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Online PID Parameter Optimization Using Genetic Algorithm for a Wind Power Generation System

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Abstract

INTRODUCTION: In wind power generation systems, the unstable variability of wind energy significantly affects control quality and power stability. Conventional PID controllers often show limitations in nonlinear systems or systems with time-varying parameters, especially when integral windup and degraded transient performance occur.
OBJECTIVES: This paper proposes an online optimization method for PID parameters based on a Genetic Algorithm (GA), applied to a simplified dynamic model of a wind power generation system, in order to improve the system response quality.
METHODS: The studied system is modeled by a second-order transfer function representing the system's inertia and friction characteristics. The GA is implemented in a real-time optimization manner, using an objective function based on the ITAE criterion to evaluate and select the optimal PID parameter set.
RESULTS: Simulation results show that the proposed online GA–PID approach improves settling time, reduces overshoot, and eliminates steady-state error more effectively than fixed PID and conventional anti-windup PID controllers.
CONCLUSION: The proposed online GA–PID method is suitable for energy systems with high variability and adaptive control requirements, especially in wind power generation applications.

Keywords: Genetic Algorithm, PID controller, online optimization, wind power generation, anti-windup control.

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1. Introduction

In the context of global energy transition, exploiting and optimally controlling renewable energy systems (RES) such as wind, solar, and hydropower has become a crucial engineering challenge. The gradual replacement of fossil-fuel sources requires control solutions capable of ensuring frequency stability, power stability, and power quality under strong input variability. Meanwhile, these systems are often nonlinear, disturbed, and subject to physical constraints, making classical control methods difficult to maintain the desired performance.

One of the most effective research directions is the use of PID (Proportional–Integral–Derivative) controllers or variants such as PI, I–PD, or FOPID combined with metaheuristic optimization algorithms, where the Genetic Algorithm (GA) is considered a powerful tool for searching optimal controller parameters. With its simple structure, ease of implementation, and high reliability, PID remains central in industrial control systems, from speed control of DC/PMSM motors [1], [2] to load frequency control (LFC) in hybrid power systems [3], [4]. However, a fundamental drawback of traditional PID is the difficulty of determining optimal parameters *Kp, Ki, Kd* for all operating conditions.

The Genetic Algorithm, introduced by Holland in 1975, is based on Darwin's principle of natural evolution and enables global search in nonlinear solution spaces through selection, crossover, and mutation. When applied to PID tuning, GA can minimize objective functions such as IAE, ISE, ITAE, or ITSE, thereby reducing transient time, overshoot, and steady-state error [5]. Recent studies have extended GA by combining it with other algorithms such as PSO, QGA, or Tree-Seed Algorithm to improve convergence speed and avoid local minima [6], [7].

In renewable energy systems, fluctuations in wind and solar irradiance generate large variations in power and frequency. To maintain system stability, load frequency control (LFC) plays an important role. Qu et al. [3] demonstrated that GA- and PSO-optimized PID controllers reduce frequency oscillation amplitude and tie-line power variations in dual-area power systems. Liu et al. [4] also confirmed the effectiveness of GA for PID tuning in a hybrid wind–solar–diesel system, especially when combined with Superconducting Magnetic Energy Storage (SMES) for frequency stabilization.

Beyond LFC, GA–PID has been widely applied in motion and power control of electric motors. Wang et al. [4] developed an Improved Quantum Genetic Algorithm (IQGA) to optimize PID control for Permanent Magnet Synchronous Motors (PMSM), achieving faster response and reduced speed ripple compared with empirical tuning methods. Similarly, Benbouhenni et al. [8] applied a GA-enhanced PI controller for a multi-rotor DFIG wind turbine system, reducing power ripple by 70% and significantly improving power factor compared with conventional DPC control. These results suggest that GA is not only suitable for linear systems but also delivers clear benefits in nonlinear, time-varying systems with physical constraints.

At the algorithmic level, many GA variants have been proposed to improve computational efficiency. Devaraj et al. [9] developed a Queen Bee Assisted Genetic Algorithm (QBGA) to optimize a FOPID controller for a non-minimum phase converter, achieving higher robustness than classical PID. Meanwhile, Ibrahim et al. [10] combined GA with PSO to optimize a Nonlinear PID (NPID) controller for photovoltaic (PV) Maximum Power Point Tracking (MPPT), reaching 99.46% tracking efficiency with a settling time of only 0.052 s. Hybrid approaches such as GA–PSO, GA–TSA, or GA–COOT show strong potential for high performance with lower computational cost.

The GA–PID combination has also proven effective in intelligent control systems. Rodríguez-Abreo et al. [12] developed a self-tuning neural network PID (NN–PID), where the training dataset was generated by GA to find stable parameter sets for desired responses. Results showed that GA helped the neural network avoid non-convergent regions and ensured that 86% of parameter combinations produced stable responses. In nonlinear industrial control, Xiao et al. [13] optimized an integral-separation PID controller using GA for a lithium battery roller press, reducing error from 10 mm to 4 mm and improving calibration accuracy by 60%.

More broadly, GA has been used for voltage and current control in autonomous systems such as UAVs or mobile robots. D'Antuono et al. [14] used GA to determine weighting factors in an LQR-RSLQR robust controller for a lightweight UAV, achieving fast and stable response and reducing control error below 5%. These applications demonstrate the scalability of GA to multi-objective control problems and real-world experimentation.

In general, current research trends focus on designing GA-optimized PI/PID controllers for renewable energy systems, electric drives, and power control, aiming to:

- Optimize system dynamics (reduce overshoot, settling time, and steady-state error).
- Improve robustness and adaptability to disturbances and load changes.
- Ensure practical feasibility for embedded hardware and real-time implementation, as shown in Liu [4] and Benbouhenni [8].

Therefore, the topic "Online PID Parameter Optimization Using Genetic Algorithm for a Wind Power Generation System" is not only academically valuable but also highly practical in modern control design. It leverages GA's global search capability together with PID's simplicity and reliability, opening pathways for smart, robust controllers capable of real-time execution in future industrial environments.

2. Literature Review

Previous studies mainly focus on optimizing PID controllers using evolutionary algorithms to improve performance in energy and drive systems. Liu et al. [4] is among the pioneering works applying GA to a hybrid wind–solar–diesel system, demonstrating that GA-optimized PID can reduce frequency fluctuations and improve power stability. Qu et al. [3] extended this approach by combining GA and PSO for a dual-area system, achieving superior ITAE performance.

In motor drives, Wang et al. [2] developed an Improved Quantum GA to tune PID control for PMSM, achieving 20% faster response compared to PSO. Rodríguez-Abreo et al. [12] used GA to generate training datasets for NN–PID models, ensuring stability for over 86% of parameter combinations. In addition, hybrid GA variants such as QBGA [9], COOT–PID [11], and GA–PSO [10] show significant improvements in convergence speed and robustness.

Reviews of studies from 2020–2025 indicate a clear trend: moving from classical PID toward PID optimized by evolutionary algorithms such as GA and hybrid variants (GA–PSO, QGA, TSA), targeting smarter operation, reduced tuning time, and improved system stability.

Based on this, the authors propose online PID tuning using GA to optimize power and speed control in wind power generation systems. This approach inherits GA's global search advantages while meeting the dynamic operating requirements of RES, where wind conditions change continuously and immediate adaptability is needed.

3. The proposed approach

In this study, the authors propose an online PID parameter optimization method based on the Genetic Algorithm, applied to a simplified dynamic model representing a wind power generation system. The proposed method follows the idea in [16] but is restructured and presented more generally to provide a basis for future extension to more complex models.

3.1. System model

The studied second-order system model is given by:

$$G(s) = \frac{127}{s2+18s}. \tag{1}$$

This transfer function represents inertia and equivalent resistance (friction) of an electromechanical system under the control input signal. Although simplified, the model still allows full evaluation of key indices such as overshoot, steady-state error, settling time, and response under parameter variations.

The input signal is a unit-amplitude step, which is suitable for evaluating controller performance in the transient region.

3.2. PID control and saturation structure

The controller has the form:

$$u(t) = K_p e(t) + K_i \int e(t)dt + \frac{K_d de(t)}{dt}. \tag{2}$$

In environments with large disturbances or strong control signals, PID controllers can easily enter control saturation, causing windup. To address this, the authors implement an anti-windup structure similar to [16], using an adaptive factor to adjust the integral action when saturation occurs:

$$\varphi = \begin{cases} -\dfrac{\alpha(u_n - u_s)}{k_i}, u_n \neq u_s, e(u_n - \bar{u}) > 0 \\ e, u_n = u_s \end{cases}. \tag{3}$$

Where $\bar{u} = (u_{min} + u_{max})/2$, $\alpha > 0$, and u_{min} and u_{max} are the minimum and maximum values of the control input, respectively. Therefore, the anti-windup PID controller is expressed as:

$$u(t) = K_p e(t) + K_i \varphi + \frac{K_d de(t)}{dt}. \tag{4}$$

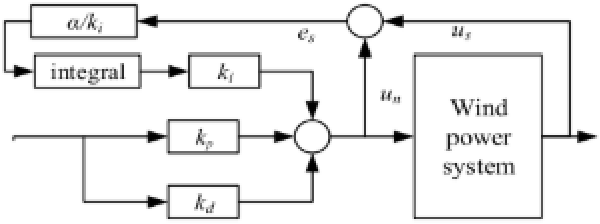

Figure 1. Block diagram of the saturation structure

This mechanism improves stability when load or parameters change abruptly while maintaining smooth control signals.

3.3. Online optimization procedure

The key difference between the proposed approach and offline studies is real-time optimization capability. GA performs optimization by encoding parameters (K_p, K_i, K_d) as chromosomes and evaluating each parameter set using the ITAE cost function:

$$J = \int_0^T t|e(t)|dt. \tag{5}$$

3.4. Online optimization procedure

The online GA–PID procedure consists of four steps:

- Initialize the population based on Ziegler–Nichols values with slight variations around initial parameters.
- Evaluate fitness for each individual within the control time window.
- Apply crossover and mutation to generate a new generation.
- Update PID parameters using the best-fitness individual before entering the next control cycle.

The process repeats continuously, allowing the controller to adapt to parameter deviations and input variations.

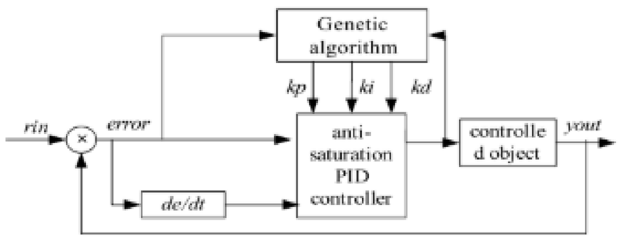

Figure 2. Structure of the Genetic Algorithm for PID parameter optimization

3.5. Feasibility for embedded implementation

The proposed online GA–PID algorithm is validated in the MATLAB/Simulink environment using a population size of 30 individuals and 100 generations. While this configuration is suitable for simulation, it would be computationally demanding for direct implementation on low-power embedded hardware. However, in practical wind turbine control systems, the Genetic Algorithm is not required to operate at the same fast sampling rate as the PID controller.

In a realistic embedded implementation, the PID controller runs at a fast sampling rate (typically 1–5 ms) to guarantee closed-loop stability, whereas the Genetic Algorithm is executed at a slower supervisory level (e.g., every 50–100 ms) to gradually update the control gains. By reducing the population size to 5–10 individuals and limiting the number of generations per update cycle to 1–5, the computational complexity can be reduced by more than 90% compared to the simulation configuration.

To illustrate this execution strategy, a practical real-time scheduling structure for the proposed GA–PID controller is presented in Figure 3, where the separation between the fast PID loop and the slow GA optimization loop is clearly demonstrated. This hierarchical structure ensures real-time stability while preserving the adaptive capability of the controller.

Furthermore, with fixed-point arithmetic implementation and reduced GA execution frequency, the estimated computational load remains within the capability of typical modern embedded platforms such as DSPs, ARM Cortex-M7 microcontrollers, and embedded Linux-based controllers commonly used in wind power generation systems. Therefore, the proposed method is not only effective in simulation but also practically feasible for future real-time hardware deployment.

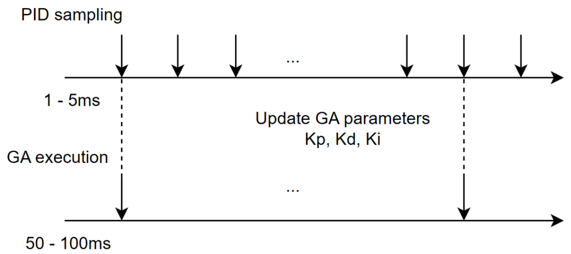

Figure 3. Real-time Scheduling Diagram of GA–PID on Embedded System

4. Results

This section presents results reproducing all experiments in [16] and extending validation through additional tests. Simulations were carried out in MATLAB/Simulink with a sampling time of 1 ms.

4.1. Comparison between conventional PID and anti-windup PID

With a unit step input, the conventional PID shows clear limitations: non-zero steady-state error, large overshoot, and clipped control signals due to saturation. In contrast, the anti-windup PID produces more stable output, tracks the reference more quickly, and avoids windup.

Notably, the control signal gradually converges to a similar waveform before and after saturation, demonstrating the effectiveness of suppressing integral action under unfavorable conditions.

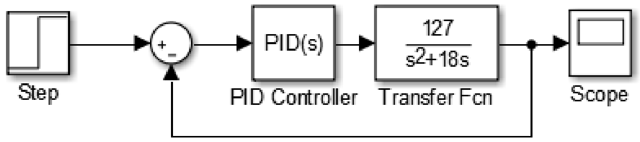

Figure 4. Conventional PID control block diagram

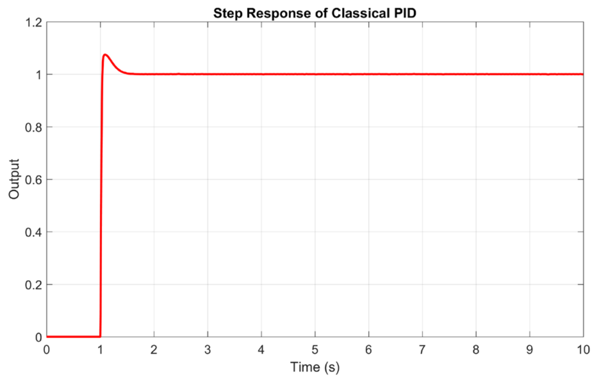

Figure 5. System response using conventional PID under saturation

Using PID Tuner in Simulink, the obtained gains are K_p = 8,719; K_i = 48.797; K_d = 0,351, with overshoot 9,73%, rise time 0,027s, and settling time 0,31s

Simulation initialization parameters:

Table 1. GA initialization parameters

Number of individuals per GA generation	30
Maximum number of GA generations	100
Crossover probability	0,9
Mutation probability	0,03

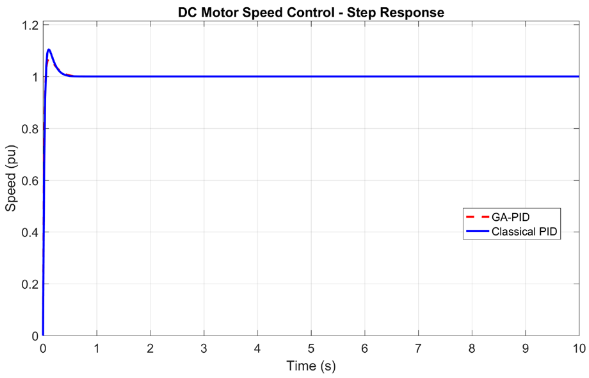

Figure 6. Comparison of system responses between anti-windup PID and conventional PID

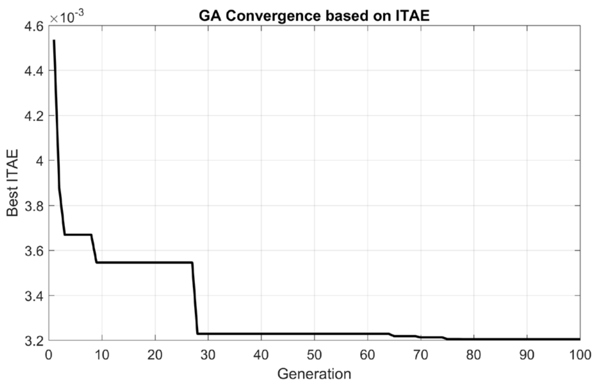

Figure 7. ITAE index

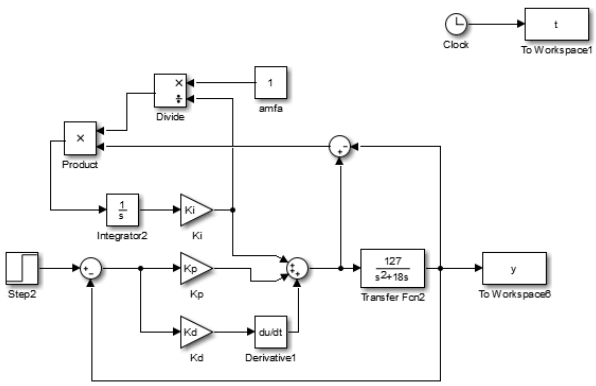

Figure 8. Anti-windup PID control block diagram

4.2. System optimization results using GA

With a GA mini-population, the system converges to a nearby parameter set (K_p; K_i; K_d) ≈ (9,1460; 49,4365; 0,4045) chỉ sau một số vòng lặp. Các chỉ tiêu quan sát:

Performance and Robustness

	Tuned	Block
Rise time	0.0273 seconds	0.0249 seconds
Settling time	0.313 seconds	0.323 seconds
Overshoot	9.73 %	7.46 %
Peak	1.1	1.07
Gain margin	-Inf dB @ 0 rad/s	-Inf dB @ 0 rad/s
Phase margin	69 deg @ 48.5 rad/s	69.7 deg @ 54.4 rad/s
Closed-loop stability	Stable	Stable

Figure 9. Comparison of parameters after optimization

- Overshoot decreases from 9.73% to 7.45%.
- Rise time decreases from 0.273s to 0.0249s.
- Settling time increases slightly from 0.313s to 0.323s, but not significantly.
- Steady-state error is nearly zero.
- Control signal becomes smoother and avoids saturation.

The optimized response shows clear improvement in both transient quality and final stability.

5. Conclusion

This paper presented a reproduction and validation procedure for an online PID parameter optimization method based on Genetic Algorithm for a linear wind power generation model. Simulation results show that the online GA–PID outperforms fixed PID and anti-windup PID under all test conditions, especially when system parameters change or when the control signal saturates. The online optimization method provides fast adaptation, reduced settling time, and improved stability. Future work includes extending the algorithm to real wind turbine models such as DFIG or PMSG and implementing it on hardware to verify real-time performance.

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