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# STABILITY OF METAHEURISTIC PID CONTROLLERS IN PHOTOVOLTAIC DC MICROGRIDS

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***Abstract.*** *This article presents the stability assessment of metaheuristic PID controllers in the hierarchical control system of photovoltaic DC microgrids. Stability is a critical aspect of DC microgrid systems. PID controllers are utilized at the primary, secondary and tertiary control levels of the DC microgrid's hierarchical control system. Tuning of multiple PID controllers using traditional methods such as Ziegler-Nichols and Cohen-Coon tuning techniques becomes challenging under dynamic conditions of photovoltaic DC microgrids. Metaheuristic optimization algorithms are used to construct self-tuning PID controllers with improved stability. Experiments are performed to assess the stability of PID controlled system. Results exhibit that metaheuristic-tuned PID controllers of photovoltaic DC microgrids achieved superior performance in comparison with the traditional methods.*

**Keywords**: DC microgrid control system, whale optimization, particle swarm optimization, photovoltaic systems, metaheuristic PID controller

# STABILNOŚĆ METAHEURYSTYCZNYCH REGULATORÓW PID W FOTOWOLTAICZNYCH MIKROSIECIACH PRĄDU STAŁEGO

***Streszczenie.*** *W artykule przedstawiono ocenę stabilności metaheurystycznych regulatorów PID w hierarchicznym systemie sterowania fotowoltaicznych mikrosieci DC. Stabilność jest krytycznym aspektem systemów mikrosieci DC. Regulatory PID są wykorzystywane na podstawowym, drugim i trzecim poziomie hierarchicznego systemu sterowania mikrosieci DC. Dostrajanie wielu regulatorów PID przy użyciu tradycyjnych metod, takich jak techniki Zieglera-Nicholsa i Cohena-Coona, staje się wyzwaniem w dynamicznych warunkach fotowoltaicznych mikrosieci DC. Metaheurystyczne algorytmy optymalizacji są wykorzystywane do konstruowania samostrojących regulatorów PID o zwiększonej stabilności. Przeprowadzono eksperymenty w celu oceny stabilności systemu sterowanego PID. Wyniki pokazują, że dostrojone metaheurystycznie regulatory PID fotowoltaicznych mikrosieci DC osiągnęły lepszą wydajność w porównaniu z tradycyjnymi metodami.*

**Słowa kluczowe**: system sterowania mikrosieciami DC, optymalizacja wieloryba, optymalizacja roju cząstek, systemy fotowoltaiczne, metaheurystyczny regulator PID

## Introduction

Control of the DC microgrid is performed through the control of individual power converters. Photovoltaic modules in DC microgrids are linked with the common DC bus through the unidirectional DC-DC converters [3, 10, 28]. The purpose of these converters is to regulate varying output voltages of photovoltaic modules [3, 7, 10, 18]. The level of temperature and solar irradiation are the primary sources of the intermittent nature of photovoltaic output voltage and power [4, 16]. Control in DC microgrids is realised at three levels of a hierarchical system, namely the primary level (first layer), secondary level and tertiary (higher) level [2, 19]. With the help of PID controllers, load sharing and individual current/voltage regulation issues can be resolved at the primary control. The purpose of the secondary layer is to compensate for the DC bus voltage deviations as a result of the droop control [14, 22]. Tertiary control is used to determine the amount of energy imported or exported [25, 33].

PID controllers are common in photovoltaic DC microgrids due to their ease of execution and effectiveness [6, 27, 30]. However, older methods of implementation, like the Ziegler-Nichols and Cohen-Coon techniques, have problems with remaining stable with dynamic situations [1]. To mitigate these issues, other methods like Differential Evolution (DE), Gravitational Search Algorithm (GSA), Ant Colony Optimization (ACO), and Cuckoo Search (CS) others have been used with great effectiveness for fine-tuning PID controllers [8, 9, 14, 15, 17, 20, 26, 29, 34].

Many studies have showed the effectiveness of these algorithms for PID tuning. GSA is famous for optimizing PID parameters as it can quickly solve non-linear multi-dimensional problems, though it suffers from slower convergence [20]. Inspired by ants' foraging behavior, ACO has been tried on PID tuning, but suffers from being to dependent on pheromone updating rules, which slows the process in high-dimensional spaces [21]. CS outperforms in global search functions. However, optimal effectiveness may take excessive cycles to achieve [9, 15]. DE shows promise with PID; nevertheless, it is highly sensitive to the selection of mutation parameters [21].

Even with these progressions, the gap that still exists is the analysis of the stability and relative optimization performance of Whale Optimization Algorithm (WOA) with other algorithms and metaheuristics. The gap of exploration and exploitation balance, computational effort, and stability in dynamic systems is filled with ease by WOA and PSO.

The Whale Optimization Algorithm [13, 21, 24], which is to be tested, was tested against 29 mathematical optimization tasks and 6 structural optimization tasks and was compared against many other leading optimization methods. Each benchmark function was executed 30 times with a randomly initialized population, and all statistical results were recorded. The results from WOA in [21] were compared with several other optimization algorithms such as PSO, GSA, DE, FEP, and CMA-ES. The majority of the PSO data was collected from recorded data.

While checking for ability to exploit unimodal functions (functions with one global optimum), WOA proved to be quite competitive to other Meta-heuristic algorithms. In many of these test cases, WOA was the best or second best performing algorithm. The result demonstrates the strong exploitation abilities.

The assessment of exploration capability was done with multimodal functions which have many local optimas and become more numerous with the increase on problem dimensions. In this scenario, WOA was either the best or second best optimizer in most of the test cases. This is due to the integrated exploration strategies of WOA that lead it towards the global optimum.

In terms of the capability to escape from local minima, as shown in [21], WOA was superior in three test functions and was very competitive in the other functions. The results in [21] show us that WOA is well calibrated between exploration and exploitation.

From a convergence analysis, we can see that WOA's search agents first tend to explore large areas around the promising regions and then focus towards the approximated best solution.

In general, the results highlight many features of WOA. It possesses an unique exploration ability, is due to a position-updating algorithm that urges the whales to initially circulate randomly about one another and subsequently adopt a spiral-like movement toward the best-found solution. By doing exploration and exploitation in approximately half of the iterations, WOA integrates avoidance of local optima with strong convergence rate. In contrast, PSO, GSA, and associated techniques depend on one position-updating formula, which can increase the chances of getting stuck in a local optima. In the next sections, more complex, real-life engineering problems demonstrate the effectiveness of WOA.

Fast convergence with little error in tuning is achieved through the efficient update of PID gains relative to the best-known global and local positions, which is why PSO, the social behavior of birds, is known to have [12, 31, 32]. WOA is a powerful algorithm for automatic tuning of PID controllers because it is able to change the search method from competition to collaboration and vice-versa during the process of searching and hence can be used to control complex control systems [21, 24, 34].The Whale Optimization Algorithm distinguishes itself from its rivals on the account of its biological reasoning, flexibility, and effective balance of exploration and exploitation; in the competitive field of optimization techniques, it is truly remarkable. Among the nature inspired heuristics, this algorithm is arguably one of the best due to its ease of use, exceptional convergence characteristics, and applicability in different areas.

The growth of WOA research demonstrates its efficiency in overcoming numerous real world problems, which continues to prove its dominance over numerous conventional and modern optimization methods. The purpose of this article is to develop metaheuristic PID controllers whose gains are tuned by Whale Optimization (WOA), Particle Swarm Optimization (PSO) and perform root-locus and bode-plot assessment to determine the level of stability, in comparison with the traditional closed-loop Ziegler-Nichols (ZN) [5, 11] and Cohen-Coon (CC) [11] method.

## 1. DC-DC boost converter modelling

Boost converter topology is chosen as a unidirectional DC-DC converter to interface PV modules with the loads to regulate output voltages. DC-DC boost converters are capable of producing output voltages which are higher than the input voltages [7, 18]. Fig. 1 illustrates a control diagram of an individual DC-DC Boost converter which contains an inductor (L), a capacitor (C), a diode (D), and a transistor (Tr). The input voltage $V_{in}$ is supplied by the photovoltaic module. The purpose of the measurement unit is to conduct voltage measurements and perform signal conditioning, while the control unit comprises PID controllers and Pulse-Width Modulators (PWM).

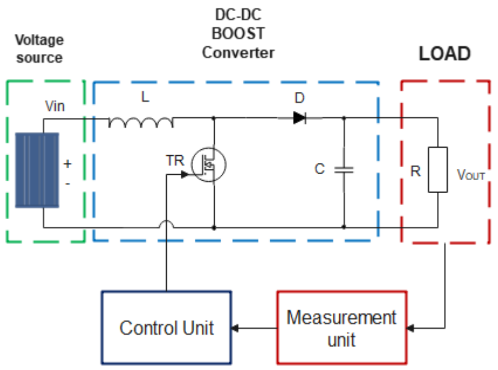


*Fig. 1. Control diagram of individual DC-DC Boost converter*

The transfer function of the DC-DC boost converter is as follows [18]:

$$\frac{V_{out}}{V_{in}}(s) = \frac{1}{\frac{LC}{1-D}s^2+\frac{L}{R(1-D)}s+1-D} \quad (1)$$

The input and reference voltages are selected to be 12 V, and 30 V respectively. In this article, the electronic component values are selected as follows:

$$L = 1\cdot10^{-6}\ \text{H},\ C = 1\cdot10^{-6}\ \text{F},\ R = 10\ \text{Ohm}$$

The final form of the transfer function of the DC-DC boost converter is as follows:

$$\frac{V_{out}}{V_{in}}(s) = \frac{12}{2.5*10^{-12}s^2+2.5*10^{-7}s+0.4} \quad (2)$$

## 2. DC microgrid control system modelling

The photovoltaic DC microgrid with its control system is depicted in Fig. 2.

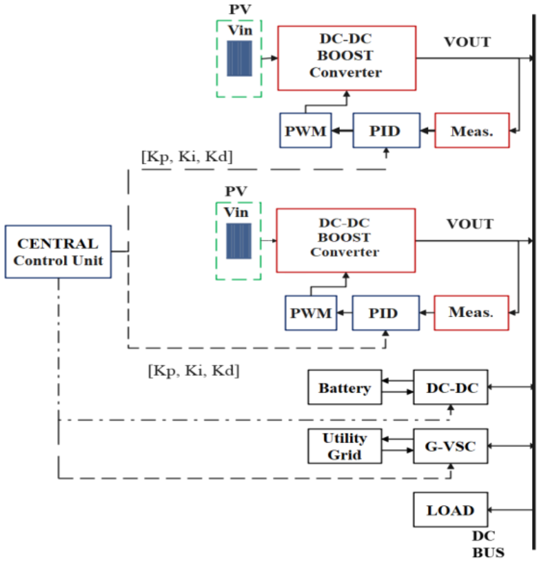


*Fig. 2. Structural diagram of DC microgrid and its control system*

All the primary, secondary and tertiary levels are realized at the central control unit. As can be seen from Fig. 2, all distributed energy resources are connected with the DC common bus using power converters such as DC-DC and G-VSC (grid-voltage source converters) converters. All the DC-DC converters in the DC microgrid is controlled by the central control unit. The mathematical form of PID controllers in the Laplace domain is as follows [5, 11]:

$$U(s) = (K_p + \frac{K_I}{s} + sK_D)E(s) \quad (3)$$

where $K_p$, $K_i$, $K_d$, $E(s)$, $U(s)$ are the proportional gain, integral gain, differential gain, error and control signal.

Fig. 3 depicts the functional diagram of the DC microgrid control system with the metaheuristic optimizer.

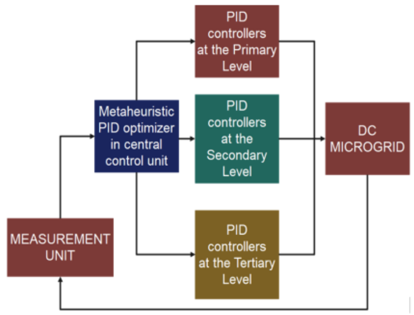


*Fig. 3. PID optimization of DC microgrid control system*

As a metaheuristic optimizer, WOA and PSO algorithms are implemented. As is the case for every metaheuristic algorithm, the population size, and number of iterations dimension of the system must be pre-determined. In both cases, the dimension of search space is selected to be 3 as we have three variables (proportional, integral and derivative gains). Iterations are 20, population size is selected to be 50. A population size of 50 offers sufficient diversity without requiring too much computation, while 20 iterations provides an adequate compromise between speed and accuracy. These parameters guarantee reliable convergence and the specified conditions for effective convergence. Population size determines diversity, but increasing it raises computation cost. Adding iterations improves accuracy, but slows down processing speed. Some balance is needed to maintain high performance of the controller.

For the evaluation of the errors the integral square error criterion is employed, which has the following discrete form:

$$ISE = \sum_{k=1}^{N} e^2[k] \tag{4}$$

Suppose we have a population of $N$ whales exploring a search space of $D$ dimensions. Let the position of the $i$-th whale in the $d$-th dimension be $\mathbf{X}_i = (X_i^1, X_i^2, \ldots, X_i^D)$ for $i = 1,2,\ldots,N$. The parameter $t_{\max}$ is the maximum number of iterations, and the globally optimal position is denoted by $\mathbf{X}_{\text{best,}}$ which we treat as the location of the prey. Whales have the ability to locate and encircle this prey, and their encircling behavior is represented by [22]:

$$\mathbf{X}_i^{t+1} = \mathbf{x}_{\text{best}}^t - A \cdot \mathbf{D} \tag{5}$$

where $\mathbf{D} = \left|C \cdot \mathbf{x}_{\text{best}}^t - \mathbf{X}_i^t\right|$ corresponds to a step size, $A = 2ar_1 - a$, and $C = 2r_2$. The parameters $r_1$ and $r_2$ are random numbers in the interval [0,1]. Meanwhile, $a = 2 - \frac{2t}{t_{\max}}$ decreases to 0 as iterations proceed, ensuring convergence. The factor $C$ falls in [0,2] and signifies the influence of the prey's position on the distance to the current whale during each iteration.

Whales also undertake a spiral movement, swimming around the prey with a decreasing spiral radius by producing a bubble net. That movement is described by [21]:

$$\mathbf{X}_i^{t+1} = \mathbf{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \mathbf{x}_{\text{best}}^t \tag{6}$$

where $\mathbf{D}' = \left|\mathbf{x}_{\text{best}}^t - \mathbf{X}_i^t\right|$ is the distance between the whale and the prey, $b$ is a constant which is responsible of controlling the logarithmic spiral's shape, while $l$ is a random number which lies in the interval $[-1,1]$. When following the spiral path, a random probability $p$ decides whether the whale uses the encircling strategy or this spiral strategy. Beyond the bubble-net behavior, whales also engage in a random predation process, influenced by the positions of other whales. This can be captured mathematically by:

$$\mathbf{X}_i^{t+1} = \mathbf{X}_r^t - A \cdot \mathbf{D}'' \tag{7}$$

where $\mathbf{X}_r^t$ is the position of a randomly chosen whale from the population, and $\mathbf{D}'' = \left|C \cdot \mathbf{X}_r^t - \mathbf{X}_i^t\right|$. Here, $C$ once again controls the effect of the prey's position on the distance between the chosen whale and the current whale.

In the algorithm, the probability of performing bubble-net behaviors (encircling or spiral) is set to 50%. When $|A| < 1$, whales focus on exploitation (the so-called "development" phase); otherwise, they undertake exploration ("search" phase). The final rule for updating $\mathbf{X}_i$ combines these possibilities and can be summarized as follows (Equation (5) in the original text) [21]:

$$\mathbf{X}_i^{t+1} = \begin{cases} \mathbf{x}_{\text{best}}^t - A \cdot \mathbf{D}, & p < 0.5, |A| < 1 \\ \mathbf{D}' \cdot e^{bl}\cos(2\pi l) + \mathbf{x}_{\text{best}}^t, & p < 0.5, |A| \geq 1 \\ \mathbf{X}_r^t - A \cdot \mathbf{D}'', & p \geq 0.5, |A| \geq 1 \end{cases} \tag{8}$$

Finally, a pseudocode implementation (referred to as Algorithm 1) captures these steps [21].

**Shortened Whale Optimization Algorithm**

1 Initialize: Set population size $N$, dimension $D$, max iterations $T$. Randomly position whales.

2 Repeat (for $t = 1 \ldots T$ ):
  - a. Evaluate fitness of each whale.
  - b. Update parameter $a_1$.
  - c. For each whale:
    - Compute $A, C, l$.
    - Draw random $p \in [0,1]$.
    - If $p < 0.5$ :
    - If $|A| \geq 1$ : use Equation (4).
    - Else: use Equation (2).
    - Else: use Equation (3).
  - d. Increment *t*.

Particle Swarm Optimization (PSO) conflicts with traditional optimization techniques and was generated by Kennedy and Eberhart in 1995, modeled after the social behavior of birds flocking and fish schooling. Individual solutions are identified as particles. In contrast, each particle utilizes its best-known position alongside previous positions from the swarm to modify its velocity and position to search the entire solution space. Every particle $i$ in a $d$-dimensional search space is represented with a position vector $\mathbf{x}_i$(t) and a velocity vector $\mathbf{v}_i$(t) at iteration *t*. The velocity update integrates the three main components: inertia (the current velocity), the appeal to the particle's individually best position, and the appeal to the best position sent by the swarm. In other words, we say that the velocity of the particle is updated as follows [12, 31]:

$$\mathbf{v}_i(t+1) = \omega\mathbf{v}_i(t) + c_1 r_1[\mathbf{p}_i - \mathbf{x}_i(t)] + c_2 r_2[\mathbf{g} - \mathbf{x}_i(t)] \tag{9}$$

where $\omega$ is the inertia weight, $c_1$ and $c_2$ are learning factors, $r_1$ and $r_2$ are random coefficients (often uniformly distributed), $\mathbf{p}_i$ is the particle's best-known position, and $\mathbf{g}$ is the global best position found across the swarm. The position is then updated by [12, 31]:

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \tag{10}$$

Through this iterative process, the swarm converges toward promising regions in the search space, making PSO a robust and efficient method for solving various optimization problems in continuous domains [12, 31].

1. Initialize positions and velocities of $N$ particles randomly within the search space; set each particle's personal best $p_i$ and the global best $g$.
2. Update Velocities using $v_i \leftarrow \omega v_i + c_1 r_1(p_i - x_i) + c_2 r_2(g - x_i)$.
3. Update Positions with $x_i \leftarrow x_i + v_i$.
4. Refine Bests by comparing each updated $x_i$ with its $p_i$ and comparing all $p_i$ with $g$.
5. Repeat Steps 2-4 until a stopping criterion (e.g., maximum iterations or convergence threshold) is met.

During every iteration, WOA and PSO will update the values using their respective optimization strategies, which entail minimizing the Integral Square Error (ISE). A metaheuristic controller initially generates random potential solutions for each tuning gain of a PID controller.

$$P = \begin{bmatrix} X_{P11} & X_{I12} & X_{D13} \\ X_{P21} & X_{I22} & X_{D23} \\ . & . & . \\ X_{Pn1} & X_{In2} & X_{Dn3} \end{bmatrix} \tag{11}$$

where subscripts of $P$, $I$ and $D$ denote the proportional, integral and derivative tuning gains, respectively.

The upper (UB) and lower boundary (LB) for both metaheuristic controllers are selected as follows:

$$UB = [100 \quad 100 \quad 100] \tag{12}$$

$$LB = [0 \quad 0 \quad 0] \tag{13}$$

Then according to the rules of WOA and PSO algorithms, each of tuning gains are updated within given iteration period [12, 15, 21, 32].

## 3. Simulation results

Fig. 4 shows the bode plot of the Closed-Loop Ziegler Nichols tuned PID controller. Gain and phase margins are infinite and 62.9 degrees, respectively, while the root-locus plot of the closed-loop Ziegler Nichols tuned PID controller is shown in Fig. 5. It has exhibited one pole at $-6.99 \cdot 10^5$, and 2 complex conjugate poles at $-1.81 \cdot 10^5 \pm 1.57 \cdot 10^6 i$. Zero was observed at $-1.35 \cdot 10^6$.

Comprehensive measurement results are presented in Table 1.

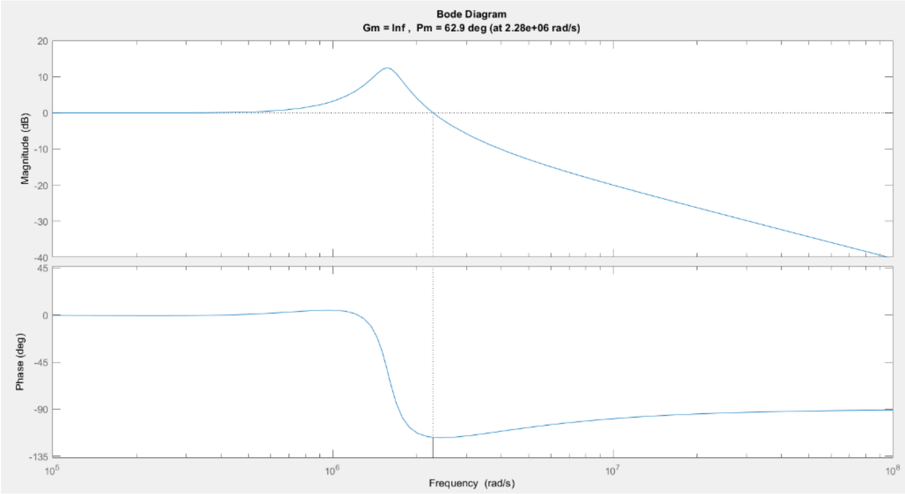


*Fig. 4. Bode plot of Closed-Loop Ziegler Nichols tuned PID controller*

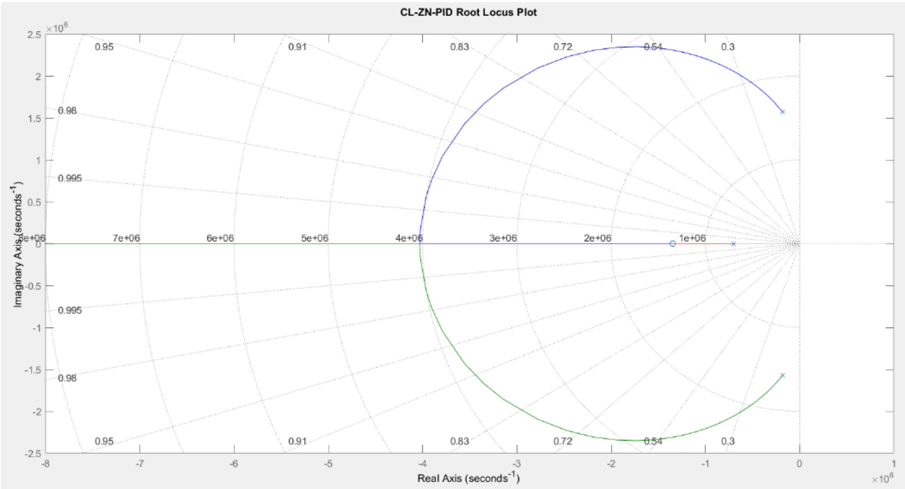


*Fig. 5. Root-Locus plot of Closed-Loop Ziegler Nichols tuned PID controller*

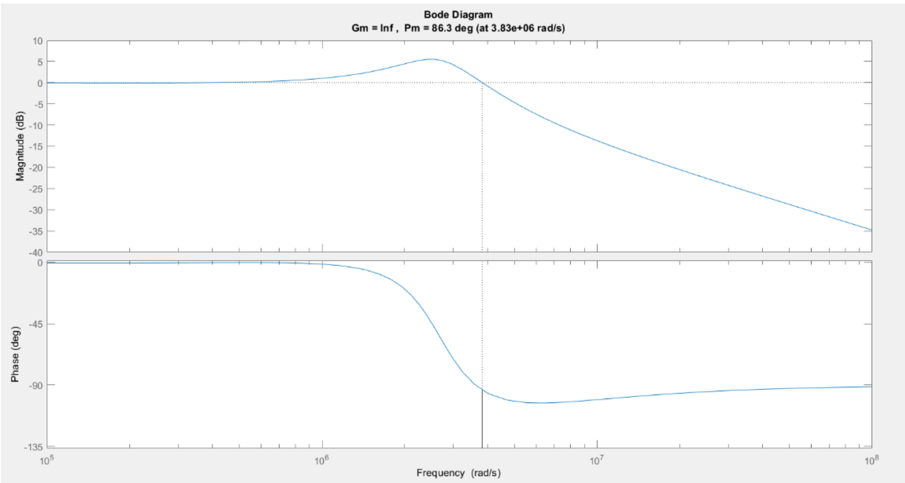


*Fig. 6. Bode plot of Cohen Coon tuned PID controller*

Fig. 6 shows the bode plot of the PID controller tuned by Cohen-Coon method. Gain and phase margins are infinite and 86.3 degrees, respectively, while the root-locus plot of a PID controller tuned by Cohen-Coon method is shown in Fig. 7.

Table 1 has shown 2 complex poles at $-8.64\cdot10^5 \pm 2.55\cdot10^6 i$, and 2 zeros at $-1.96\cdot10^5$ and $-3.89\cdot10^6$.

Fig. 8 shows a bode plot of the PID controller tuned by the PSO method. Gain and phase margins are infinite and 91.9 degrees, respectively, while the root-locus plot of a PID controller tuned by the PSO method is shown in Fig. 9.

Table 1 has shown 1 pole at $-2.4\cdot10^{14}$ and 1 zero at -1.

Fig. 10 shows the bode plot of the PID controller tuned by the WOA method. Gain and phase margins are infinite and 91.9 degrees, respectively, while the root-locus plot of a PID controller tuned by the WOA method is shown in Fig. 11.

Table 1 has shown 1 pole at $-2.4\cdot10^{14}$ and 1 zero at -1.

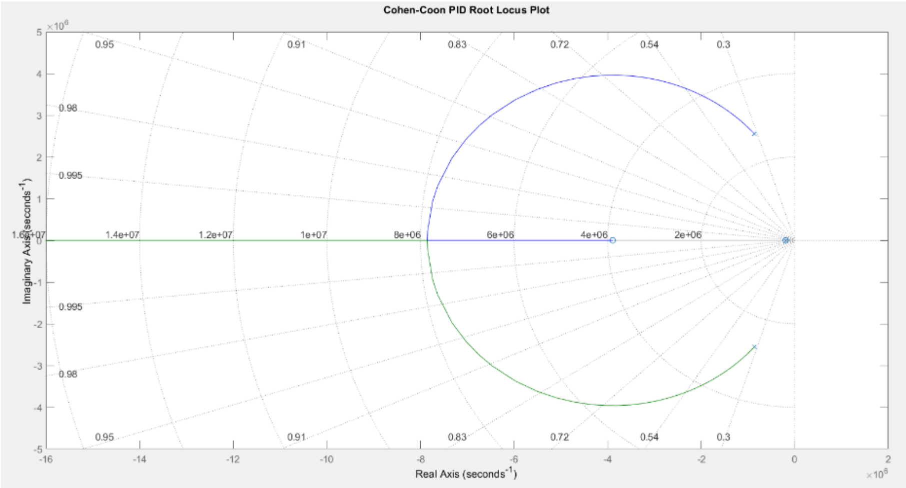


*Fig. 7. Root-Locus plot of Cohen Coon tuned PID controller*

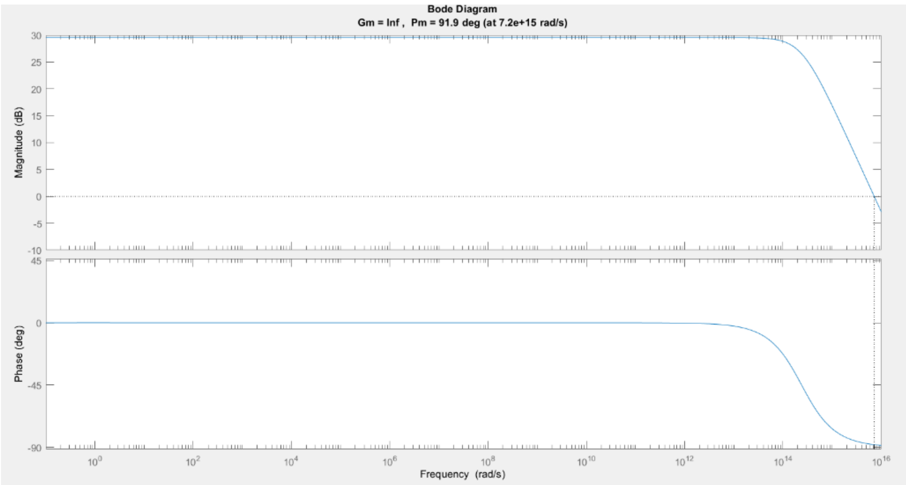


*Fig. 8. Bode plot of PSO-tuned PID controller*

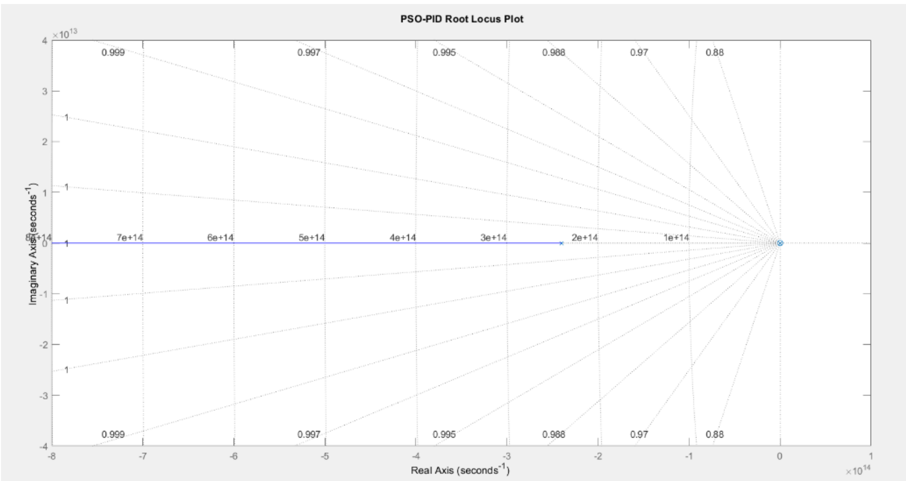


*Fig. 9. Root-Locus plot of PSO tuned PID controller*

Ziegler-Nichols tuning achieves a relatively quick rise time (s), but overshoot brings considerable challenges (59.41%) which leads to increasingly worsening instability. The settling time ($2.00 \cdot 10^{-5}$ s) is also deficiency long which suggests that struggling in reaching steady-stat conditions is rather easy. Among the controllers, the phase margin (62.9°) bares the least value which indicates low tolerance from outside disturbances, portraying it as being very weak. Moreover, the calculated ISE (11.52) depicts severe reached error which restricts the total system performance indicating no change to it. The Cohen-Coon method is superior to Closed-Loop Ziegler-Nichols in that value being overshoted now being 41.23%. While such result is favorable, it is still wanting where precise control is necessitated. The settling time ($5.04 \cdot 10^{-6}$ s) is better than Closed Loop Ziegler-Nichols, but the controller heavily relies on sought for rapid stabilization. It is more preferable than Ziegler-Nichols for moderate stability applications because of lower ISE (2.28) and higher phase margin (86.3°) which imply better, but not yet dependable, conditions. PSO-tuned PID controllers while in action maintain total transient stability because of thier zero overshot (0.0%). This superior stability minimizg error leads to very low settling time ($2.52 \cdot 10^{-14}$ s) due to precise control enabling very improved rapid stabilization. Controlling system disturbances appears to be very efficient owing to the highest observed phase margin (91.9°). Its estimated ISE (0.0) was the lowest of all methods confirming its superiority with respect to error motion over time. Like with PSO, the Whale Optimization Algorithm (WOA) tuned PID controller has no overshoot (0%) thereby ensuring optimal performance at the transient state. WOA-PID controller had the shortest settling time ($1.61 \cdot 10^{-14}$), making it the fastest stabilising controller. Phase margin of 91.9° is also indicative of ensuring high stability and robustness. The ISE (0.00), same as with PSO, indicates strong performance with zero error accumulation.

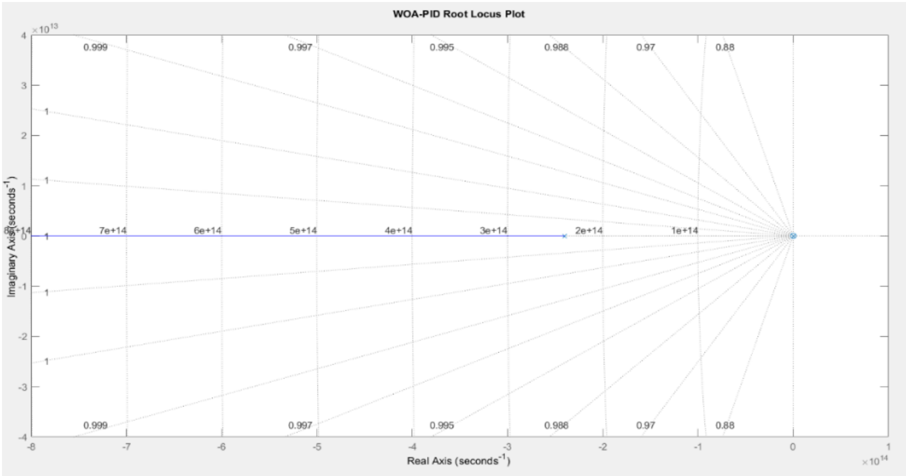


*Fig. 10. Root-Locus plot of WOA-tuned PID controller*

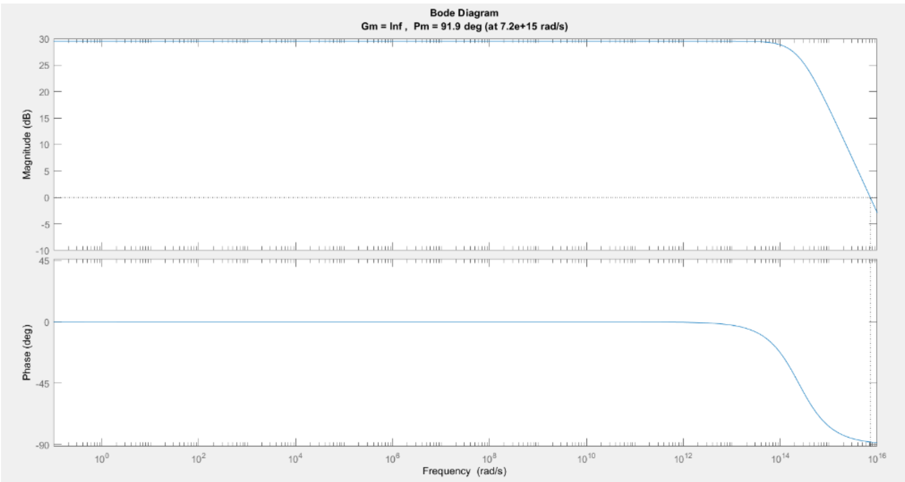


*Fig. 11. Bode plot of WOA tuned PID controller*

*Table 1. Simulation results*

| Performance indices | Closed Loop Ziegler Nichols PID | Cohen Coon PID | PSO PID | WOA PID |
|---|---|---|---|---|
| Gain Margin | Inf | Inf | Inf | Inf |
| Phase Margin (deg) | 62.9 | 86.3 | 91.9 | 91.9 |
| Phase Crossover frequency (rad/s) | $2.28 \cdot 10^{6}$ | $3.83 \cdot 10^{6}$ | $7.2 \cdot 101^{5}$ | $7.2 \cdot 101^{5}$ |
| Max Gain (dB) | 12.5 | 5.54 | 29.5 | 29.5 |
| Number of Poles (RHP) | 0 | 0 | 0 | 0 |
| Number of Zeros (RHP) | 0 | 0 | 0 | 0 |
| Number of Poles (LHP) | 3 | 2 | 1 | 1 |
| Number of Zeros (LHP) | 1 | 2 | 1 | 1 |
| Values of Poles | $-6.99 \cdot 10^{5}$,<br>$-1.81 \cdot 10^{5}+1.57 \cdot 10^{6}i$,<br>$-1.81 \cdot 10^{5}-1.57 \cdot 10^{6}i$, | $-8.64 \cdot 10^{5}+2.55 \cdot 10^{6}i$,<br>$-8.64 \cdot 10^{5}-2.55 \cdot 10^{5}i$ | $-2.4 \cdot 10^{14}$ | $-2.4 \cdot 10^{14}$ |
| Values of Zeros | $-1.35 \cdot 10^{6}$ | $-1.96 \cdot 10^{5}$,<br>$-3.89 \cdot 10^{6}$ | -1 | -1 |
| Rise Time (s) | $6.1399 \cdot 10^{-7}$ | $3.7560 \cdot 10^{-7}$ | $10.2301 \cdot 10^{-15}$ | $9.1301 \cdot 10^{-15}$ |
| Settling Time (s) | $2.0047 \cdot 10\text{-}^{5}$ | $5.0460 \cdot 10^{-6}$ | $2.5258 \cdot 10^{-14}$ | $1.6167 \cdot 10^{-14}$ |
| Overshoot (%) | 59.4092 | 41.2347 | 0 | 0 |
| Settled Voltage (V) | 29.9387 | 29.9423 | 29.9464 | 29.9686 |
| ISE | 11.52 | 2.28 | 0.0 | 0.0 |

## 4. Conclusion

In this article, the stability assessment of two metaheuristic and traditional PID controllers has been carried out. Whale Optimization and Particle Optimization algorithms are selected to develop metaheuristic controllers, while closed-loop Ziegler-Nichols and Cohen-Coon methods are used as in construction of traditional PID controllers. The stability of the developed controllers is evaluated using bode plots and root-locus plots. Results are presented in tables and figures. Results show that PID controllers tuned by metaheuristic controllers achieved improved stability in comparison with the traditional PID controllers.

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