	9.6%	9.4%	6.2%

V. CONCLUSION

This study used Benchmark Simulation Model No.1 to compare the effectiveness of three control strategies: NSGA-II-based PID, GA-tuned PID and Classic PID of a WWTP in a variety of weather situations. The outcomes unequivocally demonstrate that optimization-based PID controllers outperform conventional PID controllers in terms of control. By employing global search optimization to reduce integral error indices the GA-PID achieved significant improvements. In contrast the NSGA-II-based PID

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Volume 12, Issue 12, December 2025

performed better overall because it simultaneously optimized several competing objectives. When compared to the Classic PID and the GA-PID the NSGA-II controller reduced the integral performance indices (IAE ISE and ITAE) by roughly 21–25% and 6–10% respectively.

This demonstrates its strength and adaptability to changing circumstances. Both GA-PID and NSGA-II PID demonstrated better stability and improved transient response whereas the Classic PID suffered from high error accumulation and poor adaptability according to the comparative analysis conducted under dry rainy and stormy weather conditions. In particular the NSGA-II controller continued to function well despite numerous issues which made it simpler to adhere to setpoints and recover more quickly. These findings demonstrate how multi-objective optimization techniques improve the flexibility and intelligence of real-time process control in WWTPs resulting in improved operational efficiency and effluent quality.

REFERENCES

[1] M. H. H. Deifalla and G. A. Gasmelseed, “Genetic Algorithm-Based PID Optimization for Ethyl Acetate Saponification in a Continuous Stirred Tank Reactor,” Am. J. Chem. Eng., vol. 12, no. 6, pp. 123–131, 2024.

[2] Y. Ma, “Optimization of basic PID control algorithm based on genetic algorithm and MATLAB,” Theoretical and Natural Science, vol. 30, pp. 178–186, 2024.

[3] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II,” IEEE Trans. Evol. Comput., (historic), foundational concepts.

[4] M. Huang et al., “Multi-objective optimisation for design and operation of anaerobic digestion using GA-ANN and NSGA-II,” J. Chem. Technol. Biotechnol., vol. 91, no. 1, pp. 226–233, 2016.

[5] J. Liao, J. Huang, L. Guo, and S. Shen, “Multi-objective optimization based on simulation for wastewater treatment plants considering greenhouse gases, effluent quality and operating cost indices,” Water, vol. 16, no. 7, p. 995, Apr. 2024.

[6] J. Chen, Y. Zhang, and Z. Li, “Prediction and optimization of wastewater treatment performance via XGBoost–NSGA-II: COD removal and energy trade-offs,” Bioresource Technology, vol. 403, p. 125918, Jan. 2024.

[7] T. Liu, Y. Zeng, and P. Zhang, “Wastewater treatment process enhancement using SVM–Bayesian optimization and NSGA-II–TOPSIS multi-objective decision strategy,” Journal of Environmental Management, vol. 356, p. 120063, Jan. 2024.

[8] S. Qu, J. M. Mendel, and Z. Hou, “Model-assisted online optimization of gain-scheduled PID controllers via modified NSGA-II,” Applied Sciences, vol. 13, no. 11, p. 6444, Jun. 2023.

[9] A. J. Wang, Y. Zhang, J. Sun, and L. Li, “Digital twins for wastewater treatment: A technical review,” Engineering, vol. 26, pp. 1–13, 2024.

[10] S. M. H. Mousakazemi and M. A. Badamchizadeh, “Comparison of error-integral performance indices in a position control system,” Optimal Control Applications and Methods, vol. 42, no. 5, pp. 1237–1251, Sep. 2021.

[11] S. Mahfoud, A. S. Nouri, A. M. Fekik, and M. Tadjine, “A new PID tuning strategy optimized by genetic algorithms using ISE/IAE/ITAE criteria,” Systems, vol. 9, no. 2, p. 37, Jun. 2021.

[12] Y. Hu, Z. Chen, and H. Zhang, “Optimal tuning of multi-PID controllers as a constrained multi-objective optimization problem,” Scientific Reports, vol. 14, no. 1, p. 211, Jan. 2024.

[13] Y. Yang, J. Liu, and D. Wang, “Improving PID controller performance in nonlinear AGC systems using multi-objective optimization,” International Journal of Dynamics and Control, vol. 12, no. 3, pp. 845–856, Mar. 2024.

[14] M. Huang, J. Zhang, Y. Zhao, and H. Wang, “Multi-objective optimization of anaerobic digestion systems using GA–ANN hybrid models and NSGA-II,” Journal of Chemical Technology and Biotechnology, vol. 91, no. 1, pp. 226–233, Jan. 2016.