IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 1, February 2026, pp. 399~411
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i1.pp399-411

Optimization of maximum power point tracking in wind energy systems: a comparative study of ant colony and genetic algorithms

Najoua Mrabet[1], Chirine Benzazah[1,2], Mohssine Chakib[3], Adil Ziraoui[4], Ahmed El Akkary[1], Najma Laaroussi[5]
[1]Laboratory of Systems Analysis Information Processing and Industrial Management (LASTIMI), Higher School of Technology, Mohammed V University, Rabat, Morocco
[2]Laboratory of Fundamental and Applied Physics (LPFAS), Polydisciplinary Faculty of Safi, Cadi Ayyad University, Marrakech, Morocco
[3]Department of Electrical Engineering, High School of Technical Education, Mohammed V University, Rabat, Morocco
[4]National School of Arts and Craft, Hassan II University, Casablanca, Morocco
[5]Materials Energy and Acoustics Team (MEAT), Department of Urban and Environmental Engineering, Higher School of Technology, Mohammed V University, Rabat, Morocco

Article Info

Article history:

Received May 19, 2024
Revised Nov 8, 2025
Accepted Jan 10, 2026

Keywords:

Ant colony
Genetic algorithm
Maximum power point tracking
Permanent magnet synchronous generator
PID controller

ABSTRACT

This research focuses on optimizing maximum power point tracking (MPPT) in wind energy conversion systems (WECS) using ant colony optimization (ACO) and genetic algorithm (GA). The study evaluates these two metaheuristic techniques to optimize the parameters of a proportional-integral-derivative (PID) controller in order to maximize power output in a permanent magnet synchronous generator (PMSG)-based system. Simulations conducted in MATLAB/Simulink show that both ACO and GA effectively enhance MPPT performance by improving power output, DC bus voltage regulation, and torque stability. The results demonstrate the potential of metaheuristic algorithms to optimize wind energy conversion efficiency and support sustainable energy development.

Corresponding Author:

Najoua Mrabet
Laboratory of Systems Analysis Information Processing and Industrial Management (LASTIMI)
Higher School of Technology, Mohammed V University
Avenue des Nations Unies, Agdal Rabat, Maroc B.P, 8007 N.U., Morocco
Email: najouamrabet2@gmail.com

1. INTRODUCTION

This study examines an impact for wind energy development on environmental sustainability, focusing on pollution reduction and energy efficiency [1]. With the rise in wind energy demand, turbines, especially those using permanent magnet synchronous generators (PMSGs), offer high performance, low maintenance, and gearless operation. However, optimizing maximum power point tracking (MPPT) remains a key challenge. As wind speeds fluctuate, it's essential to adapt turbine parameters for maximum power extraction. Efficient MPPT is crucial for improving energy efficiency, reducing losses, and enhancing sustainability in wind energy systems [2], [3].

Variations in wind speed affect the rotor speed of turbines, necessitating effective MPPT techniques to optimize power points and enhance system performance. Several methods have been used for MPPT optimization, including incremental conductance (INC) and perturb and observe (P&O). While these techniques are extensively utilized, it come with limitations, like slow response times and decreased effectiveness under quickly evolving wind conditions. This study suggests employing the INC approach to MPPT in wind energy conversion systems (WECS), which addresses some of these limitations by improving tracking accuracy under varying wind speeds.

The paper compares two distinct metaheuristic methods for optimizing MPPT in WECS: genetic algorithms (GA) and ant colony optimization (ACO) [4]. Ants' foraging habits serve as an inspiration for ACO, which discover and utilize paths from their colony to food sources. Applied to MPPT, ACO can explore various parameter combinations to maximize power production and identify an optimal operating point for a wind turbine. GA employs genetic operators like to evolve toward the best option, use crossover, mutation, and selection from a population of potential solutions, representing possible turbine operating points [5]. GA, when used with MPPT, can continuously enhance the turbine's operating parameters for effective MPPT. A comparative analysis of these multi-objective metaheuristic techniques, such as ACO and GA, typically focuses on their importance and effectiveness in optimizing MPPT control in WECS. Our research introduces a new method for predicting the stability region of a proportional-integral-derivative (PID) controller using its parameters [6]. The aim is to optimize the PID controller's settings using ACO and GA, resulting in faster setup times and enhanced voltage, current, torque, and power responses.

This study proposes optimizing PID controller settings using GA and ACO techniques, offering innovative solutions to improve MPPT optimization in WECS. Unlike conventional methods like INC and P&O, ACO and GA can explore larger solution spaces and adapt more effectively to changing wind conditions, leading to faster and more accurate MPPT. An approach is evaluated using MATLAB/Simulink to manage a DC-DC boost converter for optimal voltage in WECS [7]. This work aims to advance MPPT optimization by utilizing ACO and GA for enhance an economic feasibility, reliability, and efficiency for wind energy systems [8].

A remainder for structure of the paper is as follows: section 2 offers a thorough summary, for an INC approach, the DC-DC boost converter, the WECS system, and the PID controller. Section 3 discusses the control strategy, emphasizing how ACO and GA techniques are used to swiftly modify PID controller settings. Finally, section 4 presents a main outcome of a MATLAB simulation, comparing our findings with traditional techniques and highlighting the benefits of our innovative approach. The literature applied is listed in Table 1.

Table 1. Literature review

Optimization method	Advantages	Limitations	Comparison to ACO and GA
Particle swarm optimization (PSO)	i) Simple to implement ii) Fast convergence for single objective problems	i) Susceptible to local minima ii) May struggle in complex dynamic systems	ACO and GA generally outperform PSO in complex dynamic systems due to better exploration and avoidance of local minima.
Simulated annealing (SA)	i) Effective in global optimization ii) Good for large search spaces	i) Slower convergence ii) May be computationally expensive in dynamic conditions	ACO and GA offer faster convergence and are more computationally efficient.
Differential evolution (DE)	i) Robust against local minima ii) Good for multi-dimensional optimization	i) Slower convergence rate ii) May require a long computation time in complex systems	ACO and GA are more adaptive to dynamic changes, providing better convergence and efficiency in real-time systems.
ACO	i) Excellent for large search spaces ii) Adaptable to dynamic conditions	i) May require more computational resources ii) Slower convergence in simpler cases	ACO offers superior adaptability to changing wind conditions and efficient exploration.
GA	i) Balanced between exploration and exploitation ii) Less prone to local minima	i) Computationally intensive ii) May need careful parameter tuning	GA outperforms traditional methods and other algorithms in complex dynamic conditions by maintaining solution diversity.

2. THE SYSTEM PROPOSED

A wind turbine transforms wind speed for mechanical power. With keeping a best steady voltage throughout the load, MPPT technique can get acclimated for obtaining the greatest power production from an available wind. Several MPPT techniques was utilized with WECS in previous publications. DC/DC converters serve as a maximum power point (MPP) monitor, connecting WECS with various load requirements. Buck-boost and buck-boost converters are a majority often utilized. Numerous studies have enhanced the efficiency of WECS tracking structures. Choosing a highest MPPT for a given job demands thorough evaluation of a number of aspects, including accuracy, cost, convergence speed, and sensitivity. Never matter how a great deal the load or input voltage swings, a controller should constantly maintain a voltage stable [9]. Figure 1 illustrates a wind power system architecture proposed in that paper. A wind turbine has instantly connected with a PMSG and rectifiers, where convert a generator's AC to DC. After acquisition, a DC voltage and current signals are connected of a DC-DC boost converter. An MPPT regulates pulse width modulation (PWM) duty cycles and regulate signals. At last, connect a load to a DC-DC boost converter and measure a system output power [10].

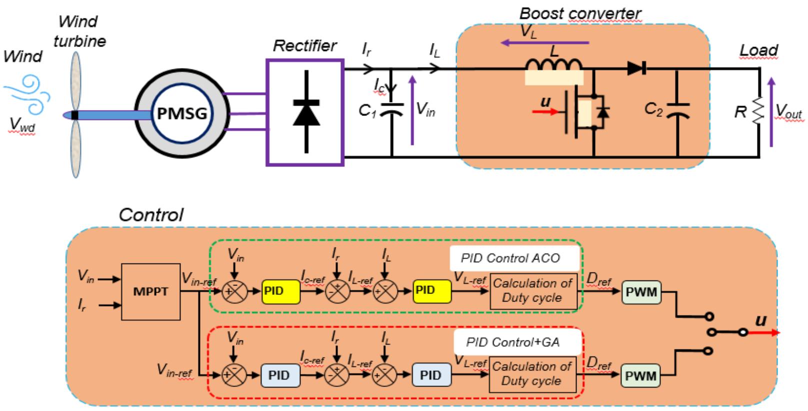


Figure 1. Design for maximum power control for WECS

2.1. Designing a wind turbine

The wind turbine's (WT) mechanical power generated as selected with (1), when ρ: air density (kg/m3), A: swept area (m2), cp: performance coefficient of a turbine where is a function for a pitch angle of rotor blades β (in degrees) and v: wind speed (in m/s). λ: a tip-speed ratio. A best rotor speed in that turbine works at maximum power symbolized in (2) [11], when R and ω_m are a blade length (in m) and a WT rotor speed (in rad/sec), accordingly, a WT mechanical torque output Tm given with (3) [12].

$$P_m = \frac{1}{2}\rho A c_p(\lambda,\theta)v^3 \tag{1}$$

$$\lambda = \omega_m R/v \tag{2}$$

$$T_m = \frac{\frac{1}{2}(\rho A C_P(\lambda,\beta)v^3)}{\omega_m} \tag{3}$$

Because of a designing turbine property described [13], a coefficient of power conversion cp=(λ, β) has depending employing an applying fundamental expression: a mechanical output power turbine has represented in Figure 2 like an outcome for turbine speed to multiple wind speeds, as in (4) and (5) [14].

$$c_p = \frac{1}{2}\left(\frac{116}{\lambda_i} - 0.4\beta - 5\right)e^{-\left(\frac{21}{\lambda_i}\right)} \tag{4}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda+0.08\beta} - \frac{0.035}{\beta^3} \tag{5}$$

As well, Figure 2 features demonstrate there is a specific turbine speed at such point a greatest power could possibly create with every wind speed. As an example, just where the turbine speed has retained in 1.2 pu could a maximum power get extracted for a wind speed of 12 m/s. As a result, a one above scenario shows that Cp may just get held at an elevated level if the rotor speed has adjusted for an ideal functioning point to diverse wind speeds. A greatest efficiency for a possible wind turbine has 16/27, which equals 59.25%. To for practical uses, performance differs from 25% to 45%. Table 2 shows a measurement with a wind turbine.

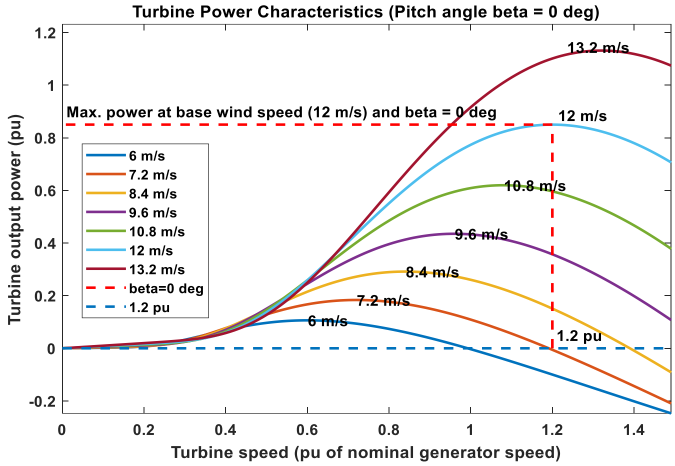


Figure 2. Turbine power profiles

Table 2. Wind turbine and PMSG simulations parameters

S.L.	Measurements	Value	S.L.	Measurements	Value
1	Minimal mechanical power output	12.3 kw	1	Resistance stator Rs	0.45572 (Ω)
2	Initial wind speed	12 m/s	2	Inductances [Ld, Lq]	[0.395 mH, 0.395 mH]
3	Maximal mechanical power (pu)	0.85 pu	3	Number of poles	3
4	Minimum rotor speed	1.2	4	Rotor inertia	0.0026 J
5	Beta frequency angle	0°	5	Fluid damping F	0.004925 N, m, s
			6	Flux linkage ψ	0.1193 wb

2.2. Modeling PMSG

This is d-q corresponding circuit's function as a model with PMSG. The synchronous d-q coordinates, an exterior attached PMSG's equations are composed as (6) and (7) [15], when Ls is an inductance for a stator winding, Rs is a resistance for a stator winding, Vds, Vqs, iqs, and iqs are a d-q components for a stator voltage and current, respectively, ψ is a magnetic flux, and ω has electrical angular speed for a generator. An generator's output power and electromagnetic torque are offered as in (8) and (9) [16]: P is a generator's pole number. Table 1 contains an amount for an PMSG.

$$\mathrm{V_{ds}} = \mathrm{R_s} + L_s \frac{di_{ds}}{dt} - \omega_e \mathrm{L_s i_{qs}} \tag{6}$$

$$\mathrm{V_{qs}} = \mathrm{R_s i_{qs}} + \mathrm{L_s} \frac{\mathrm{di_{qs}}}{\mathrm{dt}} + \omega_e \mathrm{L_s i_{qs}} + \omega_e \psi \tag{7}$$

$$\mathrm{T_e} = \frac{3}{2}\frac{\mathrm{P}}{2} \psi \mathrm{i_{qs}} \tag{8}$$

$$P_{gen} = \frac{3}{2}\frac{P}{2} \psi i_{qs} \omega_m - \frac{3}{2} R_s i_{qs}^2 - \frac{3}{2} R_s i_{ds}^2 \tag{9}$$

2.3. DC-DC converter for boost DC-DC boost an IGBT anti-parallel

A converter during study comprises for an IGBT anti-parallel diode transistor, an ultrafast diode, the capacitor, and an inductor. Based on Figure 1, a MPPT depending controller sends a PWM signal to manage the switching IGBT converter's boost. Calculating an optimum duty cycle is critical for regulating this DC-DC converter in a boost circuit. For compute PWM, an INC method has utilized [17].

2.4. Converter three phase AC-DC

An unregulated rectifier is a best simple, cost-effective, and long-lasting graphic employed in power electronics programs. Since it isn't required in our case, the diode rectifier's incapacity of work at bidirectional power flowing is a disadvantage. A booster converter and rectifier circuits are connected of a generator. That's has assumed that diode bridge rectifier circuits are used to convert AC energy source a generator for DC power. Average DC voltage and current values of the three-phase diode rectifier [18].

2.5. Incremental conductance MPPT technique

An incremental approach has essential for maximize their available power energy at any times. To wind turbines using parameters or steady speeds, an approach shows we are encircling this target operating point. An immediate conductance I/V and INC dI/dV are especially with comparison with an INC approach for determine an MPP. An MPP is discovered employing an INC technique. According to a fact, a peak to a P-V curve is zero at MPP which can be expressed as (10). Where the operating point has far from the MPP, the get size has large for rapid tracking, but it is less where a turning point has close of a MPP of reduce steady state oscillation. A writers describe the unique approach to using the INC technique with the PMSG generator [19]. That INC technique requires the DC/DC conversion step for have implemented. Since a PMSG's output power is alternating current, the literature review employs a variety of topologies to convert it to direct current. WECS uses a three-phase AC-DC rectifier and a DC-DC boost converter; past research says this structure includes an added gain owing for an intermediate boost-improved converter's reliability, giving it a finest back-to-back converter option. A writers investigated and assessed several MPPT approaches before condemning their release. They concluded this depends in efficacy, it is advised for utilize one from each strategy, an INC technique with direct control, since optimal power occurs at a point which a various variation for dP/dV=0A MPPT controller evaluates a voltage and current of the PV module which an INC technique employs for identify an MPP. If (11) has pleased, reduce a duty cycle to a converter has pleased. A duty cycle should be elevated when condition (12) has pleased. A duty cycle shouldn't be altered if (13) is attained [20].

$$\frac{dI}{dV} = -\frac{I}{V} \tag{10}$$

$$\frac{dI}{dV} > -\frac{I}{V} \tag{11}$$

$$\frac{dI}{dV} < -\frac{I}{V} \tag{12}$$

$$\frac{dP}{dV} = 0 \tag{13}$$

2.6. PID controller design

A PID controller has a majority extensively utilized controllers in a business, meeting over 90% of industrial control requirements. It is effective and simple. Accounting to its supremacy [21]. The delay systems incorporate the system mentioned in a previous paragraph. The delay not only depicts physical reality, but also simplifies the explanation of system dynamics compared to a more detailed description. This article discusses how to determine the whole stability range of a system's PID regulator factors. Where designing and fine-tuning PID controllers, that step has critical. Some research studies have identified multiple configurations for the PID regulator [22]. C(s) has a PID controller, G(s) has a controlled plant, and yc, e, u, and y represent an expected output signals, commands, and errors, and appropriately, a Laplace transform enables a subsequent construction for a PID regulator's control law, as in (14), where KP, Ki and KD are, appropriately, a proportional, integral, and derivative gains of a PID controller.

$$C(s) = \frac{u(s)}{e(s)} = k_p + \frac{k_p}{s} + sk_d \tag{14}$$

3. PROPOSED MULTI-OBJECTIVE METAHEURISTIC TECHNIQUES

3.1. Genetic algorithm approach

GA are popular optimization techniques, ideal for solving complex problems that involve approximations and uncertainty. Developed by John Holland in 1975, GA uses a heuristic-based approach that mimics natural selection. In this study, GA is utilized for maximize a PID controller parameters (Kp, Ki, and Kd) in a WECS. An GA works by iteratively selecting solutions based on their fitness, which reflects their ability to achieve optimal power output.

The GA process begins by initializing a random population of potential PID parameter sets within defined search spaces. Each set is evaluated for its ability for direction a maximum power point under varying wind speeds. Through selection, a best solution is selected as parents of a next generation. The crossover operation combines parent solutions, and mutation introduces randomness to maintain diversity. The process continues until the fitness function shows no significant improvement, indicating that the optimal PID parameters have been found [23].

Performance is evaluated using standard metrics such as ISE, IAE, ITAE, and ITSE, which assess error minimization and stability. The GA is compared with ACO in the experimental setup, using varying wind speed profiles to evaluate robustness and computational efficiency. The results are compared to determine the best algorithm for optimizing PID parameters in WECS. Figure 3 displays a WECS's implemented GA. An GA takes into consideration the fitness function of each parameter as it codes, reproduces, and evaluates the PID controllers' parameters (Kp, Ki, and Kd) in our optimization design process. Only the chosen people are merged to create a new generation, and the evaluation cycle is continued until the algorithm produces the best solution for the system with the best fitness function.

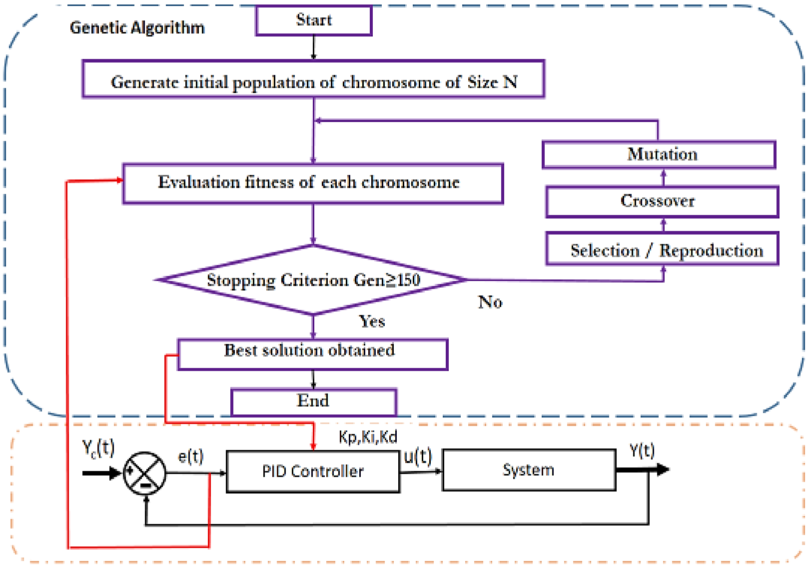


Figure 3. Schematic for genetic algorithm technique

3.2. Ant colony optimization approach

ACO is the sort of meta-heuristic optimization this is based on the activities of ants the initial notion has grown for solve a larger variety of issues, and new algorithms affected with different features for ant behavior have evolved. An ants use pheromone tracks for trace their movements to source i to source j, for an expectation this a colony will select a quickest path for origin j. A probability that ant K is going to follow from city i to city j: $\forall \epsilon N_i^k$, as in (15).

$$p_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{I \epsilon N_i^k} [\tau_{ij}]^\alpha [\eta_{ij}]^\beta} \tag{15}$$

ACO is a metaheuristic that draws inspiration from ants' foraging habits, where ants deposit pheromones on the paths they take. Other ants follow these pheromone trails, leading them to the most optimal paths over time. ACO is utilized to maximize an PID controller parameters (Kp, Ki, and Kd) in a WECS. A movement of ants between solutions is influenced by pheromone intensity and a heuristic value, controlled by settings α and β, which ascertain the impact that pheromones and heuristics. The ACO optimization processes involve three key steps:

i) Solution creation: each ant generates a potential solution for the PID parameters.
ii) Algorithm setup: parameters such as the numeric of ants, pheromone intensity, evaporation rate, and the numeric the iterations are defined.
iii) Pheromone update: following assessing the solutions, pheromone levels are changed based on the performance of the solutions, guiding future ants toward better PID settings.

Through multiple iterations, the optimization process adjusts the PID parameters until the system reaches optimal tracking performance a maximum power point below varying wind condition. This method ensures that the system is continuously fine-tuned for efficiency and stability [24]. Figure 4 shows the flowchart for ACO approach. In fact, as illustrated in Figure 4, there are three fundamental stages to the basic algorithm: initialization, ant solution construction, and pheromone updating.

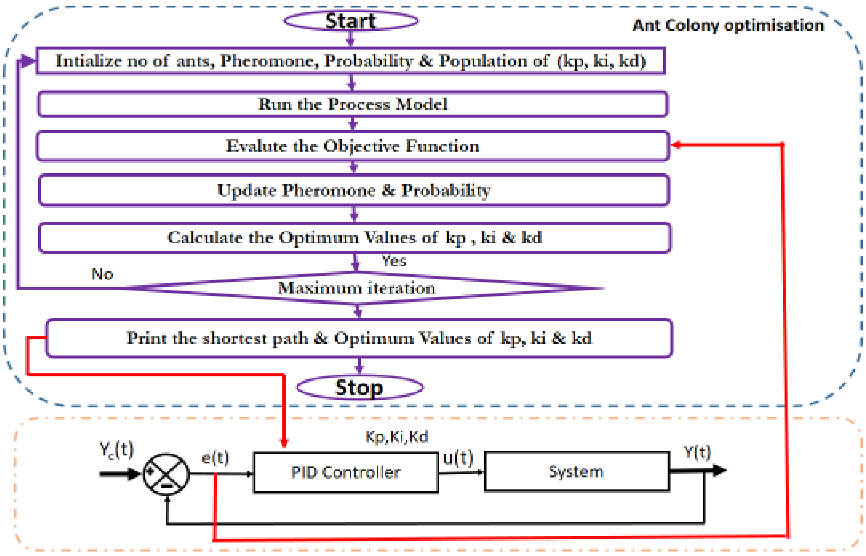


Figure 4. Illustration of PID tuning with ACO

3.3. Objective functions cost value

Before employing an ACO, a goal function cost value should be determined. Several articles employ an integral of absolute magnitude of error (IAE), ITAE, integral to a squared error (ISE), and integral time multiplied by squared error (ITSE) for optimize a PID controller [25]. Calculating an objective functions yield as in (16).

$$\mathrm{ITAE} = \sum_0^{t_{max}} t|e(t)|\,,\ \mathrm{ISE} = \sum_0^{t_{max}} e(t)^2,\ \mathrm{IAE} = \sum_0^{t_{max}} |e(t)|,\ \mathrm{ITSE} = \sum_0^{t_{max}} te(t)^2 \tag{16}$$

4. RESULTS AND DISCUSSION

Our study revealed that integrating MATLAB/Simulink software to model a recommended WECS with ACO and GA significantly enhances system performance. The proposed method consistently achieved a higher proportion of optimized parameters compared to conventional approaches. GA was employed to generate code for four fitness function specifications, which were then integrated into an optimization tool. Table 3 display a first parameters commonly utilized in simulations employing GA methods. Additionally, we used simulations to evaluate the efficacy of a closed-loop system incorporating an ACO-PID controller. The results demonstrated a closed-loop system's efficiency of evaluating it against four multi-objective performance indicators. Our study explored a comprehensive PID controller optimization approach using ACO and GA algorithms. However, further in-depth studies are necessary to confirm its applicability, especially regarding dynamic behavior under varying wind conditions. The PID controller aims to stabilize voltage, power levels, current, and torque in wind turbine systems. The ACO and GA approaches optimize PID settings by analyzing references and outputs within MATLAB. Design optimization strategies typically rely on methods that assess system performance using distinct input parameters, adjusting them to maximize an objective function. Subsequent sections outline optimization factors, with optimal PID values determined using ACO and GA approaches based on criteria like ITAE, IAE, ISE, and ITSE, all implemented at MATLAB. For assess a system's dynamic behavior under a unit step response, various standard performance indicators were selected for their relevance to wind turbine models. These indicators give a thorough assessment for a system's performance, ensuring that the optimized PID controller settings help maintain stability and effectiveness for a WECS under different operating conditions.

Table 3. GA and ACO algorithms input measurements

S.L.	Measurements	Value	Measurements	Value
1	Generation	150	Number of ants	60
2	Population size N	60	Constant values	α=0.7
3	Reduced bound	[-30 300]	Constant values	β=0.4
4	Upper limit	[30 300]	Evaporation rate	μ=0.8
5	Selection process	Stochastic uniform	Number of iterations	Ni=200
6	Elite count	0.08	Number of nodes	N=20000

Figure 5 shows a MATLAB/Simulink programming architecture to a GA for PID controller. The proposal suggests a 12.3 kW generated WECS centered power, DC-DC bus converter voltage, load current, output power, and torque electromagnetic for a model. This section describes how to design a PMSG under certain needs and constraints, including time measurements and `power optimization. A toolset to GA written in MATLAB was employed for finished it.

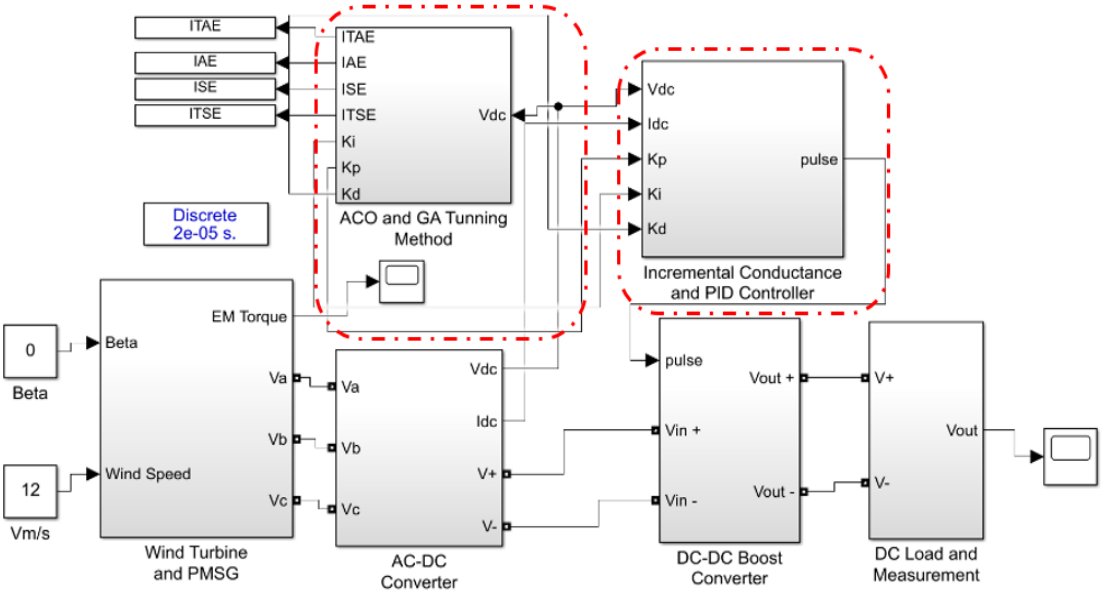


Figure 5. Simulink depiction of the WECS system ACO and GA

This section compares the outcomes of the planned PID controller with MPPT employing GA and ACO. The study and comparison of test results illustrate the contrasts among both of them methodologies. Figure 6 shows a DC bus voltage examined for a model when GA and ACO optimize a PID controller in the wind speed to 12 m/s. A system's planned reference DC bus voltage is 177.19 VA system successfully attained the DC bus reference voltage using the PID controller and ACO. On the other hand, a system does not achieve the DC bus reference voltage, indicating a quicker reaction. However, the optimized controller with ACO exhibits substantial voltage overshoot in comparison with a model with GA. The benefits of overshoot, a model with ACO optimization regulate accomplishes a standard 177.19 V DC bus voltage faster and stabilizes with no the more oscillation. A recommended model improves WECS security outcomes. As seen at a current (Figure 7), a phase currents to a PID-controlled organize with ACO are higher than those to a PID-controlled organization optimized by GA. Still, an end outcome clearly shows that the response time of a WECS system controlled by PID optimized by ACO is faster than that of a WECS system controlled by PID with GA optimized. The primary characteristics investigated at that study were power output, response time, electromagnetic torque, and currents. The opposition and study for those variables demonstrates a benefit for a suggested GA and ACO technique for optimizing a PID controller at a WECS.

A study of a response to couple (Tem) for a suggested system was also conducted at a perspective of the electromagnetic couple, as demonstrated in Figure 8. An ACO-optimized PID controller has improved efficiency in terms for response time and faster tracking for reference values, which contributes for an overall performance improvement of an energy conversion system. Figure 9 depicts the PMSG machine's beginning operation in motor mode. This chart shows that the suggested ACO to optimize the PID controller uses only 10.20 kW of electricity at its peak, while a PID controller system with GA consumes 9.20 kW. Then, the two systems begin producing power. A model should produce 10.20 kW to power in the modest wind speed of 12 m/s. A DC bus voltages of this planned model were also investigated. The figures include details regarding for a rising time, settling time, overshoot, and steady-state error numbers, that was presented at Table 3. A multi-objective genetic algorithm (MOGA) technique's efficiency is apparent of a step response, showing progress regulate and model events on a wind energy conversion model.

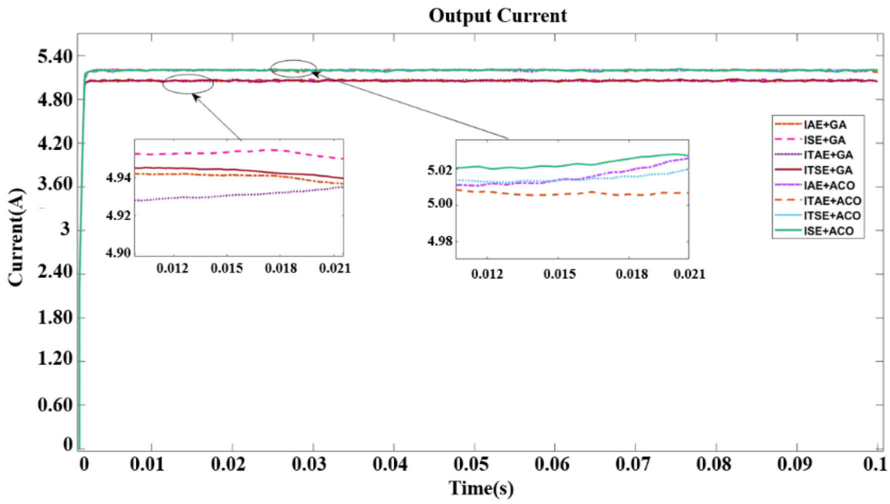


Figure 6. Voltage results of four fitness factors of ACO and GA

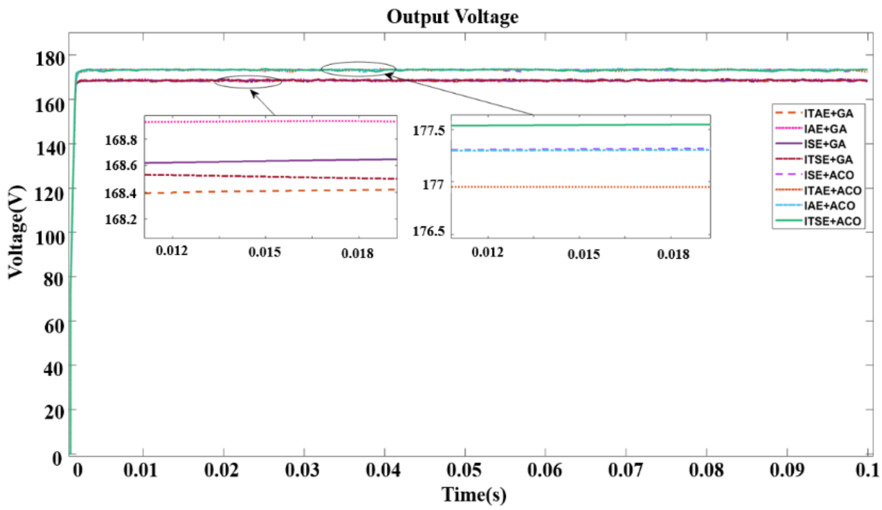


Figure 7. Current results of four fitness factors of ACO and GA

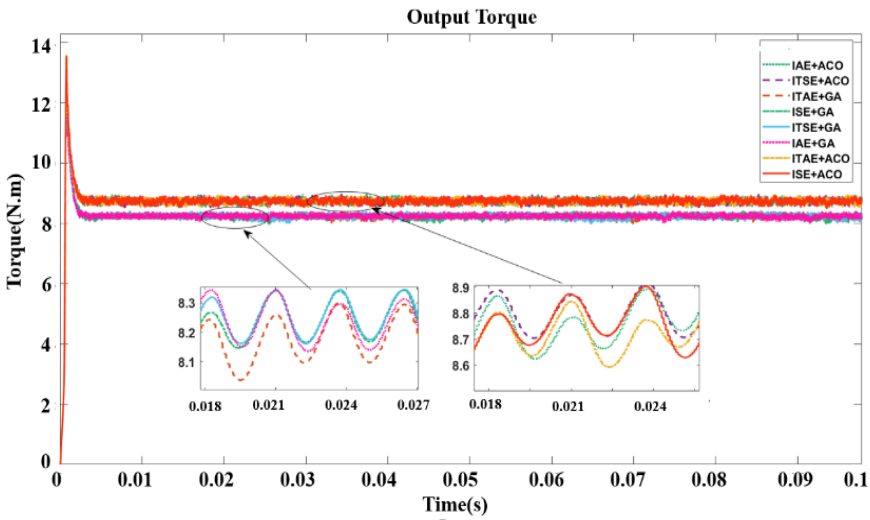


Figure 8. Torque results of four fitness factors of ACO and GA

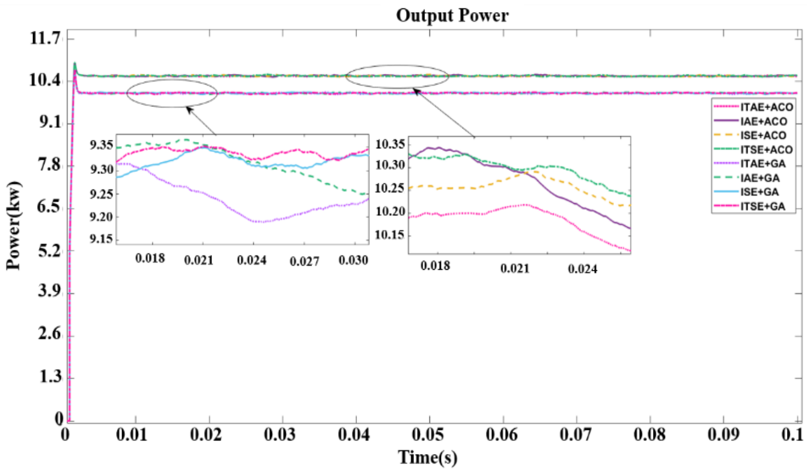


Figure 9. Power results of four fitness factors of ACO and GA

Table 3 shows this rising and settling times produced utilizing an ITAE objective function are comparatively shorter than those derived utilizing an IAE, ISE, and ITSE criteria. An overrun rate has somewhat greater were using ITAE criteria, but an IAE function produces a substantially excellent result. Our study suggests that higher "ITAE" values are not associated with poor performance in wind energy extraction systems. The proposed method may benefit from GA and ACO algorithms without adversely impacting system stability or control performance. When comparing our approach to other methods in the literature, it becomes evident that GA and ACO algorithms, particularly when guided by the ITAE objective function, excel in achieving reduced rising and settling times. This improvement in Response time of the system is important to enhancing an overall efficiency for WECS. In summary, from comparing and discussing these results with existing literature, we can emphasize the strengths for our methods, particularly in terms for enhanced system reaction time, stability, and control performance in WECS [25]. In this section, we compare the performance of ACO and GA with traditional MPPT methods like INC, focusing on key metrics such as power output, voltage, torque, and current under different wind conditions. The results are summarized in the Table 4, which includes performance metrics (ISE, IAE, ITAE, and ITSE) and convergence times for each algorithm.

Table 4. Numeric evaluations calculated for a closed loop response for four objective functions of ACO and GA

	S.L.	Criterion (GA)	ISE	ITAE	IAE	ITSE	Criterion (ACO)	ISE	ITAE	IAE	ITSE
Voltage	1	Kp	3.0775	0.2123	0.4220	21.0991	Kp	1.0021	0.0257	0.0551	2.0222
	2	Ki	2.0672	0.1112	0.3554	18.0871	Ki	0.7884	0.0042	0.0111	2.0001
	3	Kd	2.7789	0.1552	0.3990	18.2788	Kd	0.9221	0.0109	0.0223	2.4088
	4	Settling time (ms)	7.5201	0.1988	0.4422	10.1001	Settling time (ms)	2.9910	0.0012	0.0669	1.5042
	5	Rise time (ms)	0.0711	0.0700	0.7009	0.0728	Rise time (ms)	0.0086	0.0041	0.0066	0.0099
	6	Overshoot (%)	0.0107	0.0023	0.0054	0.0110	Overshoot (%)	0.0033	0.0011	0.0018	0.0041
	7	The steady state error	0.0505	0.0150	0.0171	0.0712	The steady state error	0.0300	0.0140	0.0135	0.0674
Power	1	Settling time (ms)	0.0275	0.0230	0.0250	0.0284	Settling time (ms)	0.0119	0.0106	0.0112	0.0132
	2	Rise time (ms)	0.0073	0.0047	0.0052	0.0076	Rise time (ms)	0.0051	0.0020	0.0031	0.0066
	3	Overshoot (%)	1.6771	1.2572	1.2660	1.8001	Overshoot (%)	1.0661	1.0083	1.0106	1.0790
	4	The steady state error	0.5788	0.3441	0.3919	0.6009	The steady state error	0.2302	0.2064	0.2197	0.2554

5. CONCLUSION

This study demonstrates that ACO and GA are effective of optimizing MPPT for WECS. By utilizing these techniques to tune PID controller parameters, we achieve enhanced system functionality in different wind situations. The research shows that ACO can adapt quickly to internal system changes, even during significant disruptions, ensuring stable and efficient energy production. The practical implications of this work are significant for real-world applications. The optimized MPPT systems, using ACO and GA, can increase the wind power generation's dependability and efficiency, making it a more viable and sustainable energy source. These techniques can also help mitigate the effects of fluctuating wind speeds, providing a more stable power output that benefits utility operations, power markets, and energy distribution networks. Future research should focus on integrating these optimization algorithms with advanced forecasting systems for wind speeds. This would further improve the dynamic adaptability of MPPT controllers. Additionally, exploring the application of ACO and GA to other renewable energy systems, such as solar or hydroelectric power, could lead to broader advancements in optimizing renewable energy generation. An integration for energy storage solutions for enhance stability and reliability, especially during variable conditions, is another promising direction for future studies.

ACKNOWLEDGMENTS

This research was supported by the Laboratory of Systems Analysis, Information Processing and Industrial Management (LASTIMI), Higher School of Technology, Mohammed V University, Rabat, Morocco.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	**C**	**M**	**So**	**Va**	**Fo**	**I**	**R**	**D**	**O**	**E**	**Vi**	**Su**	**P**	**Fu**
Najoua Mrabet	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Chirine Benzazah	✓	✓			✓	✓			✓	✓				
Mohssine Chakib	✓		✓							✓	✓			
Adil Ziraoui	✓				✓				✓		✓			
Ahmed El Akkary	✓	✓	✓		✓	✓			✓		✓			
Najma Laaroussi	✓				✓				✓					

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The bibliometric data supporting the findings of this study were obtained from the Scopus and Web of Science databases, which are subject to subscription access. The derived dataset generated after screening, cleaning, and merging these records is available from the corresponding author [NM] upon reasonable request.

REFERENCES

[1] J. Pande and P. Nasikkar, "A maximum power point tracking technique for a wind power system based on the trapezoidal rule," *Energies*, vol. 16, no. 6, Mar. 2023, doi: 10.3390/en16062799.

[2] N. Mrabet, C. Benzazah, A. El Akkary, and M. Chakib, "Enhancing wind power estimation for Dakhla, Morocco: a comparative exploration of four numerical methods leveraging the Weibull distribution," in *2024 International Conference on Global Aeronautical Engineering and Satellite Technology, GAST 2024-Proceedings*, Apr. 2024, pp. 1–4, doi: 10.1109/GAST60528.2024.10520789.

[3] S. A. Adegoke, Y. Sun, Z. Wang, and O. Stephen, "A mini review on optimal reactive power dispatch incorporating renewable energy sources and flexible alternating current transmission system," *Electrical Engineering*, vol. 106, no. 4, pp. 3961–3982, Jan. 2024, doi: 10.1007/s00202-023-02199-2.

[4] Z. Qu, W. Younis, Y. Wang, and P. M. Georgievitch, "A multi-source power system's load frequency control utilizing particle swarm optimization," *Energies*, vol. 17, no. 2, Jan. 2024, doi: 10.3390/en17020517.

[5] H. Kord, A. A. Zamani, and S. M. Barakati, "Active hybrid energy storage management in a wind-dominated standalone system with robust fractional-order controller optimized by Gases Brownian Motion optimization algorithm," *Journal of Energy Storage*, vol. 66, Aug. 2023, doi: 10.1016/j.est.2023.107492.

[6] N. Mrabet, C. Benzazah, A. El Akkary, N. Sefiani, I. Lahlouh, and R. Benchrifa, "Performance evaluation of six methods for estimating Weibull distribution parameters for wind energy: applications to three sites in Morocco," *International Review on Modelling and Simulations*, vol. 16, no. 4, pp. 201–209, Aug. 2023, doi: 10.15866/iremos.v16i4.22899.

[7] O. Hachana, B. Meghni, A. Benamor, and I. Toumi, "Efficient PMSG wind turbine with energy storage system control based shuffled complex evolution optimizer," *ISA Transactions*, vol. 131, pp. 377–396, Dec. 2022, doi: 10.1016/j.isatra.2022.05.014.

[8] D. A. Umar *et al.*, "Evaluating the efficacy of intelligent methods for maximum power point tracking in wind energy harvesting systems," *Processes*, vol. 11, no. 5, May 2023, doi: 10.3390/pr11051420.

[9] M. R. Sarkar, S. Julai, C. W. Tong, M. Uddin, M. F. Romlie, and G. M. Shafiullah, "Hybrid pitch angle controller approaches for stable wind turbine power under variablewind speed," *Energies*, vol. 13, no. 14, Jul. 2020, doi: 10.3390/en13143622.

[10] D. Song *et al.*, "Review on the application of artificial intelligence methods in the control and design of offshore wind power systems," *Journal of Marine Science and Engineering*, vol. 12, no. 3, Feb. 2024, doi: 10.3390/jmse12030424.

[11] F. Yu and L. Pei, "The application of RAGA-PP model in environmental accounting information disclosure of enterprises in heavy pollution industries," *Results in Engineering*, vol. 21, Mar. 2024, doi: 10.1016/j.rineng.2023.101663.

[12] M. Kobbi, M. Saada, M. Chenafa, and A. Souahlia, *Advances in technology and materials green energies*. Singapore: Springer Singapore, 2021, doi: 10.1007/978-981-16-0378-5.

[13] Z. J. Mohammed, M. O. Mustafa, and S. E. Mohammed, "Adaptive hybrid pitch angle control and MPPT for PMSG-based wind power generator systems," *International Journal on Energy Conversion*, vol. 10, no. 5, pp. 153–161, 2022, doi: 10.15866/irecon.v10i5.22586.

[14] M. Nasiri, J. Milimonfared, and S. H. Fathi, "Modeling, analysis and comparison of TSR and OTC methods for MPPT and power smoothing in permanent magnet synchronous generator-based wind turbines," *Energy Conversion and Management*, vol. 86, pp. 892–900, Oct. 2014, doi: 10.1016/j.enconman.2014.06.055.

[15] H. Abouri, F. El Guezar, and H. Bouzahir, "An overview of control techniques for wind energy conversion system," in *2019 7th International Renewable and Sustainable Energy Conference, IRSEC 2019*, Nov. 2019, pp. 1–6, doi: 10.1109/IRSEC48032.2019.9078207.

[16] N. Mrabet, C. Benzazah, A. El Akkary, Y. Ennaciri, and I. Lahlouh, "Maximum power optimization of a direct-drive wind turbine connected to PMSG using multi-objective genetic algorithm," *International Journal of Applied Power Engineering*, vol. 13, no. 2, pp. 453–464, Jun. 2024, doi: 10.11591/ijape.v13.i2.pp453-464.

[17] A. I. M. Ali and H. R. A. Mohamed, "Improved P&O MPPT algorithm with efficient open-circuit voltage estimation for two-stage grid-integrated PV system under realistic solar radiation," *International Journal of Electrical Power and Energy Systems*, vol. 137, May 2022, doi: 10.1016/j.ijepes.2021.107805.

[18] S. Motahhir and B. Bossoufi, *Digital technologies and applications proceedings of ICDTA'24*, Cham, Switzerland: Springer, 2024, doi: 10.1007/978-3-032-07785-1.

[19] I. Toumi, A. Boulmaiz, B. Meghni, and O. Hachana, "Robust variable step P&O algorithm based MPPT for PMSG wind generation system using estimated wind speed compensation technique," *Sustainable Energy Technologies and Assessments*, vol. 60, Dec. 2023, doi: 10.1016/j.seta.2023.103420.

[20] S. André, F. Silva, S. Pinto, and P. Miguens, "Novel incremental conductance feedback method with integral compensator for maximum power point tracking: a comparison using hardware in the loop," *Applied Sciences*, vol. 13, no. 7, Mar. 2023, doi: 10.3390/app13074082.

[21] N. K. Agarwal, N. Singh, and A. Saxena, "PID/FO-PID controller implementation for the optimal controlling of wind driven PMSG," in *2nd International Conference on Edge Computing and Applications, ICECAA 2023*, Jul. 2023, pp. 1571–1575, doi: 10.1109/ICECAA58104.2023.10212188.

[22] S. M. Tripathi, U. P. Singh, S. Singh, N. K. Rai, Himani, and A. K. Srivastava, "Hardware-in-the-loop testing of grid-tied PMSG-based wind power generation system with optimum PI parameters," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 5, Sep. 2023, doi: 10.1016/j.prime.2023.100282.

[23] N. Mrabet, C. Benzazah, A. El Akkary, and N. Sefiani, "Multi-objective ant colony optimization for enhancing the maximum power of variable-speed wind turbines based on PMSG," *International Journal on Energy Conversion*, vol. 11, no. 5, pp. 195–204, Sep. 2023, doi: 10.15866/irecon.v11i5.24121.

[24] K. H. Huang, K. H. Chao, and T. W. Lee, "An improved photovoltaic module array global maximum power tracker combining a genetic algorithm and ant colony optimization," *Technologies*, vol. 11, no. 2, Apr. 2023, doi: 10.3390/technologies11020061.

[25] N. Mrabet *et al.*, "Enhancing wind energy conversion efficiency: a novel MPPT approach using P&O with ADRC controllers versus PI Controllers with Kp and Ki optimization via genetic algorithm and ant colony optimization," *Cleaner Energy Systems*, vol. 9, Dec. 2024, doi: 10.1016/j.cles.2024.100159.

BIOGRAPHIES OF AUTHORS

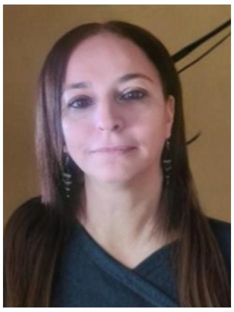
Najoua Mrabet is a Ph.D. student at Mohammadia Engineers School Rabat/ Mohamed V University, in Control Systems Engineering. She obtained the master's degree in energy mechanics option renewable energy materials from the Faculty of Sciences Rabat in December, 2020. Her research interests including synthesis of nonlinear control laws for the control of generator power supply and storage system, dedicated to a wind power production system. She can be contacted at email: najouamrabet2@gmail.com.

Chirine Benzazah received her engineering degree in Electric Systems and Telecommunications from the Faculty of Sciences and Technology, Cadi Ayyad University, Morocco, in 2012. She obtained a Ph.D. in Electrotechnics and Power Electronics from the Faculty of Sciences and Technology, Sultan Moulay Slimane University, Beni Mellal, Morocco, in 2018. From 2019 to 2023, she served as a professor of physics at the Higher School of Technology of Salé, Mohammed V University of Rabat, Morocco. Currently, she holds the position of a professor of physics at the Polydisciplinary Faculty of Safi, Cadi Ayyad University, of Marrakech, Morocco. Her research interests span across various fields, including electrical and electronics engineering, electrical power engineering, power converters, renewable energy technologies, harmonics, grid integration, high power electronics, power factor correction, and voltage regulation. She can be contacted at email: ch.benzazah@gmail.com.

Mohssine Chakib is having a master's degree in Electrical Engineering from The Superior Normal School of Technical Education (ENSET) Rabat in 2015. He obtained a Ph.D. in Electrical Engineering from The Superior Normal School of Arts and metiers (ENSAM), Morocco, in 2022. He can be contacted at email: chakib1mohssine@gmail.com.

Adil Ziraoui is currently pursuing his doctoral studies in Civil Engineering at the Hassan II University, National School of Arts and Crafts. His research is primarily dedicated to investigating the seismic vulnerability of reinforced concrete structures. He can be contacted at email: adil_ziraoui@hotmail.com.

Ahmed El Akkary graduated at The Superior Normal School of Technical Education (ENSET) Rabat in 1995. In 2003 he obtained his Advanced Diploma of Higher Education (DESA) specialty automatic and manufacturing. Then, in 2009, he obtained his Ph.D. from the Mohammadia School of Engineers at Mohammed V University, Rabat, in automatic specialty. He obtained the ability degree professor in July, 2017. His research interest is in control systems. He can be contacted at email: aelakkary@gmail.com.



Najma Laaroussi holds a master's degree in Thermal and Energy from the National Institute of Applied Sciences (INSA) in Lyon, France, and a Ph.D. in Energy Systems and Thermal Processes from the University of Paris-Est, France, obtained in 2008. From 2009 to 2011, she worked as a research and development engineer at Socotec Industries, France. Since 2011, she has been part of a research team specializing in materials, energy, and acoustics in Morocco. Her primary research interests include energy efficiency in buildings, as well as thermal solar and photovoltaic systems. She has an extensive international scientific publication record, including numerous journal articles and conference proceedings. She supervises and co-supervises various Ph.D. and master's students focusing on building energy efficiency. She can be contacted at email: najma.laaroussi@est.um5.ac.ma.