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# Fine-Tuning PI Controller Parameters for an Efficient Wind Energy Extraction System through Mean Squared Error (MSE): A Control System based on Ant Colony Optimization for Maximum Power Point Tracking (MPPT)

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*Abstract*— **This study presents a novel approach for optimizing Maximum Power Point Tracking (MPPT) control in a wind energy conversion system (WECS) utilizing a Permanent Magnetic Synchronous Generator (PMSG). The proposed method integrates Ant Colony Optimization (ACO) to enhance power extraction efficiency. Specifically, a Proportional Integral (PI) controller is employed to stabilize the maximum power point of the wind turbine, yielding crucial parameter values 'P' and 'I' within a stable range. To tackle conflicting closed-loop system performance criteria, a multi-criterion ACO approach is utilized, focusing on Mean Squared Error (MSE) for controller settings. Simulation results demonstrate the successful attainment of the desired Maximum Power Point, evidenced by outputs such as generated power, DC bus voltage, electromagnetic torque, and current. This innovative approach offers a comprehensive strategy for optimizing MPPT control in wind energy systems, contributing to enhanced overall performance and efficiency.**

**Keywords—Wind turbine, Permanent magnet synchronous generator, Maximum Power Point Tracking , Proportional Integral *controller, Ant Colony Optimization, Mean Squared Error***

## NOMENCLATURE

| | |
|---|---|
| MPP | Maximum Power Point |
| MPPT | Maximum Power Point Tracking |
| MSE | Mean Squared Error |
| ACO | Ant Colony Optimization |
| PI | Proportional Integral |
| PMSG | Permanent magnet synchronous generator |
| WT | Wind turbine |
| AI | Artificial Intelligence |
| WECS | Wind Energy Conversion Systems |

## I. INTRODUCTION

As nuclear and fossil fuels become more expensive, there is a shift towards renewable energy sources. Wind energy and other renewable energy sources have grown in popularity. Popular for their dependability, accessibility, and environmental friendliness. Wind turbines convert wind energy into electricity by adjusting shaft acceleration to perform efficiently at various wind speeds. Wind turbines equipped with Permanent Magnet Synchronous Generators (PMSGs) have gained popularity among wind energy conversion technologies [1].

PMSGs have various advantages, including simple design, low-speed operation, ease of maintenance, and high reliability. Power converters are utilised in these. Generators optimise Maximum Power Point Tracking (MPPT) at different wind speeds, resulting in maximum power extraction [2]. Our research offers a novel method for forecasting the region of stability by analysing the PI controller's properties. Stabilising delayed systems presents a challenge since their characteristic equations contain infinitely many roots, unlike those of non-delayed systems. Studying the first class of systems is challenging due to its complexity. This method involves extending the model using a proportional-integral (PI) controller [3].

This work aims to minimise the rising time, settling time, and overshoot rate of the closed-loop system's step response using Pareto optimality or multi-objective optimisation [4]. The system's dynamic performance requirements sometimes clash, making it difficult to optimise all objectives simultaneously. To optimise Wind Energy Conversion Systems, we use a meta-heuristic approach called Ant Colony Optimisation with many objectives. The Ant Colony Optimisation (ACO) algorithm ensures reliable data transmission. This method is ideal for routing issues due to its ability to determine the optimal solution and generate the shortest path, which can then be borrowed [5].

We want to apply ant colony optimisation (ACO) to fine-tune the PI controller settings, leading to improved performance. Results include reduced setup time and improved voltage, current, torque, and power responses. The ACO heuristic approach, developed and tested in MATLAB/Simulink, can help determine optimal PI controller settings. The main purpose is to properly control the DC-DC boost converter and get the greatest power point in Wind Energy Conversion Systems (WECS). This study contributes significantly by using ACO-based soft technology to modify the parameters of a Proportional Integral (PI) controller [6]. According to the explanation above, the following are the primary aims of the proposed work:

- Improve duty cycle calculation using the Incremental Inductance technique to achieve MPP. - Evaluate dynamic performance of voltage, torque, current, and power for different target functions.- The usual approach Five cost functions are used to optimize the standard PI controller in a wind turbine system.

The subsequent section delves into an in-depth discussion of various components within the Wind Energy Conversion System (WECS), including the DC-DC boost converter, incremental conductance approach, and Proportional Integral (PI) controller. The strategy outlined in the third part focuses on leveraging the Ant Colony Optimization (ACO) method to efficiently adjust the PI controller's parameters. This strategic control approach aims to optimize the performance of the WECS. Following this strategy, the essay concludes by highlighting crucial discoveries and insights obtained from the MATLAB simulations in the final part.

### A. General System Description

The suggested energy conversion system relies on a Permanent Magnet Synchronous Generator (PMSG). This gadget includes significant characteristics for wind energy. Applications include rotor losses, soft start, and permanent magnetization [7]. Figure 1 shows the anticipated architecture for the wind energy conversion system. The system consists of a diode bridge rectifier, boost converter, permanent magnet synchronous generator, and a wind turbine. The rectifier's output is coupled to a DC-DC boost converter. The MPPT (Maximum Power Point Tracking) control signal activates the boost converter, increasing the voltage across the load.

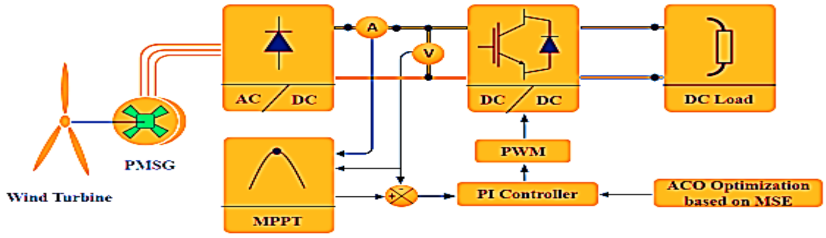


Figure 1. Schematic of maximum power optimization of WECS

### B. Modeling of wind turbine

The wind turbine's (WT) mechanical power generated is determined by [8]:

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

Where, ρ is the air density ( $kg/m^3$ ), A is the swept area (m2) , cp is the performance coefficient of the turbine which is a function of the pitch angle of rotor blades β ( in degrees ) and v is the wind speed (in m/s). λ: The tip-speed ratio .Eq (2) represents the ideal rotor speed at which the turbine works at maximum power [9].

$$\lambda = \omega_m R/v \quad (2)$$

Where R and ωm are the blade length (in m) and the wind turbine rotor speed (in rad/sec), respectively [8]. The wind turbine mechanical torque output Tm given as

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

Due to the modeling turbine features mentioned in, the coefficient of power conversion cp= (λ, β) is modelled using the following general equation [10]:

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

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

A mechanical output power turbine is depicted in Figure 2 as a result of turbine speed in several wind speeds.

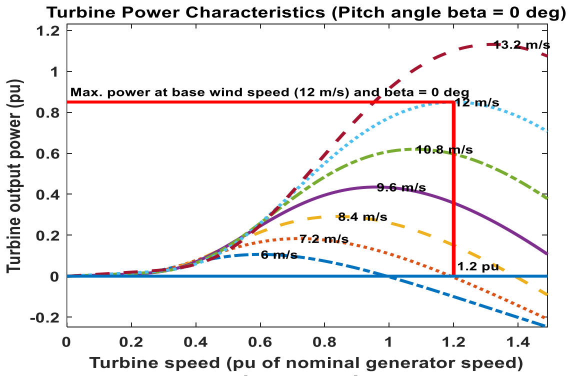


Fig. 2. Turbine power characteristics

Figure 2 shows that a specific turbine speed is optimal for generating the maximum electricity from a given wind speed. Holding the turbine speed at 1.2 pu allows for maximum power generation from a wind speed of 12 m/s. To maintain a high Cp value, the rotor speed must be adjusted to the optimal operating point for different wind speeds. The greatest efficiency of a hypothetical wind turbine is 16/27, which equals 59.25 percent. For all practical purposes, effectiveness ranges from 25% to 45%.

### C. PMSG modeling

Its d-q equivalent circuits serve as a paradigm for PMSG. In synchronous d- q coordinates, a surface mounted PMSG's equations are written as [11]:

$$V_{ds} = R_s + L_s\frac{di_{ds}}{dt} - \omega_e L_s i_{qs} \quad (6)$$

$$V_{qs} = R_s i_{qs} + L_s\frac{di_{qs}}{dt} + \omega_e L_s i_{qs} + \omega_e\psi \quad (7)$$

Where Ls is the inductance of the stator winding, Rs is the resistance of the stator winding, Vds,Vqs, iqs , and iqs are the d-q components of the stator voltage and current, respectively, $\psi$ is the magnetic flux, and $\omega$ is electrical angular speed of the generator. The generator's output power and electromagnetic torque are provided as [12]:

$$T_e = \frac{3}{2}\frac{P}{2}\psi i_{qs} \quad (8)$$

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

P is the generator's pole number

### D. PI controller design

Proportional Integral, or PI for short, is a type of device used in industrial settings to regulate various process variables. A control loop feedback device governs all of the process parameters in this controller. To steer a structure towards an otherwise level of target, use this form of command. To maintain a technique's real output as close to the target as feasible, this controller employs closed-loop feedback; if this is not possible, fixed-point output is used. The transfer function c(s) given by [13] equation eq (14): Without a doubt, the process control industry's most extensively used control algorithm is the PI controller [13].

$$C(s) = k_p + \frac{k_i}{s} \quad (10)$$

In this study, the PI parameters will be modified using the tuning methodology, ant colony optimisation (MOACO), which has been shown to yield good PI increases and improve controller efficiency and has recently gained favour as a method of optimising the value of Kp and Ki. Figure 3 depicts a block graph for MOACO with a PI controller. This shows how MOACO adjusts the gain amount to lessen the disparity between the reference values and feedback [14].

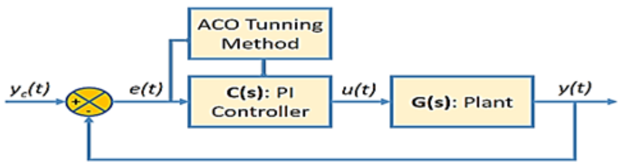


Fig. 3. Turbine power MOACO desing method of the PI controller

## II. METHOD DESCRIPTION

### A. ACO Approach

The technique's resolution specifying the apparatus in question, which is what turns the PI controller variable optimisation challenge into an NP problem, is exponentially complicated, necessitating the use of meta-heuristics.Ant Colony Optimisation is a sort of meta-heuristic optimisation based on ant behaviour. The original concept has been expanded to solve a broader variety of issues, and new algorithms influenced by various aspects of ant behaviour have evolved.

The ants use pheromone trails to trace their movements from source i to source j, with the expectation that a colony will choose the quickest path to source j. The probability that ant k will go from city i to city j is as follows [15]:

$$p_{ij}^k = \frac{\left[\tau_{ij}\right]^\alpha\left[\eta_{ij}\right]^\beta}{\sum_{i\in N_i^k}\left[\tau_{ij}\right]^\alpha\left[\eta_{ij}\right]^\beta} \qquad \forall \in N_i^k \quad (11)$$

Ant k is prospective neighbourhood is determined by where he is located in city i. The factors α and β determine the influence of trail pheromones and heuristics. The three basic steps of the ACO optimisation approach are employed in the PI controller tuning process. The ant solution is created first, then the algorithm parameters are set (the number of ants, the pheromone, the rate of evaporation, and the number of iterations), and finally the pheromone concentration is updated. The optimal PI controller settings are proportional gain (Kp) and integral gain (Ki). Before employing the ACO, the cost value of the aim function should be determined.

### A. Objective functions cost value

The objective function cost value should be chosen before the ACO can be used. The mean squared error (MSE) is utilised in several papers to fine-tune the PI controller. Calculating the objective function yields [16]:

$$MSE = \sum_0^{t\max} e(t)/n \quad (12)$$

In order to illustrate how well the closed-loop system performs, a model simulation of MSE objective performance indices is employed. The default starting variables used in ACO algorithm simulations are listed in Table 1.

## III. MODELING RESULTS AND ANALYSIS

When modelling the mentioned mechanism, the MATLAB/SIMULINK programme is utilised to study how the proposed WECS works with MSE. This project's MATLAB/Simulink programming architecture for the ACO to PI controller delivers a 12.3kW as gererated WECS-based power, DC-DC bus converter voltage, load current, output power, and system torque electromagnetic. To create a PMSG in compliance with a set of requirements and limitations.

TABLE I. ANT COLONY ALGORITHMS INPUT PARAMETERS

| Dimensions | Values |
|---|---|
| Number of ants | 50 |
| Constant values | $\alpha$=0.6;$\beta$=0.5 |
| Evaporation rate | $\mu$=0.6 |
| Multiple iterations | Ni=100 |
| Number of nodes | N=10000 |

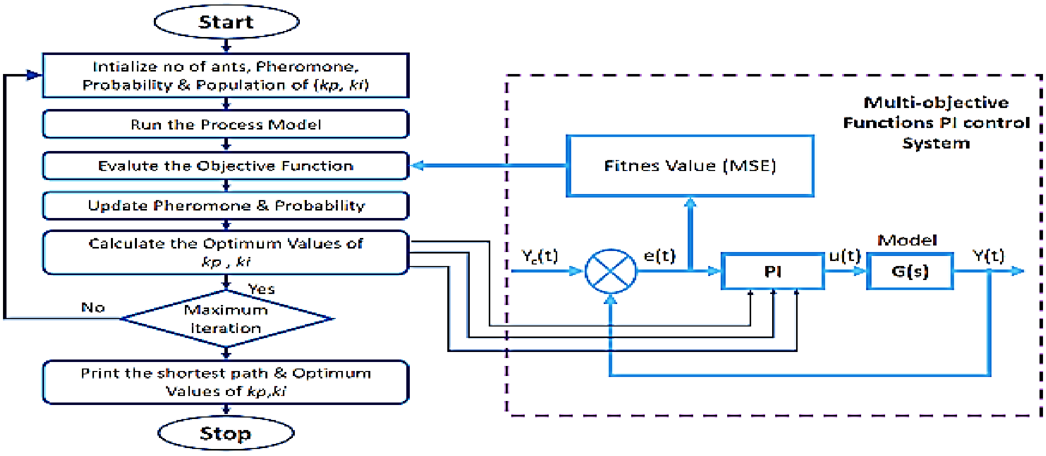


Fig. 4. Flowchart for proportional-integral tuning using Ant colony Optimization

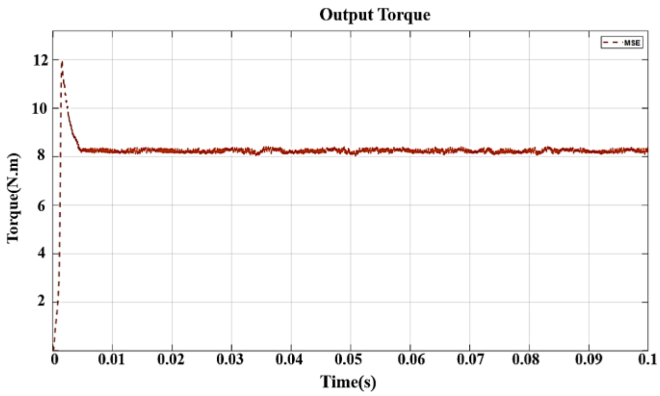


Fig. 5. Torque output with the MSE fitness factor

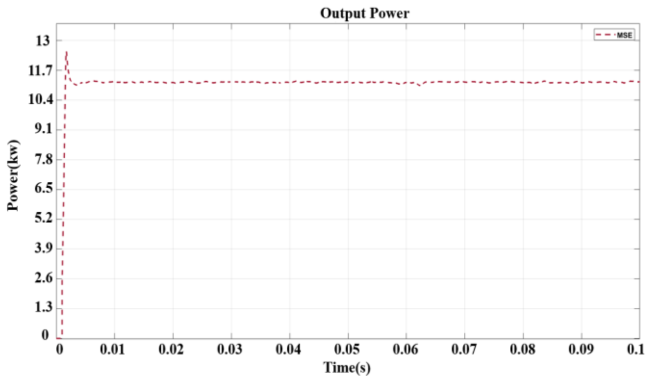


Fig. 7. Power output with the MSE fitness factor

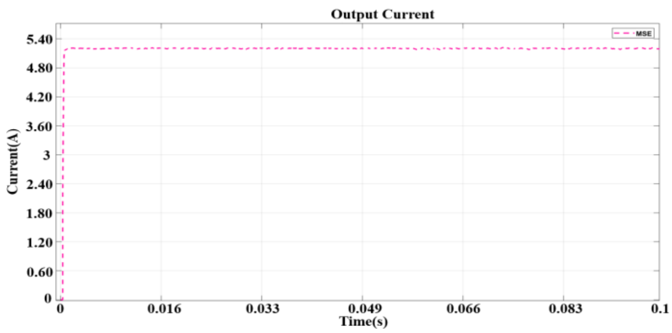


Fig. 6. Current output with the MSE fitness factor

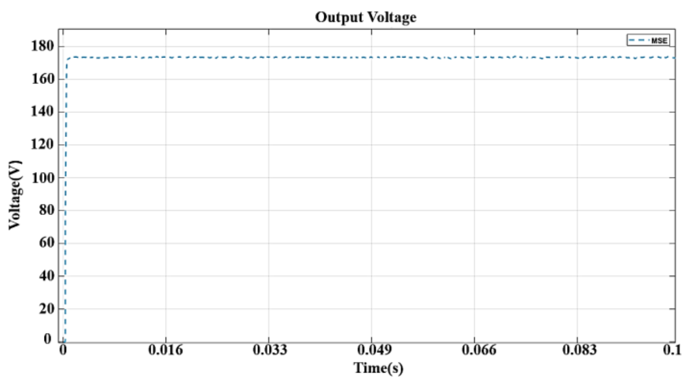


Fig. 8. Vower output with the MSE fitness factor

Figures 5, 6, 7, and 8 show the ACO algorithm's closed-loop step response to the given voltage, power, set current, and electromagnetic torque. These figures show the values for rising time, settling time, overshoot, and steady-state error, which are summarised in Table 1. The step answers demonstrate the performance of the ACO algorithm, exhibiting enhanced control and system behaviour in the wind energy conversion system.

Table 1 shows that the rising and settling times achieved using the MSE objective function are ideally reduced. When using the MSE criteria, however, the overshoot rate is somewhat greater. The rising and settling time values produced utilising the various ACO optimisation objective functions are generally closer. This suggests that the MSE goal function delivers enhanced system reaction time and stability.

TABLE II. NUMERICAL PERFORMANCE MEASURED OF THE CLOSED LOOP REPONSE WITH MSE OBJECTIVE FUNCTIONS

| **Voltage** | |
|---|---|
| Criterion | MSE |
| kp | 0.0023 |
| ki | 0.0031 |
| Settling time (ms) | 7.4552 |
| Rise time (ms) | 0.1022 |
| Overshoot (%) | 0.1001 |
| The steady state error | 0.1303 |
| **Power** | |
| Criterion | MSE |
| kp | 0.3020 |
| ki | 0.2001 |
| Settling time (ms) | 0.4550 |
| Rise time (ms) | 0.7011 |
| Overshoot (%) | 9.0330 |
| The steady state error | 0.8422 |

The results obtained from Figures 5, 6, 7, and 8 and summarized in Table 1 provide valuable insights into the performance of the ACO algorithm in our wind energy conversion system. These results can be further enriched by comparing and discussing them with other approaches from the literature to highlight the strengths of our methodology. When comparing our approach to other methods, it becomes evident that the ACO algorithm, particularly when guided by the MSE objective function, excels in achieving reduced rising and settling times. This improvement in system response time is crucial for enhancing the overall efficiency of wind energy extraction systems [17].

However, it is also important to note that while our method reduces rising and settling times significantly, it does result in a slightly higher overshoot rate compared to some other approaches. This trade-off between faster response time and overshoot rate should be carefully considered and discussed in the context of specific application requirements.

Moreover, the closeness of the rising and settling time values achieved through different ACO optimization objective functions indicates the robustness and versatility of the ACO algorithm. This suggests that our chosen MSE goal function effectively balances system reaction time and stability, leading to improved overall control and system behavior.

In summary, by comparing and discussing these results with existing literature, we can emphasize the strengths of our approach, particularly in terms of enhanced system reaction time, stability, and control performance in wind energy conversion system [18].

## III. CONCLUSION

Despite falling yields, there is a considerable need for extremely reliable wind power. Wind turbine dynamic modelling, equation-based PMSG modelling, and MPPT controller implementation using MATLAB/Simulink have all been investigated and analysed for both constant and changing wind speeds. Variable penetration rates due by wind strength variations have a negative impact on utility operations, power markets, and energy delivery. The results of this inquiry into voltage, current, torque, electromagnetics, and power regulations. Use an ant colony optimisation (ACO) technique to determine the best tuning parameters for the PI controller. The multi-loop control approach was utilised to simulate the synthesis of a wind MPPT system application in typical test conditions. The settling time and least overshoot were calculated using the Mean Squared Error (MSE) criterion. The WECS results demonstrate good overall system performance, demonstrating the validity of the ACO strategy for PI dimension optimisation discussed in this short, as well as the PI controller tuning approach employed.

In the future, wind power generation research can be broadened to include enhanced control systems that employ Artificial Intelligence (AI) algorithms and predictive models. Furthermore, future research might focus on integrating energy storage devices to increase the stability and reliability of wind power plants in the face of changing wind conditions.

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