Graylag Goose Optimization Algorithm-Based PI Controller Tuning for Enhanced Control of Permanent Magnet Synchronous Generator Wind Turbines with Tip Speed Ratio Maximum Power Point Tracking

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Abstract

A new proportional–integral (PI) controller tuning method for permanent magnet synchronous generator (PMSG) wind energy conversion system based on the recently developed Graylag Goose Optimization (GGO) algorithm is presented in this paper. The control scheme is for the control of the rotor side and grid side converters of a 2 MW back-to-back converter topology. The GGO algorithm optimizes eight PI gains of d–q axis current regulation, DC-link voltage control and reactive power management inspired by the cooperation in foraging of flocks of birds Anser anser and the exchange of leaders in a flock while flying in V-formation. For the aerodynamic power extraction in the variable wind conditions, there is an optimum speed ratio for the wind and the blades, which is incorporated in the present invention as tip speed ratio (TSR) based maximum power point tracking (MPPT) strategy and does not need to measure the wind speed directly. The proposed GGO-PI controller is compared with the well-known Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA) and conventional Ziegler-Nichols (ZN) tuning algorithms with the same stochastic Kaimal-spectrum wind profile and 40% grid voltage sag disturbance. The simulation results in MATLAB R2023b/Simulink show that the proposed approach yields a superior dynamic response, improved tracking accuracy, and even better robustness, and the smallest ITAE is 0.0317. The voltage overshoot of the DC-link is decreased by 31.4% compared to the standard methods, and the power ripple is decreased by 27.6% compared to the standard methods. Further, the system total harmonic distortion (THD) at the grid point is kept below 2.31%, which is compliant with the IEEE 519-2022 standard. Results from 30 independent Monte Carlo runs converge within 87 iterations and have the smallest performance variation compared to all the other optimizers tested. The method also has the highest MPPT efficiency of 97.2%, which shows a higher energy capturing capability. These results validate that the proposed GGO-based PI tuning algorithm is a strong, efficient and practically applicable tuning method for grid connected PMSG wind energy systems.

Keywords: Graylag Goose Optimization; GGO algorithm; PI controller tuning; PMSG wind turbine; tip speed ratio MPPT; rotor-side converter; grid-side converter; metaheuristic optimization; wind energy conversion systems; ITAE

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Nomenclature

Symbol	Description	Unit
P_m	Mechanical power extracted from wind	W
ρ	Air mass density	kg/m^3
A_r	Rotor swept area	m^2
R	Blade radius	m
V_w	Upstream wind velocity	m/s
$C_p(\lambda, \beta)$	Aerodynamic power coefficient	—
λ	Tip speed ratio	—
λ_{opt}	Optimal tip speed ratio	—
β	Blade pitch angle	deg
ω_r	Rotor angular velocity	rad/s
J	Combined rotor-generator moment of inertia	$kg \cdot m^2$
T_m	Aerodynamic torque	N·m
T_{em}	Electromagnetic torque	N·m
B	Viscous friction coefficient	N·m·s/rad
v_{ds}, v_{ds}	d- and q-axis stator voltages	V
i_{ds}, i_{qs}	d- and q-axis stator currents	A
R_s	Stator winding resistance	Ω
L_{ds}, L_{qs}	d- and q-axis stator inductances	H
ω_e	Electrical angular velocity	rad/s
p	Number of pole pairs	—
ψPM	Permanent magnet flux linkage	Wb
v_{dc}	DC-link voltage	V
C	DC-link capacitance	F
L_f, R_f	Grid filter inductance and resistance	H, Ω
K_p, K_i	PI proportional and integral gains	—
ITAE	Integral Time Absolute Error	—
THD	Total Harmonic Distortion	—
TSR	Tip Speed Ratio	—
MPPT	Maximum Power Point Tracking	—
GGO	Graylag Goose Optimization	—
PSO	Particle Swarm Optimization	—
GWO	Grey Wolf Optimizer	—
PMSG	Permanent Magnet Synchronous Generator	—
RSC / GSC	Rotor-Side / Grid-Side Converter	—
WECS	Wind Energy Conversion System	—
FOC	Field-Oriented Control	—
MTPA	Maximum Torque Per Ampere	—

1. Introduction

The accelerating global imperative to decarbonize the electricity sector has positioned wind energy as one of the most strategically significant pillars of the clean energy transition [1, 2]. As of 2024, global installed wind capacity surpassed 1,100 GW, with projections from the International Renewable Energy Agency (IRENA) indicating that wind power will supply approximately 35% of global electricity generation by 2050 [2]. Within the generator technology landscape, the permanent magnet synchronous generator (PMSG) has emerged as the preferred configuration for utility-scale variable-speed, direct-drive wind turbine applications. Its principal merits encompass high power density, absence of rotor windings and associated copper losses, elimination of brush-ring maintenance requirements, high reliability, and inherently superior partial-load efficiency relative to doubly-fed induction generatorsand electrically excited synchronous machines [3, 4]. The full-scale back-to-back power converter interface employed in PMSG systems affords complete electromagnetic decoupling between the mechanical subsystem and the utility network, enabling independent regulation of active and reactive power flows under grid code compliance requirements [5].

The performance of PMSG-based wind energy conversion systems (WECS) is profoundly contingent upon the quality of the control algorithms governing the rotor-side converter (RSC) and grid-side converter (GSC). The prevailing industrial control paradigm employs proportional-integral (PI) regulators embedded within cascaded current and voltage control loops, implemented in the synchronous dq reference frame [6-8]. Despite their structural simplicity and interpretability, PI controllers exhibit critical performance sensitivity to the selection of the proportional gain Kp and integral gain Ki. Poorly calibrated gains manifest as oscillatory transients, excessive DC-link voltage excursions, degraded power quality, reactive power regulation errors, and, under severe conditions, converter instability when subjected to rapid wind speed variations or grid disturbance events [9, 10].

Classical tuning methodologies including Ziegler-Nichols (ZN) frequency response methods, pole-placement techniques, and internal model control (IMC) yield satisfactory performance under narrow linearized operating conditions but exhibit pronounced deterioration when confronted with the inherently nonlinear, time-varying, and stochastic dynamics of wind-driven generation systems [11]. The multi-parameter, nonlinear, and frequently multimodal nature of the simultaneous PI tuning optimization problem encompassing up to eight independent gain parameters when both RSC and GSC are considered renders gradient-based and analytical approaches conceptually insufficient [12, 13]. This recognition has catalysed extensive application of nature-inspired metaheuristic optimization algorithms to the PI tuning problem, leveraging their stochastic global search capability to navigate high-dimensional, non-convex objective spaces without demanding gradient information [14, 15].

An extensive body of literature has applied metaheuristic algorithms to PI controller optimization in WECS contexts. Kennedy and Eberhart's Particle Swarm Optimization (PSO) [16, 17] was among the earliest applied to this domain, demonstrating improved transient response relative to classical methods. Genetic Algorithms (GA) [18] introduced evolutionary selection mechanisms but exhibited high computational overhead. The Grey Wolf Optimizer (GWO) of Mirjalili et al. [19] introduced hierarchical predator-prey social dynamics and demonstrated competitive convergence on benchmark functions. The Whale Optimization Algorithm (WOA) [20], Artificial Bee Colony (ABC) [21], and Salp Swarm Algorithm (SSA) [22] have been independently evaluated with varying degrees of success. Mahmoud et al., [23] applied an improved GWO to a 2 MW PMSG system, reporting an ITAE of 0.0489, a benchmark value contextualized in the present study. Souag et al. [24] conducted a comparative PSO-GWO study for PMSG MPPT control, while Hasanien and Muyeen [25] applied genetic algorithms to variable-speed wind controller parameter optimization. Despite these contributions, persistent limitations remain: premature convergence in high-dimensional gain spaces, sensitivity to algorithm hyperparameters, and insufficient exploration-exploitation balance across the full optimization trajectory.

The Graylag Goose Optimization (GGO) algorithm, introduced by Mohammadi-Balani et al. in 2024 [26], represents a biologically motivated addition to the metaheuristic repertoire. The GGO encodes three behaviorally distinct mechanisms observed in Anser anser migratory flocks: aerodynamic V-formation drafting (exploitation), stochastic leadership rotation (diversification), and opportunistic foraging dispersal (exploration). Preliminary benchmarking on the CEC-2017 standard test suite demonstrated GGO's competitive performance relative to PSO, GWO, and WOA, particularly on high-dimensional multimodal functions characterized by deceptive local optima structures [26]. Critically, its application to

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power electronics control parameter optimization and specifically to multi-loop PI tuning in PMSG-WECS has not been previously reported in the open literature, constituting a genuine research gap addressed by the present work.

Equally critical to converter control quality is the maximum power point tracking (MPPT) strategy. The tip speed ratio (TSR)-based MPPT approach maintains the instantaneous tip speed ratio λ at its aerodynamic optimum λ_{opt} by regulating rotor speed, thereby maximizing the power coefficient Cp [27, 28]. Compared with perturb-and-observe (P&O) methods, which introduce persistent oscillations around the maximum power point and can mistrack under rapidly varying wind conditions [29, 30], TSR-MPPT provides deterministic, physically transparent reference generation amenable to rigorous optimization-driven control design.

Against this background, the present paper makes the following original contributions to the field:

(i) The first documented application of the GGO algorithm to simultaneous multi-loop PI controller gain optimization in a full-scale PMSG-WECS with back-to-back converter topology, optimizing eight gain parameters across RSC and GSC control structures.

(ii) Development and validation of a TSR-MPPT integrated GGO-PI control architecture for variable-speed wind turbine operation under realistic stochastic Kaimal-spectral wind profiles.

(iii) A rigorous comparative evaluation of GGO-PI against PSO-PI, GWO-PI, WOA-PI, and ZN-PI controllers across comprehensive transient, steady-state, power quality, and grid disturbance rejection performance metrics.

(iv) Statistical robustness analysis via 30-trial Monte Carlo simulation with Wilcoxon signed-rank hypothesis testing to validate the probabilistic superiority of the proposed approach.

(v) Physical interpretation of optimized gain configurations and their correspondence with classical cascade control stability theory, enhancing the engineering interpretability of the proposed framework.

This paper is organized as follows. Section 2 presents the mathematical modelling of the PMSG-WECS. Section 3 details the TSR-MPPT strategy and vector control architecture. Section 4 introduces the GGO algorithm and formulates the PI tuning optimization problem. Section 5 describes the simulation environment and comparative results. Section 6 provides statistical analysis and discussion. Section 7 identifies study limitations and future directions. Section 8 concludes the paper.

2. Mathematical Modeling of The Pmsg Wind Energy Conversion System

2.1 Wind Turbine Aerodynamic Model

The mechanical power extracted from the wind stream by the turbine rotor is expressed through the fundamental aerodynamic relationship:

$$P_m = \frac{1}{2}\rho A_r V_w^3 C_p(\lambda, \beta) \quad (1)$$

Where

$$A_r = \pi R^2$$

where $\rho\,(\mathrm{kg/m^3})$ denotes the air mass density, A_r is the rotor swept area with blade radius R (m), V_w (m/s) is the upstream wind velocity, and $C_p(\lambda, \beta)$ is the dimensionless aerodynamic power coefficient, which is a nonlinear function of the tip speed ratio λ and the blade pitch angle β (degrees).

The tip speed ratio is defined as the ratio of the blade tip tangential velocity to the free-stream wind velocity:

$$\lambda = \frac{\omega_r R}{V_w} \quad (2)$$

where ω_r (rad/s) is the rotor angular velocity. The power coefficient C_p is commonly approximated using the following analytical expression derived from blade element momentum theory [31]:

$$C_p(\lambda, \beta) = 0.5176\left(\frac{116}{\lambda_i} - 0.4\beta - 5\right)e^{-21/\lambda_i} + 0.0068\lambda \quad (3)$$

With

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1+\beta^3} \quad (4)$$

For the simulation study reported herein, the standard turbine coefficients c1 = 0.5176, c2 = 116, c3 = 0.4, c4 = 5, c5 = 21, and c6 = 0.0068 are adopted, yielding a maximum power coefficient Cp, max = 0.48 at an optimal tip speed ratio λ_{opt} = 8.1 and zero pitch angle [31]. The aerodynamic torque delivered to the generator shaft is:

$$T_{aero} = T_m = \frac{P_m}{\omega_r} = \frac{1}{2}\rho A_r R V_w^2 C_q \quad (5)$$

Where $C_q = \frac{C_p}{\lambda}$ is the torque coefficient.

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2.2 Drive Train Model

For direct-drive PMSG configurations, the drive train is represented by a single-mass lumped inertia model, which neglects the gearbox dynamics:

$$J\frac{d\omega_r}{dt} = T_m - T_{em} - B\omega_r \quad (6)$$

Where $J\,(\mathrm{kgm}^2)$ is the combined rotor-generator moment of inertia, T_{em} (Nm) is the electromagnetic torque of the PMSG, and $B\,(\mathrm{Nms/rad})$ is the viscous friction coefficient. This simplified model is appropriate for direct-drive systems in which the gearbox resonance modes are absent [32].

2.3 PMSG Electrical Model in the Synchronous dq Reference Frame

The dynamic equations of the PMSG are most conveniently expressed in the rotor-flux-oriented synchronous reference frame, where the d-axis is aligned with the permanent magnet flux vector ψPM. The stator voltage equations are [33]:

$$v_{ds} = R_s i_{ds} + L_{ds}\frac{di_{ds}}{dt} - \omega_e L_{qs} i_{ds} \quad (7)$$

$$v_{qs} = R_s i_{qs} + L_{qs}\frac{di_{qs}}{dt} + \omega_e (L_{ds} i_{ds} + \psi PM) \quad (8)$$

Where v_{ds} and v_{qs} are the d and q axis stator voltages; i_{ds} and i_{qs} are the d and q axis stator currents; Rs is the stator winding resistance per phase; L_{ds} and L_{qs} are the d and q axis stator inductances; $\omega_e = P\omega_r$ is the electrical angular velocity with p being the number of pole pairs; and ψPM is the permanent magnet flux linkage.

The electromagnetic torque is:

$$T_{em} = \frac{3}{2} p\left[\psi PM i_{qs} + \left(L_{ds} - L_{qs}\right) i_{ds} i_{qs}\right] \quad (9)$$

For surface-mounted PMSG (SPMSM), the saliency ratio is unity ($L_{ds} = L_{qs} = Ls$), reducing Equation (9) to:

$$T_{em} = \frac{3}{2} p\psi PM i_{qs} \quad (10)$$

This expression reveals that the electromagnetic torque is linearly proportional to the q-axis current component alone, enabling straightforward torque control through i_{qs} regulation. Setting the d-axis current reference $i_{ds} = 0$ implements the maximum torque per ampere (MTPA) strategy for non-salient machines, minimizing copper losses.

2.4 DC-Link and Grid-Side Converter Model

The DC-link capacitor dynamics are governed by the energy balance equation:

$$CV_{dc}\frac{dV_{dc}}{dt} = P_{RSC} - P_{GSC} \quad (11)$$

Where C is the DC-link capacitance, Vdc is the DC-link voltage, P_{RSC} is the power delivered by the RSC to the DC bus, and P_{GSC} is the power drawn by the GSC from the DC bus. Maintaining Vdc at its rated value V_{dc} = 1200 V is the primary control objective of the GSC. The GSC is modeled in a voltage-oriented reference frame (VOF) synchronized to the positive-sequence grid voltage vector [34]. The grid-side current dynamics are:

$$L_f\frac{di_{dg}}{dt} = -R_f i_{dg} + \omega_g L_f i_{dg} + v_{dg} - e_{dg} \quad (12)$$

$$L_f\frac{di_{qg}}{dt} = -R_f i_{qg} + \omega_g L_f i_{dg} + v_{qg} - e_{qg} \quad (13)$$

where L_f and Rf are the filter inductance and resistance; i_{dg} and i_{qg} are the d- and q-axis grid currents; v_{dg} and v_{qg} are the converter output voltages; e_{dg} and e_{qg} are the grid voltages; and ω_g is the grid angular frequency.

3. Control Strategy: Tsr-Mppt and Vector Control Architecture

3.1 Tip Speed Ratio-Based MPPT

The TSR-MPPT strategy formulates the speed reference for the generator as that which maintains the instantaneous tip speed ratio at its aerodynamic optimum λ_{opt} [34, 35]. The optimal rotor speed reference is computed as:

$$\omega_r^* = \frac{\lambda_{opt} V_w}{R} \quad (14)$$

In practical implementations, the wind speed V_w required by Equation (14) is typically obtained from an anemometer measurement or from a wind speed estimator. Given the reliability challenges of direct wind speed measurement in turbulent environments, a sliding-mode-based wind speed estimator is employed in this work. The speed error signal:

$$e_\omega(t) = \omega_r^* - \omega_r \quad (15)$$

is processed by a speed-loop PI controller, the output of which yields the q-axis current reference i_{qs}^*. Since the optimal power curve follows:

$$T_e^* = K_{p1} e_\omega(t) + K_{i1}\int e_\omega(t)\, dt \quad (16)$$

The MPPT target is uniquely defined by the rotor speed, ensuring smooth convergence to

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maximum power extraction across the entire operating wind speed range.

3.2 Rotor-Side Converter Control

The RSC implements field-oriented control (FOC) in the PMSG dq reference frame. The outer speed loop generates i_{qs}^*, while $i_{ds}^* = 0$ for MTPA operation [36]. The inner current control loops employ PI regulators with decoupling feedforward compensation to counteract the cross-coupling terms omega_e*Lqs*i_qs and omega_e*(Lds*i_ds + psi_PM) present in Equations (7) and (8). The RSC voltage references are:

$$v_{qs}^* = K_{p1}\left(i_{qs}^* - i_{ds}\right) + K_{i1}\int(i_{ds}^* - i_{ds})\,dt - \omega_e L_{qs} i_{qs} \quad (17)$$

$$v_{qs}^* = K_{p2}\left(i_{qs}^* - i_{qs}\right) + K_{i2}\int\left(i_{qs}^* - i_{qs}\right)dt + \omega_e(L_{ds} i_{ds} + \psi PM)$$
(18)

where $(K_{p1},\ K_{i1})$ and $(K_{p2},\ K_{i2})$ are the proportional and integral gains of the d-axis and q-axis current controllers, respectively. These four gain parameters constitute the RSC PI optimization subspace.

3.3 Grid-Side Converter Control

The GSC is controlled in a voltage-oriented frame aligned with the positive-sequence grid voltage vector, ensuring e_{dg}= |Eg| and e_{qg} = 0. The outer DC voltage loop produces the d-axis current reference i_{dg}^*, while the q-axis current reference i_{qg}^*regulates reactive power exchange with the grid:

$$Q_g^* = \frac{3}{2}\left|E_g\right| i_{qg}^* \quad (19)$$

For unity power factor operation, i_{qg}^* = 0. The inner current controllers generate the PWM voltage references with decoupling feedforward:

$$v_{dg}^* = K_{p3}\left(i_{dg}^* - i_{dg}\right) + K_{i3}\int\left(i_{dg}^* - i_{dg}\right)dt - \omega_g L_f i_{qg} + e_{dg}$$
(20)

$$v_{qg}^* = K_{p4}\left(i_{qg}^* - i_{qg}\right) + K_{i4}\int\left(i_{qg}^* - i_{qg}\right)dt - \omega_g L_f i_{dg} + e_{qg}$$
(21)

The gains $(K_{p3},\ K_{i3})$ control the DC-link voltage loop and $(K_{p4},\ K_{i4})$ regulate the reactive power loop. The combined RSC and GSC parameterization yield a six-dimensional optimization problem: $\theta = (K_{p1},\ K_{i1},\ K_{p2},\ K_{i2},\ K_{p3},\ K_{i3})$ with K_{p4}, K_{i4} appended as a four-dimensional GSC subspace in extended formulations.

4. Graylag Goose Optimization Algorithm And Pi Tuning Formulation

4.1 Biological Inspiration

The Graylag Goose Optimization (GGO) algorithm [37] draws its computational metaphors from three key behavioral characteristics of Anser anser flocks during migratory flight:

(a) V-formation aerodynamic drafting: Each individual in the flock, except the lead goose, exploits the aerodynamic upwash generated by the preceding individual's wingtip vortices, reducing metabolic cost of sustained flight. In the optimization analogy, each candidate solution updates its position by partially following a superior neighbor, implementing directed exploitation toward high-fitness regions.

(b) Leadership rotation: Geese periodically rotate the lead position to distribute energetic burden, preventing exhaustion of any individual. This mechanism prevents premature convergence by stochastically selecting new reference individuals, diversifying search trajectories.

(c) Opportunistic foraging dispersal: During rest periods, geese disperse widely from roosting sites to forage in surrounding areas, re-aggregating thereafter. This provides global exploration capability, enabling the swarm to escape local attraction basins.

4.2 Mathematical Formulation

Let the population of N candidate solutions be denoted$X_i = \left[x_{i,1}, x_{i,2}, \dots, x_i, D\right] \quad i = 1, 2, \dots, N$ where D is the problem dimension and each solution represents a candidate PI gain vector. The algorithmic phases proceed as follows:

4.2.1 Initialization

Candidate solutions are initialized via uniform random sampling within the defined search bounds:

$$x_{i,j}^{(0)} = LB_j + r(0,1)\left(UB_j - LB_j\right) \quad (22)$$

where LB_j and UB_j are the lower and upper bounds for the j^{th}gain parameter, and rand(0,1) is a uniformly distributed random number.

4.2.2 V-Formation Drafting Phase (Exploitation)

In each iteration t, the fitness of all individuals is evaluated. The global best solution $\mathrm{X}_{\mathrm{best}}^{\mathrm{t}}$ is identified. The position update for each individual during the drafting phase is:

$$\mathrm{X}_{\mathrm{i}}^{\mathrm{t+1}} = \mathrm{X}_{\mathrm{i}}^{\mathrm{t}} + \alpha\left(\mathrm{X}_{\mathrm{best}}^{\mathrm{t}} - \mathrm{X}_{\mathrm{i}}^{\mathrm{t}}\right)\cos(\theta_{\mathrm{i}}) + \beta \mathrm{r} \mathrm{X}_{\mathrm{best}}^{\mathrm{t}}$$

(23)

where alpha is the drafting coefficient modulating the attraction toward the current leader, $\theta_{\mathrm{i}} = \frac{2\pi \mathrm{i}}{\mathrm{N}}$ is the angular offset corresponding to the i-th position in the V-formation, and beta is a self-confidence weight. The cosine term introduces a formation-dependent directional bias, ensuring that geese at different formation positions update their trajectories with appropriate phase diversity.

4.2.3 Leadership Rotation Phase

At each iteration, the leader is probabilistically replaced according to:

$\mathrm{X}_{\mathrm{leader}} = \mathrm{X}_{\mathrm{i}} \quad \text{if} \quad \mathrm{f}(\mathrm{X}_{\mathrm{i}}) < \mathrm{f}(\mathrm{X}_{\mathrm{leader}})(1 + \delta \mathrm{r})$
(24)

where δ is a leadership sensitivity parameter that prevents premature fixation on a single leader. This stochastic perturbation of the acceptance threshold emulates the leadership transition dynamics observed in real goose formations.

4.2.4 Foraging Dispersal Phase (Exploration)

To maintain population diversity and escape local optima, a foraging dispersal operator is applied with probability pf:

$\mathrm{X}_{\mathrm{i}}^{\mathrm{t+1}} = \mathrm{LB} + \mathrm{r}\left(\mathrm{UB}_{\mathrm{j}} - \mathrm{LB}_{\mathrm{j}}\right)$ (25)$\mathrm{X}_{\mathrm{i}}^{\mathrm{t+1}} = \mathrm{X}_{\mathrm{i}}^{\mathrm{t}} + \gamma\left(\mathrm{X}_{\mathrm{rand}}^{\mathrm{t}} - \mathrm{X}_{\mathrm{i}}^{\mathrm{t}}\right)$ otherwise (26)

where γ is a step-size scaling factor and $\mathrm{X}_{\mathrm{rand}}^{\mathrm{t}}$ is a randomly selected population member. The foraging probability pf decreases adaptively from pfmax to pfmin over the course of the optimization run:

$\mathrm{p}_{\mathrm{f}}(\mathrm{t}) = \mathrm{p}_{\mathrm{f,max}} - \left(\mathrm{p}_{\mathrm{f,max}} - \mathrm{p}_{\mathrm{f,min}}\right)\frac{\mathrm{t}}{\mathrm{T}_{\mathrm{max}}}$ where $0 \leq \mathrm{t} \leq \mathrm{T}_{\mathrm{max}}$ (27)

where $\mathrm{T}_{\mathrm{max}}$ is the maximum number of iterations, $\mathrm{p}_{\mathrm{f,max}}$ denotes the initial exploration probability, $\mathrm{p}_{\mathrm{f,min}}$ represents the final exploration probability. This formulation implements a controlled transition from exploration-dominant early iterations to exploitation-dominant later iterations, mirroring the energy management observed in long-range migratory bird species.

4.2.5 Boundary Handling

Violated bounds are corrected by reflection to preserve solution diversity near constraint boundaries without truncating gradient information:

$$\mathrm{x}_{\mathrm{i,j}} = \mathrm{LB}_{\mathrm{j}} + \mathrm{mod}\left(\left|\mathrm{X}_{\mathrm{i,j}} - \mathrm{LB}_{\mathrm{j}}\right|, \mathrm{UB}_{\mathrm{j}} - \mathrm{LB}_{\mathrm{j}}\right) \quad \text{if } \mathrm{X}_{\mathrm{i,j}} < \mathrm{LB}_{\mathrm{j}}$$

(28)

$$\mathrm{x}_{\mathrm{i,j}} = \mathrm{UB}_{\mathrm{j}} - \mathrm{mod}\left(\left|\mathrm{X}_{\mathrm{i,j}} - \mathrm{UB}_{\mathrm{j}}\right|, \mathrm{UB}_{\mathrm{j}} - \mathrm{LB}_{\mathrm{j}}\right) \quad \text{if } \mathrm{X}_{\mathrm{i,j}} > \mathrm{LB}_{\mathrm{j}}$$

(29)

4.3 PI Tuning as a Constrained Optimization Problem

The PI gain tuning problem is cast as a continuous, bound-constrained optimization problem. The objective function is formulated as the Integral Time Absolute Error (ITAE) summed across all regulated outputs, which yields superior transient performance compared with ISE or ITSE criteria in power converter applications [38, 39]:

$$J(\theta) = \int_0^{T_{sim}} t\left[w_1|e_\omega(t)| + w_2\left|e_{V_{dc}}(t)\right| + w_3|e_{id}(t)| + w_4\left|e_{iq}(t)\right|\right]dt$$

(30)

Where e_ω, $e_{V_{dc}}$, e_{id}, and e_{iq} are the speed error, DC-link voltage error, d-axis current error, and q-axis current error signals, respectively; w_1 through w_4 are weighting coefficients that reflect the relative importance of each regulated variable; and Tsim is the simulation horizon for objective function evaluation. A penalty function $P(\theta)$ is appended to handle inequality constraints arising from transient performance specifications:

$\mathrm{J}_{\mathrm{total}}(\theta) = \mathrm{J}(\theta) + \mathrm{P}(\theta)$ (31)

$\mathrm{P}(\theta) = \mu_1 \max\left(0, \Delta \mathrm{V}_{\mathrm{dc,max}} - \Delta \mathrm{V}_{\mathrm{dc}}^{\mathrm{lim}}\right) + \mu_2 \max\left(0, \mathrm{t}_{\mathrm{s}} - \mathrm{t}_{\mathrm{s}}^{\mathrm{lim}}\right)$ (32)

and,

$$\theta = \left[\mathrm{K}_{\mathrm{p1}}, \mathrm{K}_{\mathrm{i1}}, \mathrm{K}_{\mathrm{p2}}, \mathrm{K}_{\mathrm{i2}}, \mathrm{K}_{\mathrm{p3}}, \mathrm{K}_{\mathrm{i3}}, \mathrm{K}_{\mathrm{p4}}, \mathrm{K}_{\mathrm{i4}}\right]$$

Where $\Delta \mathrm{V}_{\mathrm{dc,max}}$ is the maximum DC-link voltage overshoot, $\mathrm{V}_{\mathrm{dc}}^{\mathrm{lim}} = 120$ V is the permissible overshoot limit, t_{s} is the settling time, $\mathrm{t}_{\mathrm{s}}^{\mathrm{lim}} = 0.15$ s is the settling time constraint, and μ_1, μ_2 are penalty multipliers. The optimization bounds are set as Kp in [0.001, 100] and Ki in [0.001, 1000]. The GGO algorithm parameters adopted in this study are: N = 50 agents, Tmax = 200 iterations, $p_{\mathrm{f,max}}$ = 0.8, $p_{\mathrm{f,min}}$ = 0.05, α = 0.7, β = 0.3, γ = 0.5, δ = 0.1. The algorithm is initialized with 30 independent random seeds to facilitate statistical robustness analysis.

5. Simulation Setup and Results

5.1 MATLAB/Simulink Model Description

The complete PMSG-WECS was implemented in MATLAB R2023b/Simulink using the Simscape Electrical toolbox. The system parameters correspond to a 2 MW direct-drive configuration as summarized in Table 1. The back-to-back converter employs IGBT switches at 5 kHz switching frequency with sinusoidal PWM modulation. The grid is modelled as an ideal positive-sequence three-phase voltage source at 690 V (line-to-line RMS), 50 Hz. A 10 mΩ source impedance is included to model distribution feeder resistance.

The wind speed profile used for controller evaluation consists of a turbulent time series generated by the Kaimal spectral model at hub height, with mean wind speed of 10 m/s, turbulence intensity of 15%, and integral length scale of 340.2 m over a 600-second simulation window representing realistic open-terrain wind conditions. A 40% depth, 200 ms symmetrical grid voltage sag event was superimposed at t = 300 s to assess disturbance rejection and low-voltage ride-through (LVRT) capability.

Table 1: PMSG-WECS Simulation System Parameters

Parameter	Symbol	Value	Unit
Rated power	Prated	2	MW
Rotor blade radius	R	40	m
Air density	ρ	1.225	kg/m^3
Moment of inertia	J	3.5×10^6	$kg\cdot m^2$
Number of pole pairs	p	40	—
Stator resistance	Rs	0.008	Ω
Synchronous inductance	Ls	0.6	mH
PM flux linkage	ψPM	7.5	Wb
DC-link voltage (rated)	V_{dc}^*	1200	V
DC-link capacitance	C	50	mF
Grid filter inductance	L_f	3	mH
Grid filter resistance	R_f	0.1	Ω
Switching frequency	f_{sw}	5	kHz
Grid voltage (L-L, RMS)	E_g	690	V
Grid frequency	F_g	50	Hz
Optimal tip speed ratio	λ_{opt}	8.1	—
Maximum power coefficient	$C_{p,max}$	0.48	—
Turbulence intensity	TI	15	%
Mean wind speed (test)	V_w	10	m/s

5.2 Comparative Controller Performance and Optimized Gain Values

Five controller configurations were evaluated: (i) GGO-PI (proposed), (ii) PSO-PI, (iii) GWO-PI, (iv) WOA-PI, and (v) ZN-PI. For PSO, parameters were: inertia weight w = 0.729, cognitive and social constants $c_1 = c_2$ = 1.494, N = 50, T_{max} = 200. For GWO and WOA: N = 50, T_{max} = 200 with standard parameter settings from the literature [12,13]. ZN gains were determined from the closed-loop oscillation method applied to each PI loop independently. All optimization-based methods employed identical ITAE objective function and gain bounds to ensure fair comparison.

5.3 Transient Response Analysis

The GGO-PI controller demonstrated the fastest and most overdamped transient response to step changes in wind speed. For a step increase from 8 m/s to 12 m/s at t = 100 s,

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GGO-PI reached the new optimal rotor speed reference within 91 ms with zero oscillatory overshoot, compared with 127 ms for PSO-PI and 118 ms for GWO-PI. The ZN-PI controller exhibited pronounced speed undershoot of approximately 4.2% and settling time of 214 ms, confirming the inadequacy of gradient-based tuning for the nonlinear WECS operating regime. The superior transient performance of GGO-PI is attributed to the V-formation adaptive exploitation strategy, which locates a gain configuration in a broader basin of attraction with favourable closed-loop eigenvalue placement, particularly in the q-axis current regulator.

The DC-link voltage regulation performance under the same step wind disturbance showed peak overshoots of 41.2 V, 60.1 V, 55.7 V, and 112.4 V for GGO-PI, PSO-PI, GWO-PI, and ZN-PI, respectively. The 31.4% reduction in DC overshoot achieved by GGO-PI relative to PSO-PI is of practical significance, as excessive DC-link transients can trigger protection relay operation in grid-connected inverter systems operating near rated capacity.

Table 2: Optimized PI Gain Parameters for All Controller Configurations

Parameter	GGO-PI	PSO-PI	GWO-PI	ZN-PI	Bound
Kp1 (d-RSC)	12.47	11.83	13.02	8.50	[0.001, 100]
Ki1 (d-RSC)	284.3	271.5	263.9	195.0	[0.001, 1000]
Kp2 (q-RSC)	15.92	14.71	16.44	10.20	[0.001, 100]
Ki2 (q-RSC)	312.6	298.4	287.1	210.0	[0.001, 1000]
Kp3 (DC-GSC)	9.34	8.97	10.11	6.80	[0.001, 100]
Ki3 (DC-GSC)	198.7	185.6	179.3	145.0	[0.001, 1000]
Kp4 (Q-GSC)	7.82	7.31	8.24	5.60	[0.001, 100]
Ki4 (Q-GSC)	156.4	148.9	143.7	112.0	[0.001, 1000]

Table 3: Comprehensive Performance Metric Comparison Under Turbulent Wind Profile

Performance Metric	GGO-PI	PSO-PI	GWO-PI	ZN-PI
ITAE (J)	0.0317	0.0521	0.0448	0.1183
Speed settling time (s)	0.091	0.127	0.118	0.214
DC-link overshoot (V)	41.2	60.1	55.7	112.4
Active power ripple (kW)	18.4	25.4	25.3	57.8
THD of grid current (%)	2.31	3.47	3.12	6.84
Voltage sag recovery (ms)	63	91	85	218
Average Cp utilization (%)	97.2	95.6	96.1	91.3
RMS TSR deviation	0.23	0.31	0.28	0.54
Reactive current overshoot (%)	8.3	12.7	11.4	31.2

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5.4 MPPT Efficiency and Power Coefficient Utilization

MPPT efficiency, defined as the ratio of actual captured energy to the theoretically extractable maximum over the 600-second simulation window, was computed for each controller. GGO-PI achieved an average aerodynamic power coefficient utilization of 97.2%, versus 95.6% for PSO-PI, 96.1% for GWO-PI, and 91.3% for ZN-PI. The 1.6 percentage-point improvement over PSO-PI corresponds to approximately 32 kWh of incremental daily energy capture for the 2 MW turbine at rated wind conditions — a commercially significant figure projected over a 20-year operational lifetime. TSR tracking fidelity quantified by root-mean-square deviation from $\lambda_{\text{opt}} = 8.1$ confirmed GGO-PI's tightest aerodynamic operating point regulation (RMS deviation = 0.23 vs. 0.31 for PSO-PI).

5.5 Power Quality and Grid Current THD

Total harmonic distortion (THD) of the injected grid current was evaluated via Fast Fourier Transform (FFT) analysis at rated operating conditions. GGO-PI yielded a grid current THD of 2.31%, satisfying the IEEE 519-2022 limit of 5% for utility-scale generators with a 53.6% safety margin [25]. PSO-PI and GWO-PI produced THDs of 3.47% and 3.12%, respectively, while ZN-PI yielded 6.84% — a value violating the applicable harmonic standard. The improved harmonic performance of GGO-PI is attributable to enhanced integral gain precision in the GSC current regulators, which more effectively attenuates baseband current ripple components arising from converter switching and wind power fluctuations.

5.6 Grid Voltage Sag Disturbance Rejection

The 40% depth, 200 ms grid voltage sag event imposed at t = 300 s revealed marked differencesin ride-through performance. GGO-PI recovered DC-link voltage to within 5% of rated value in 63 ms following sag clearance, compared with 91 ms (PSO-PI), 85 ms (GWO-PI), and 218 ms (ZN-PI). The GSC reactive current injection during the sag was more precisely modulated under GGO-PI, with reactive current overshoot limited to 8.3% above the commanded reference versus 12.7% under PSO-PI. These results confirm that the improved PI gain quality translates not merely to steady-state performance advantages but also to meaningful LVRT resilience under grid disturbance conditions compliant with modern grid code requirements [26].

6. Statistical Analysis and Discussion

6.1 Algorithm Convergence and Statistical Robustness

To assess statistical robustness, 30 independent optimization runs were performed for each algorithm with different pseudo-random seeds. Final ITAE values and convergence iteration counts were recorded for each trial. Table 4 summarizes statistical measures.

Table 4: Statistical Results Over 30 Independent Optimization Runs

Metric	GGO	PSO	GWO	WOA	SSA
Mean ITAE	**0.0319**	**0.0527**	**0.0451**	**0.0483**	**0.0612**
Std Dev	**0.0021**	**0.0048**	**0.0039**	**0.0071**	**0.0089**
Best	**0.0317**	**0.0521**	**0.0448**	**0.0461**	**0.0583**
Worst	**0.0378**	**0.0641**	**0.0554**	**0.0619**	**0.0814**
Median	**0.0318**	**0.0523**	**0.0449**	**0.0476**	**0.0605**
Convergence iter.	**87**	**134**	**119**	**141**	**158**
p-value vs GGO	**—**	**0.0031**	**0.0074**	**0.0018**	**0.0007**

GGO achieved the lowest mean ITAE of 0.0319 with the smallest standard deviation of 0.0021, reflecting superior solution quality consistency across trials. The convergence iteration count of 87 indicates GGO reaches its optimal solution approximately 35% faster than PSO (134 iterations) and 27% faster than GWO (119 iterations), which is practically important in scenarios requiring rapid controller re-tuning following generator parameter drift, maintenance, or operational regime transitions.

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The Wilcoxon signed-rank test confirmed that GGO's performance superiority over PSO ($p = 0.0031$), GWO ($p = 0.0074$), WOA ($p = 0.0018$), and SSA ($p = 0.0007$) was statistically significant at the 5% significance level, validating the probabilistic superiority of the proposed approach beyond deterministic comparison and accounting for the stochastic nature of metaheuristic algorithms.

6.2 Sensitivity to Algorithm Hyperparameters

A parametric sensitivity analysis was conducted to evaluate GGO performance robustness. Population size N was varied over [1 70, 100], and the foraging probability bounds p_{fmax} and p_{fmin} were swept across plausible ranges. The results indicated that GGO exhibited low sensitivity to N for $N \geq 30$, with mean ITAE varying by less than 2.3% across the tested range. The drafting coefficient α showed the most significant influence, with optimal performance observed in $\alpha \in [0.65, 0.80]$, consistent with the original algorithm's recommendations [19]. These findings confirm that GGO does not require intensive hyperparameter tuning, enhancing its practical deployability.

6.3 Computational Cost Analysis

The computational cost per iteration of GGO is $O(N \cdot D)$, identical to PSO and GWO, ensuring no additional computational burden relative to established methods. For $D = 8$ gain parameters with $N = 50$ agents and $T_{max} = 200$ iterations, the total wall-clock optimization time on a standard workstation (Intel Core i7-11th Generation, 16 GB RAM, MATLAB R2023b) was 11.2 minutes an entirely acceptable offline tuning duration inconsequential compared with the multi-year operational horizon of a deployed wind turbine. Real-time adaptation was not attempted in the current study; feasibility of accelerated variants for online re-tuning remains an open research question.

6.4 Physical Interpretation of Optimized Gains

Examination of the optimized gain vectors in Table 2 reveals physically consistent trends. The q-axis current controller (K_{p2}, K_{i2}) consistently receives higher gains than the d-axis controller across all optimization methods, reflecting the larger signal bandwidth requirement of the torque-producing current loop relative to the flux-producing channel, consistent with the higher effective loop gain required for rapid electromagnetic torque response. The DC-link voltage controller ((K_{p3}, K_{i3}) optimized gains are moderately lower, consistent with the cascade control requirement for a slower outer voltage loop to maintain adequate phase margin in the cascaded inner-outer loop interaction. These physically interpretable trends confirm that GGO discovers gain configurations that are not only numerically ITAE-optimal but also structurally coherent from a classical control design perspective.

6.5 Comparison with Published Literature

Table 3 results may be contextualized against recently published studies. Prasad and Kumar [16] reported an ITAE of 0.0489 using an improved GWO on a comparable 2 MW PMSG system, 54.3% higher than the GGO-PI value of 0.0317 reported here. The average Cp utilization of 97.2% achieved by GGO-PI compares favorably with the 95.8% reported by Errami et al. [27] using sliding mode control a structurally more complex approach demonstrating lower MPPT efficiency under stochastic wind conditions. Souag et al. [17] reported grid current THD of 3.1% using GWO-tuned PI, compared with 2.31% achieved by the proposed GGO-PI. These cross-study comparisons, while necessarily approximate given differences in system parameters, turbine ratings, and wind profiles, collectively support the conclusion that GGO-PI represents a substantive advancement over current literature benchmarks.

7. Limitations and Future Research Directions

This study carries several acknowledged limitations that define the scope of the reported findings and inform future research directions.

First, the optimization and validation framework is entirely simulation-based using an idealized MATLAB/Simulink Simscape model. While the Kaimal spectral wind model and grid voltage sag scenario represent realistic operating conditions, hardware-in-the-loop (HIL) validation using a real-time digital simulator (RTDS or Opal-RT) and ultimately physical prototype testing are necessary steps

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toward confirming the practical deployment viability of the proposed GGO-PI framework. Simulation models inevitably abstract certain real-world phenomena, including sensor noise, actuator delays, converter dead-time effects, and thermal derating of power electronics.

Second, the current study employs static offline tuning, the PI gain vector is optimized once against the training wind profile and then fixed for evaluation. Real wind turbines encounter parameter drift arising from winding temperature variation, demagnetization of permanent magnets over decades of operation, and gradual changes in mechanical constants due to wear. An adaptive online re-tuning mechanism capable of tracking plant parameter changes in near-real-time would substantially enhance the practical value of the GGO framework.

Third, the current control architecture employs conventional integer-order PI regulators. Extension to fractional-order PI (FOPI) controllers, which offer an additional degree of freedom through the fractional differentiation order μ, has been demonstrated to yield superior robustness in power electronics applications and warrants dedicated investigation with the GGO tuning framework.

Fourth, the TSR-MPPT strategy adopted herein relies on a sliding-mode wind speed estimator. While this avoids direct anemometer measurement uncertainties, the estimator performance under extreme turbulence conditions or sensor saturation scenarios was not comprehensively evaluated in this study.

Future research directions include: (i) HIL validation using RTDS or Opal-RT platforms; (ii) adaptive online GGO-PI re-tuning for time-varying plant parameters; (iii) extension to fractional-order PI and model predictive control (MPC) parameterization; (iv) multi-objective GGO formulations incorporating simultaneous ITAE minimization and harmonic constraint satisfaction as Pareto objectives; (v) application to offshore wind turbine configurations with marine-environment-specific grid codes; and (vi) assessment of GGO applicability to coordinated control of wind-PV-battery hybrid microgrid systems.

8. Conclusion

This paper has presented, formulated, and validated a Graylag Goose Optimization (GGO) algorithm-based PI controller tuning framework for a full-scale 2 MW permanent magnet synchronous generator wind turbine system interfaced to the utility grid via a back-to-back voltage source converter. The integration of a TSR-based MPPT strategy provided a physically transparent and noise-robust rotor speed reference generation mechanism, while the GGO algorithm navigated an eight-dimensional PI gain optimization landscape with demonstrated global convergence performance superior to established metaheuristic benchmarks.

The principal findings of the study may be summarized as follows. The GGO-PI configuration achieved the lowest ITAE of 0.0317 among all evaluated controllers, representing a 39.2% reduction relative to PSO-PI and 29.2% relative to GWO-PI. DC-link voltage overshoot was reduced by 31.4% compared with the PSO-PI benchmark, a safety-critical margin in grid-connected inverter systems. MPPT efficiency reached 97.2%, translating to measurable incremental energy capture over the operational lifetime. Grid current THD of 2.31% satisfied IEEE 519-2022 requirements with 53.6% margin. Voltage sag recovery time of 63 ms demonstrated competitive LVRT performance. The GGO algorithm converged in a mean of 87 iterations with significantly lower solution variance across 30 independent trials than any competing method, and the Wilcoxon signed-rank test confirmed statistical significance of all performance differences at $p < 0.01$.

These results collectively establish GGO-PI tuning as a compelling, practically viable, and computationally feasible strategy for PMSG-based WECS control optimization that advances the current state of the art in metaheuristic-driven PI gain selection for wind power applications.

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