

A Novel Hybrid Prairie Dog Optimization Algorithm - Marine Predator Algorithm for Tuning Parameters Power System Stabilizer

Widi Aribowo ^{1*}, Miftahur Rohman ², Farid Baskoro ³, Rina Harimurti ⁴, Yuni Yamasari ⁵, Wiyli Yustanti ⁶

¹ Department of Electrical Engineering, Faculty of Vocational, Universitas Negeri Surabaya, Surabaya, Indonesia

^{2,3,4} Department of Electrical Engineering, Faculty of Engineering, Universitas Negeri Surabaya, Surabaya, Indonesia

^{5,6} Department of Informatics, Faculty of Engineering, Universitas Negeri Surabaya, Surabaya, Indonesia

Email: ¹ widiaribowo@unesa.ac.id, ² miftahurrohman@unesa.ac.id, ³ faridbaskoro@unesa.ac.id, ⁴ rinaharimurti@unesa.ac.id, ⁵ yuniyamasari@unesa.ac.id, ⁶ wiyliyustanti@unesa.ac.id

*Corresponding Author

Abstract—The article presents the parameter tuning of the Power System Stabilizer (PSS) using the hybrid method. The hybrid methods proposed in this article are Prairie Dog Optimization (PDO) and Marine Predator Algorithm (MPA). The proposed method can be called PDOMPA. In the PDOMPA method, the marine predator algorithm (MPA) is able to search around optimal individuals when updating population positions. MPA is used to make the exploration and exploitation stages of PDO more valid and accurate. PDO is an algorithm inspired by the life of prairie dogs. Prairie dogs are adapted to colonizing in burrows underground. Prairie dogs have daily habits of eating, observing for predators, establishing fresh burrows, or preserving existing ones. Meanwhile, MPA is a duplication of marine predator life which is modeled mathematically. In order to validate the performance of the PDOMPA method, this article presents a comparative simulation of the objective function and the transient response of PSS. This research uses validation by comparing with conventional methods, Whale Optimization Algorithm (WOA), Grasshopper Optimization Algorithm (GOA), Marine Predator Algorithm (MPA), and Prairie Dog Optimization (PDO). Based on the simulation results, PDOMPA presents fast convergence in some cases and shows optimal results compared to competitive algorithms. From the simulation results using load variations, it was found that the proposed method has the ability to reduce the average undershoot and overshoot of speed by 42.2% and 85.37% compared to the PSS-Lead Lag method. Meanwhile the average settling time value of speed is 50.7%.

Keywords—Prairie Dog Optimization; Power System Stabilizer; Marine Predator Algorithm; Metaheuristic; Single Machine.

I. INTRODUCTION

The stability of the electricity network system is important. Technological developments increase the complexity of the electrical network which is increasingly playing an important role [1–4]. Demand for electrical energy from consumers has increased rapidly [5][6–9]. In addition, the remote location of the plant and away from the load increases the complexity of the power system [10–14]. The important keys in distributing electric power systems are stability and consistency [15–21]. The ability of a system to recover after experiencing a shock is an important focus [22–28]. Changes in loads and additions to loads that are well planned or sudden are things that worry the electric power

system [29]. This will cause a tremendous shock to the power plant, especially the generator. This causes the generator to experience a decrease or loss of synchronization which creates the need for a damping torque [30][31]. This can be fulfilled by the power system stabilizer.

Power System Stabilizer (PSS) is an additional control on the generator. PSS is maintaining the frequency and terminal voltage locally or globally on each generator [32–38]. An unreliable response can cause frequency oscillations over long periods [39]. This can result in a reduction in power transfer strength. Over the decades, the development of methods for maintaining stability has increased significantly [40–45]. This should be of particular concern in its application. Various methods and approaches to Power System Stabilizers have been presented in the popular literature as conventional PSS. It is known to have a simple structure. Besides that, it is easy to apply [46]. The development of power systems that have different characteristics and are always changing. This demands an adaptive and established control. The existing control is a linear-based control so that it experiences problems when dealing with nonlinear systems that are often found in the industry [47][48].

Previously, PSS control with conventional methods has been widely presented [49–56]. In recent years, the PSS control method has been integrated with several optimization methods. Several optimization methods that are better known as metaheuristics have been widely presented, such as the Tunicate Swarm Algorithm (TSA) [57][58], Gorilla Troops Optimizer (GTO) [59], Atom Search Optimization (ASO) [60], Salp Swarm Algorithm (SSA) [61][62], Particle Swarm Optimization (PSO) [63–65], and Antlion Algorithm [66].

Although several studies have presented optimization approaches for power system stabilizers. Research on optimizing the power system stabilizer still has a lot of room to explore and is still popular. In this article, a hybrid method is presented, namely the Prairie Dog Optimization algorithm and the Marine Predator Algorithm to obtain the power system stabilizer parameter. MPA has the advantage of looking into exploitation and exploration, besides that it is also easier to go beyond the local optimum and find a global



optimal solution by considering environmental impacts. The application of MPA to PDO will sharpen the accuracy of the convergence curve. Research contributions are:

1. A hybrid method of the Prairie Dog Optimization Algorithm and the Marine Predator Algorithm called PDOMPA is presented.
2. Application of PDOMPA to PSS.
3. Investigating the ability of PDOMPA-based controllers to improve PSS performance.
4. Comparing PDOMPA applied to PSS with conventional methods, Whale Optimization Algorithm (WOA), Grasshopper Optimization Algorithm (GOA), Marine Predator Algorithm (MPA), and Prairie Dog Optimization (PDO).

The article consists of methods and mathematical formulations in section 2. Section 3 is a presentation of the proposed method approach along with its pseudocode. Section 4 is a simulation and discussion. The last section contains the conclusions of the research.

II. METHODS

A. Prairie Dog Optimization Algorithm (PDO)

Prairie Dog Optimization Algorithm adopts the behavior of prairie dogs in nature. The prairie dog (genus *Cynomys*) is a herbivorous rodent found mainly in the Great Plains and desert prairies of the southwestern US, Canada, and Mexico [67]. In PDO, the optimization phase that characterizes the optimization method is exploration and exploitation using four activities of prairie dogs. Prairie dogs in small groups in one unit are called coterie. In one coterie, there are several numbers of prairie dogs. The coterie concept can be modeled mathematically in equation (1) to (6).

$$C = \begin{bmatrix} C_{1,1} & C_{1,2} & \dots & C_{1,d} \\ C_{2,1} & C_{2,2} & \dots & C_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ C_{m,1} & C_{m,2} & \dots & C_{m,d} \end{bmatrix} \quad (1)$$

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} & \dots & X_{1,d} \\ X_{2,1} & X_{2,2} & \dots & X_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ X_{k,1} & X_{k,2} & \dots & X_{k,d} \end{bmatrix} \quad (2)$$

$$C_{1,j} = rand \times (UB_j - LB_j) + LB_j \quad (3)$$

$$X_{1,j} = rand \times (ub_j - lb_j) + lb_j \quad (4)$$

$$ub_j = \frac{UB_j}{m} \quad (5)$$

$$lb_j = \frac{LB_j}{m} \quad (6)$$

Where C is the j -th dimension of the i -th neighborhood in a herd. The location of the prairie dogs in the coterie is modeled in equation (2). X is the j th dimension of the i th prairie dog in a coterie. Equations (3) and (4) are uniform distributions of the locations of the coterie and prairie dogs. The upper and lower bounds of the j -th matrix of the optimization problem are denoted by UB and LB. $rand$ is a random value [0,1]. The value of the fitness function of each prairie dog is a representation of the quality of food, new burrows and the

accuracy of response to predators. this is evaluated by plugging into the fitness function in equation (7).

$$f(X) = \begin{bmatrix} f_1[X_{1,1} & X_{1,2} & \dots & X_{1,d}] \\ f_2[X_{2,1} & X_{2,2} & \dots & X_{2,d}] \\ \vdots & \vdots & \ddots & \vdots \\ f_n[X_{k,1} & X_{k,2} & \dots & X_{k,d}] \end{bmatrix} \quad (7)$$

1) Exploration Phase

In the exploration phase, prairie dogs are foraging for food and digging nearby burrows. The optimization problem space is explored from foraging activities and building tunnels in the ground. These animals build tunnels in the ground around which there is a food source. The concept of these passages is that they will connect because these prairie dogs build tunnels in the ground at each new food source. On the other hand, this underground tunnel is used as a refuge from predators. New burrows will be dug depending on the quality of the food source. The position update for foraging in the exploration phase of our algorithm is given in equation (8) and the position update for the underground passage building is given in equation (9).

$$X_{i+1,j+1} = Gb_{i,j} - eCb_{i,j} \times \rho - CX_{i,j} \times Levy(n), \text{ if } iter < \frac{M_{iter}}{4} \quad (8)$$

$$X_{i+1,j+1} = Gb_{i,j} \times randX \times CDS \times Levy(n), \text{ if } \frac{M_{iter}}{4} < iter < \frac{M_{iter}}{2} \quad (9)$$

$$eCb_{i,j} = Gb_{i,j} \times \Delta \times \frac{X_{i,j} \times mena(X_{n,m})}{Gb_{i,j} \times (UB_j - LB_j) + \Delta} \quad (10)$$

$$CX_{i,j} = \frac{Gb_{i,j} - randX}{Gb_{i,j} + \Delta} \quad (11)$$

$$CDS = 1.5 \times sp \times \left(1 - \frac{iter}{M_{iter}}\right)^{\left(2 \frac{iter}{M_{iter}}\right)} \quad (12)$$

Where $Gb_{i,j}$ is the optimal solution achieved. $eCb_{i,j}$ represents the effect of the optimal solution. Signal indicating the source of food is symbolized by ρ . The random combined effect on the herd of prairie dogs is symbolized by $CX_{i,j}$. $Levy(n)$ is the levy distribution. The ability to dig a herd is represented by CDS . To ensure the exploration process used stochastic items symbolized by sp with a value of -1 or 1. The difference between prairie dogs is represented by Δ .

2) Exploitation Phase

This section describes the steppe dog exploitation phase. Prairie dogs have the ability to communicate among themselves by different signals or sounds when looking for food and avoiding predators. This is modeled in equations (13) and (14). The exploitation process aims to find promising spots as shown in (15).

$$X_{i+1,j+1} = Gb_{i,j} - eCb_{i,j} \times \varepsilon - CX_{i,j} \times rand, \text{ if } \frac{M_{iter}}{2} < iter < 3 \frac{M_{iter}}{4} \quad (13)$$

$$X_{i+1,j+1} = Gb_{i,j} \times eP \times rand, \text{ if } 3 \frac{M_{iter}}{4} < iter < M_{iter} \quad (14)$$

$$eP = 1.5 \times \left(1 - \frac{iter}{M_{iter}}\right)^{\left(2 \frac{iter}{M_{iter}}\right)} \quad (15)$$

Where eP is a symbol of predatory effect. $iter$ is the current iteration and M_{iter} is the maximum number of iterations.

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B. Marine Predator Algorithm (MPA)

Marine Predator Algorithm (MPA) is an optimization method based on the behavior of marine predators in nature [68]. This algorithm has three important steps in solving optimization problems, namely:

1) Step 1: High Speed

In this stage ($t < \frac{1}{3} \times \max_iter$), the prey is finding for feed and the predator is observing the mobility of the prey. The stage can be formulated in equations (16) and (17).

$$\vec{Sh}_i = \vec{R}_b \otimes (\vec{Elite}_i - \vec{R}_b \otimes \vec{Prey}_i) \quad i = 1, 2, \dots, n \quad (16)$$

$$\vec{Prey}_i = \vec{Prey}_i + P \times \vec{R} \otimes \vec{Sh}_i \quad (17)$$

The \otimes is operation of element-wise multiplication. \vec{R}_b is a random value. It is based on brownian motion with normal distribution. $\vec{R} \in [0, 1]$. P is uniform random value equal to 0.5.

2) Stage 2: Equal Speed

In this stage ($\frac{1}{3} \times \max_iter < iter < \frac{2}{3} \times \max_iter$), the exploration is turned into exploitation. Predators and prey have the same speed.

$$\vec{Sh}_i = \vec{R}_L \otimes (\vec{Elite}_i - \vec{R}_L \otimes \vec{Prey}_i) \quad i = 1, 2, \dots, n/2 \quad (18)$$

$$\vec{Prey}_i = \vec{Prey}_i + P \times \vec{R} \otimes \vec{Sh}_i \quad (19)$$

In the first population, \vec{R}_L denotes random numbers based on the distribution. Prey movement is simulated by \vec{R}_L Multiplication. While the second half of the population, the mathematical equation is as (20) to (22).

$$\vec{Sh}_i = \vec{R}_b \otimes (\vec{R}_b \otimes \vec{Elite}_i - \vec{Prey}_i) \quad i = n/2, \dots, n \quad (20)$$

$$\vec{Prey}_i = \vec{Prey}_i + P \times CF \otimes \vec{Sh}_i \quad (21)$$

$$CF = \left(1 - \frac{iter}{M_{iter}}\right)^{\left(2 \frac{iter}{M_{iter}}\right)} \quad (22)$$

Predatory movements are controlled by adaptive parameters, namely CF .

3) Stage 3: Low-Speed

In this last stage, the prey has a speed below the predator. When $iter > \frac{2}{3} \times \max_iter$, the mathematical equation is as (23) and (24).

$$\vec{Sh}_i = \vec{R}_L \otimes (\vec{R}_L \otimes \vec{Elite}_i - \vec{Prey}_i) \quad i = 1, \dots, n \quad (23)$$

$$\vec{Prey}_i = \vec{Prey}_i + P \times CF \otimes \vec{Sh}_i \quad (24)$$

One of the environmental issues that influence the attitude of marine ecosystems is Fish Aggregating Devices (FADs). The FADs modeling is as (25).

$$\vec{Prey}_i = \begin{cases} \vec{Prey}_i + CF \times [Z_0 = Z_{min} + \vec{R} \otimes (Z_{max} - Z_{min})] \otimes A & \text{if } r \leq FADs \\ \vec{Prey}_i + [FADs(1-r) + r](\vec{Prey}_{r1} - \vec{Prey}_{r2}) & \text{if } r > FADs \end{cases} \quad (25)$$

Where r is a uniform random variable. x_{max} is the upper limit and x_{min} is the lower limit. the optimization process is affected when the $FADs$ is 0.2. A is a binary vector.

Algorithm 1 Marine Predator Algorithm (MPA)

Input: Fitness function, Population size

Output: The Best Solution, Objective Function

1: **procedure** MPA

2: Initialize the parameters

3: **While** termination criteria are not meet

4: **Calculate** of the fitness and construct The Elite

5: **If** ($iter < \frac{\max_iter}{3}$) **then**

6: Update X

7: **Else If** ($\frac{\max_iter}{3} < iter < 2 * \frac{\max_iter}{3}$)

8: **For** the the first half ($i=1, \dots, n/2$)

9: Update $X \rightarrow$ Equation (19)

10: **For** the the other half ($i=1/2, \dots, n$)

11: Update $X \rightarrow$ Equation (21)

12: **Else If** ($iter < 2 * \frac{\max_iter}{3}$) **then**

13: Update $X \rightarrow$ Equation (24)

14: **End If**

15: **End While**

16: return Best Soluton

17: **End procedure**

C. Power System Stabilizer (PSS)

The addition of PSS will dampen generator rotor oscillations in the excitation system by supplying an additional feedback stabilization signal [69]. The modeling scheme of PSS can be seen in Fig. 1.

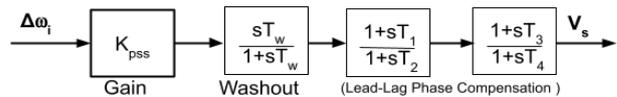


Fig. 1. PSS mathematical modeling [32]

III. PROPOSED HYBRID PDO-MPA

In improving the method, we propose a hybrid algorithm called Prairie Dog Optimization based on marine predator algorithm (PDOMPA). In the proposed PDOMPA, the marine predator algorithm (MPA) is applied to the PDO to sharpen the exploration and exploitation stages so that they are more valid and accurate as well as avoiding local optimal traps and preventing premature convergence. In this article, the PDO and MPA methods are integrated by replacing equation (11) with equation (16). The advantage of the PDOMPA hybrid algorithm is that the individuals in the top layer are not only affected by each individual in the PDO, but also have an effect on the global optimal solution.

IV. SIMULATION RESULTS AND DISCUSSION

The Matlab/Simulink application is used to write the PDOMPA method code with a laptop with RAM specifications: 8 GB, CPU Intel I5-5200: 2.19GHZ 64 bit. The PDOMPA is applied to obtain the optimal power system stabilizer parameters. To determine the performance of the PDOMPA, a test of twenty-three benchmark functions was carried out. Benchmark function has three categories: unimodal (Fig. 2 (a)-(g)), multimodal (Fig. 2 (h)-(m)) and multimodal with fixed dimensions (Fig. 2 (m)-(w)). The three categories have their own characteristics. The unimodal function has one global ideal and no local optimal, making it a good candidate for benchmarking algorithm exploitation. The multi-modal function is particularly useful for assessing exploration and deducting the algorithm's local optima position since it has a large number of local optimum points. Multi-modal test functions that have been rotated, shifted, and biased make up the composite function. PDOMPA was compared with the PDO, MPA, GWO, and WOA.

Algorithm 1 Prairie Dog Optimization- Marine Predator Algorithm (PDOMPA)

Input: Fitness function, Population size, Digging strength, Predator effect, Levy random number vector, Maximum number of iteration,
Output: The Best Solution, Objective Function

- 1: **procedure PDOMPA**
- 2: Initialize the parameters
- 3: Set n, m, ρ and ε
- 4: Set G_b, eCb , and M_{iter}
- 5: Set C and X
- 6: **while** ($iter < M_{iter}$) **do**
- 7: **For** ($i=1$ to m) **do**
- 8: **For** ($j=1$ to n) **do**
- 9: Calculate of the fitness X
- 10: Find the Best Solution so far
- 11: Update G_b
- 12: Update DS and $PE \rightarrow$ Equation (12) and (15)
- 13: Update $CPD \rightarrow$ Equation (16)
- 14: **If** ($iter < \frac{M_{iter}}{4}$) **then**
- 15: Update $X \rightarrow$ Equation (8)
- 16: **Else If** ($\frac{M_{iter}}{4} < iter < \frac{M_{iter}}{2}$) **then**
- 17: Update $X \rightarrow$ Equation (9)
- 18: **Else If** ($\frac{M_{iter}}{2} < iter < 3 \frac{M_{iter}}{4}$) **then**
- 19: Update $X \rightarrow$ Equation (13)
- 20: **Else**
- 21: Update $X \rightarrow$ Equation (14)
- 22: **End If**
- 23: **End For**
- 24: **End For**
- 25: $iter = iter + 1$
- 26: **End While**
- 27: return Best Solution
- 28: **End procedure**

Here, Fig. 2 displays a number of convergence graphs taken from each benchmark, demonstrating how all of the algorithms' convergence curves differ significantly from one another and can be quickly identified for purposes of analysis

and interpretation. In comparison to other methods, the convergence speed of PDOMPA was examined. The algorithm has the highest rate of convergence, as seen by the curve's fastest decline towards the global minimum. PDOMPA has a satisfactory convergence rate, as seen in Fig. 2. On several benchmark functions, PDOMPA's convergence speed is a little bit slower than WOA's, but it is clear that PDOMPA can reach a more minimum global best objective fitness.

The proportional distribution to exploration and exploitation is primarily determined by the linear reduction of the weight vector's fluctuation range. Overall, PDOMPA's convergence speed is competitive, occasionally even outpacing that of all other comparable methods. These reasons lead to the conclusion that PDOMPA is a well-behaved algorithm in terms of convergence rate.

Furthermore, the PDO-MPA performance was measured by applying to tune the PSS parameter. PDOMPA is used to obtain parameters that match the optimal output criteria. This article tests a single machine system owned by Heffron-Philips by conducting several case studies. The case study is to change the load on the system by 25%, 50% and 95%. The first step is to optimize the PSS parameter by using the integral of time multiplied absolute error (ITAE). ITAE is adopted as the objective function for the design problem. This can be seen in equation (26).

$$ITAE = \int_0^{T_s} t \cdot |\Delta\omega(t)| \cdot dt \quad (26)$$

1) Case 1: 25% Of Load

The first test by giving a light load of 25% on the system. The output of system gives a different transient response for each algorithm. The output graph of the speed and rotor angle can be seen in Fig. 3 and Fig. 4. The transient response of the worst undershoot speed is owned by MPA. MPA was only able to reduce undershoot speed from PSS-lead lag by 13.11%. Meanwhile, the worst overshoot of speed was owned by WOA which was only able to reduce pss-lead lag by 68.82%. The application of PDOMPA is able to reduce the undershoot and overshoot values of the PSS-lead lag speed by 42.14% and 85.37%. In the transient response of the angel rotor, the undershoot value of PDOMPA is better than the PSS-Lead Lag of 78.26%. The details of case study 1 can be seen in Table I.

2) Case 2: 50% Of Load

The second case study by increasing the loading by 25%. The total load is 50%. The graphs of the second case study can be seen in Fig. 5 and Fig. 6. Details of case study 2 can be seen in Table 3. In the second case study, pdompa applied to pss was able to reduce the undershoot and overshoot speed of pss-lead lag by 42.21% and 85% .42 %. Meanwhile, the undershoot value of the rotor angle PDOMPA is better than PSS-Lead lag by 78.25 %. Table II is detail of case study 2.

3) Case 3: 95% Of Load

The third case study is by 95% of load. With maximal load, PDOMPA-optimized PSS gives good transient

response. The graphs of the second case study can be seen in Fig. 7 and Fig. 8. The undershoot and overshoot values of speed with the pdompa method are better by 42.26% and 85.53% than the PSS-Lead Lag method. speed in 95 % load

in Fig. 9, speed in 50 % load in Fig. 10, rotor angle in 95 % load in Fig. 11. Meanwhile, the settling time value is better than the PSS-Lead Lag of 48%. The details of case study 3 can be seen in Table III.

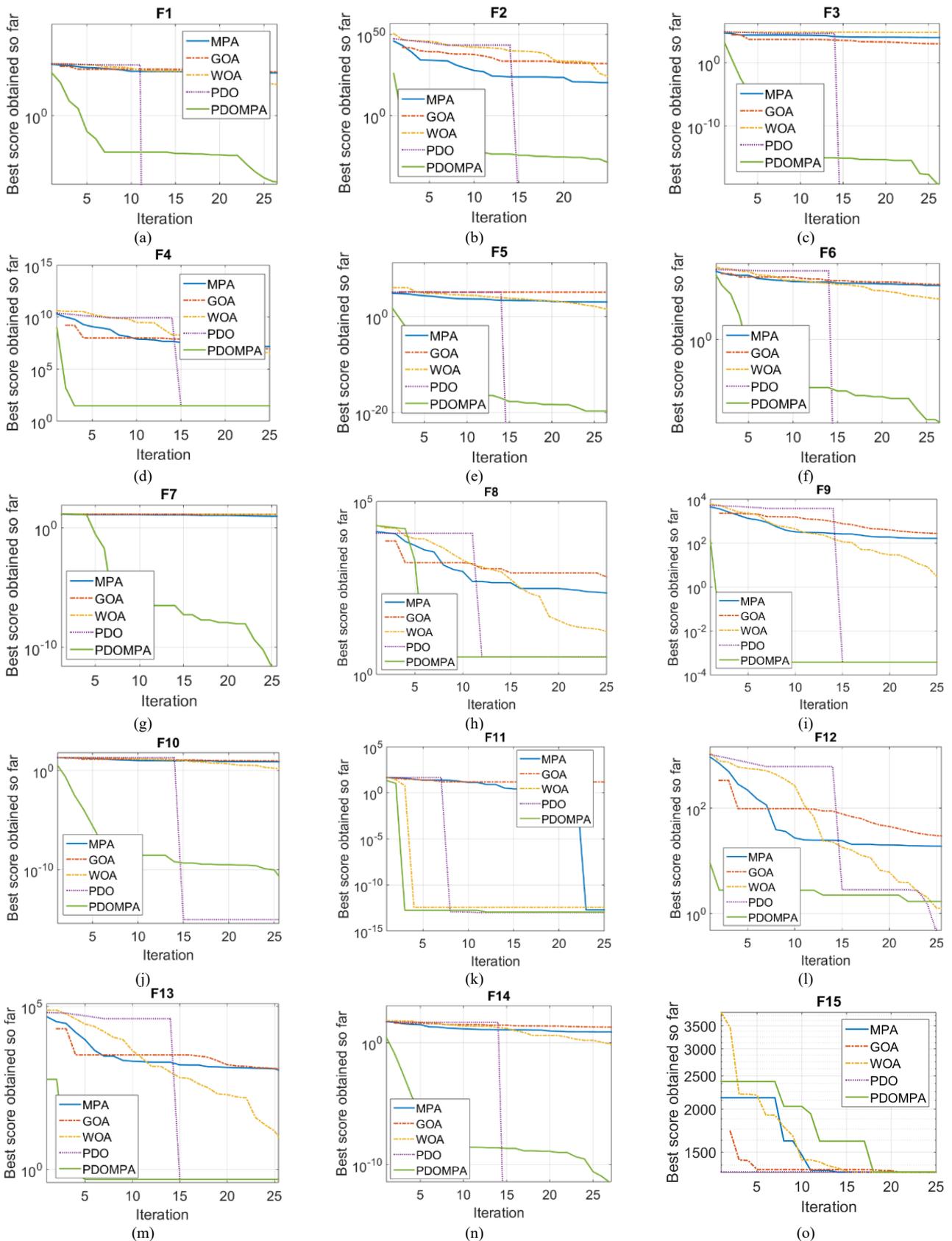


Fig. 2. Convergence Curve (a)F1, (b) F2, (c) F3, (d) F4, (e)F5, (f)F6, (g) F7, (h) F8, (i) F9, (j) F10, (k) F11, (l) F12, (m) F13, (n) F14, (o) F15

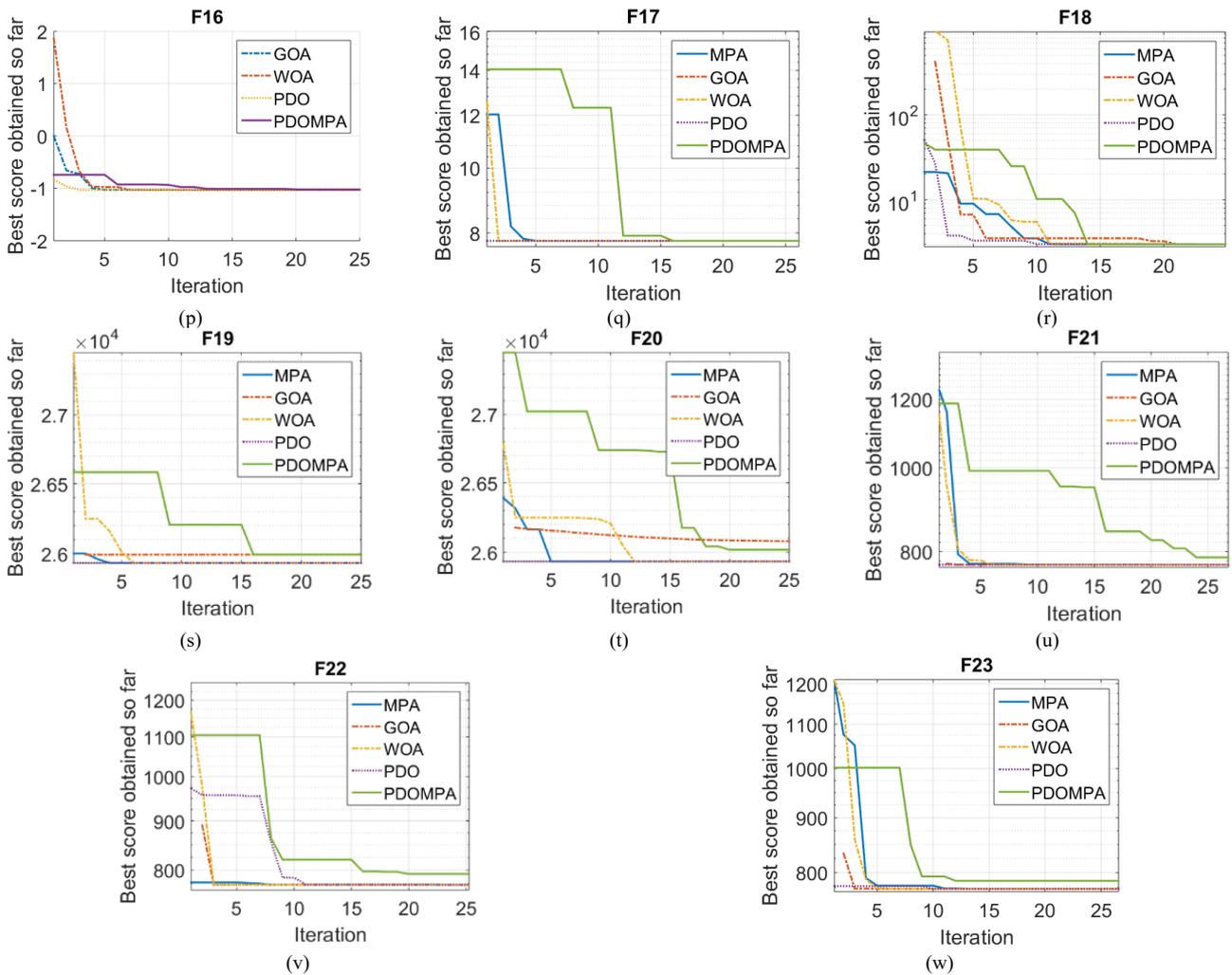


Fig. 3. Convergence Curve (p) F16, (q) F17, (r) F18, (s) F19, (t)F20, (u)F21 (v)F22, (w)F23 (continue)

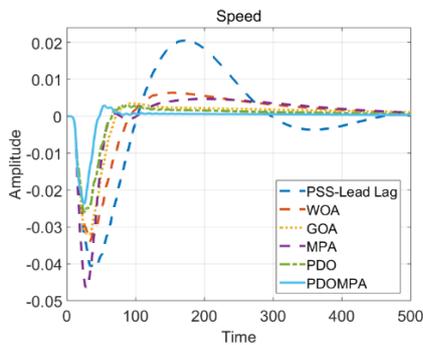


Fig. 4. Speed in 25 % Load

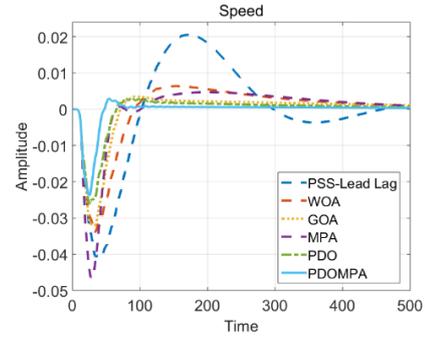


Fig. 6. Speed in 25 % Load

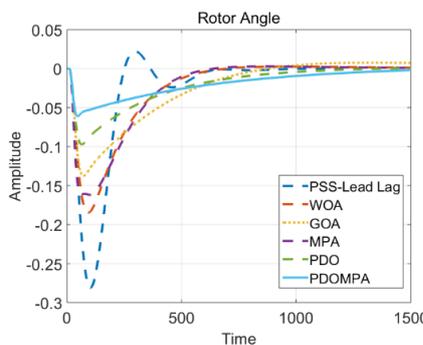


Fig. 5. Rotor Angle in 25 % Load

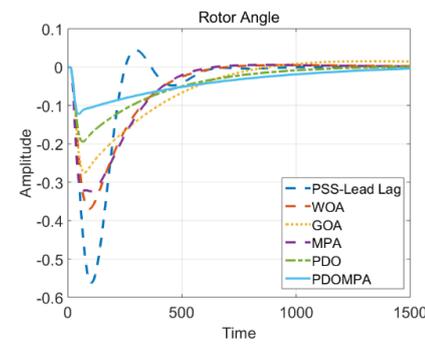


Fig. 7. Rotor Angle in 50 % Load

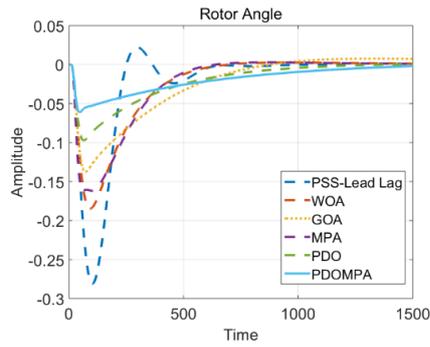


Fig. 8. Rotor Angle in 25 % Load

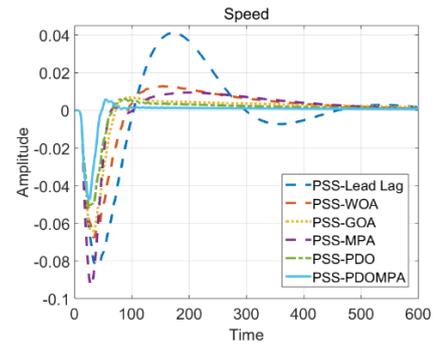


Fig. 10. Speed in 50 % Load

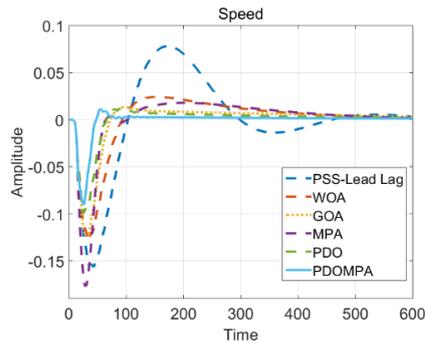


Fig. 9. Speed in 95 % Load

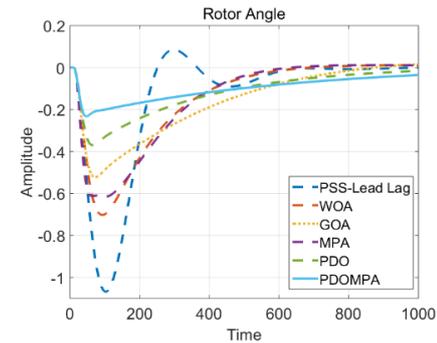


Fig. 11. Rotor Angle in 95 % Load

TABLE I. CASE 1: 25 % OF LOAD

Method	Speed Response			Rotor Angle Response		
	Undershoot	Overshoot	Settling Time (s)	Undershoot	Overshoot	Settling Time (s)
PSS-Lead Lag	-0.0412	0.02057	601	-0.2811	0.02217	593
PSS-WOA	-0.0339	0.006414	544	-0.1849	0.002783	607
PSS-GOA	-0.03217	0.003525	680	-0.1375	0.007685	979
PSS-MPA	-0.0466	0.004712	506	-0.1619	0.002922	576
PSS-PDO	-0.02604	0.00314	556	-0.0976	No Overshoot	1439
PSS-PDOMPA	-0.02384	0.00301	310	-0.0611	No Overshoot	2017

TABLE II. CASE 2: 50 % OF LOAD

Method	Speed Response			Rotor Angle Response		
	Undershoot	Overshoot	Settling Time (s)	Undershoot	Overshoot	Settling Time (s)
PSS-Lead Lag	-0.08237	0.0408	702	-0.5622	0.0154	893
PSS-WOA	-0.0679	0.01284	545	-0.3697	No Overshoot	807
PSS-GOA	-0.06436	0.00703	681	-0.2749	No Overshoot	980
PSS-MPA	-0.0933	0.009425	506	-0.3238	No Overshoot	576
PSS-PDO	-0.052	0.00606	556	-0.1947	No Overshoot	1440
PSS-PDOMPA	-0.0476	0.00595	311	-0.1223	No Overshoot	2100

TABLE III. CASE 3: 95 % OF LOAD

Method	Speed Response			Rotor Angle Response		
	Undershoot	Overshoot	Settling Time (s)	Undershoot	Overshoot	Settling Time (s)
PSS-Lead Lag	-0.1564	0.07814	602	-1.068	0.0842	593
PSS-WOA	-0.1291	0.0244	545	-0.7025	No Overshoot	607
PSS-GOA	-0.1221	0.01339	681	-0.5223	No Overshoot	980
PSS-MPA	-0.1773	0.01791	506	-0.6153	No Overshoot	577
PSS-PDO	-0.0991	0.01192	556	-0.37	No Overshoot	1401
PSS-PDOMPA	-0.0903	0.01131	313	-0.2325	No Overshoot	2013

V. CONCLUSION

PDOMPA is a method that combines the PDO and MPA methods. PDO is an algorithm inspired by the life of prairie dogs in nature. Meanwhile, MPA is inspired by the life of marine predators. MPA is used to accelerate convergence and

improve PDO performance. In this article PDOMPA is applied to get the best PSS parameters. The PSS transient response using the PDOMPA method was measured and compared using the PSS-Lead Lag, PSS-WOA, PSS-GOA, PSS-MPA and PSS-PDO methods. Testing uses 3 loading case studies. The test results show that PDOMPA applied to

PSS has the ability to reduce undershoot, overshoot and speed timing. From the simulation results using load variations, it is known that the proposed method has the ability to reduce the average undershoot and overshoot speeds by 42.2% and 85.37% compared to the PSS-Lead Lag method. Meanwhile, the average value of speed settling time is 50.7%. On the rotor angle side, PDOMPA has a longer settling time than other methods but has the best undershoot.

The PDOMPA method is a combination of the PDO and MPA methods. The application for binary and complex systems needs to be studied again to obtain more optimal exploration and exploitation performance.

REFERENCES

- [1] T. Ahmad et al., "Energetics Systems and artificial intelligence: Applications of industry 4.0," *Energy Reports*, vol. 8, pp. 334–361, 2022.
- [2] P. Rodríguez-Ortega, J. Roldán-Pérez and M. Prodanovic, "Multivariable-Controlled Shunt Compensator for Damping Subsynchronous Interactions in Electrical Distribution Networks," *IEEE Transactions on Smart Grid*, vol. 14, no. 5, pp. 3707-3718, 2023, doi: 10.1109/TSG.2023.3239010.
- [3] R. Ishak, A. S. M. Shah, M. I. M. Ridzuan, and N. M. Bunnori, "Widespread compact fluorescent lamp evaluations in 50 Hz electrical network," *Bull. Electr. Eng. Informatics*, vol. 12, no. 3, pp. 1267–1275, 2023.
- [4] W. Aribowo, R. Rahmadian, M. Widyartono, A. Wardani, and A. Prapanca, "An Improved Feed-Forward Backpropagation Neural Network Based on Marine Predators Algorithm for Tuning Automatic Voltage Regulator," *ECTI Trans. Electr. Eng. Electron. Commun.*, vol. 21, no. 2, p. 249830, 2023.
- [5] L. Silva-Rodriguez, A. Sanjab, E. Fumagalli, A. Virag, and M. Gibescu, "Short term wholesale electricity market designs: A review of identified challenges and promising solutions," *Renew. Sustain. Energy Rev.*, vol. 160, p. 112228, 2022.
- [6] C. Syranidou et al., "Development of an open framework for a qualitative and quantitative comparison of power system and electricity grid models for Europe," *Renew. Sustain. Energy Rev.*, vol. 159, p. 112055, 2022.
- [7] D. Kamani and M. M. Ardehali, "Long-term forecast of electrical energy consumption with considerations for solar and wind energy sources," *Energy*, vol. 268, p. 126617, 2023.
- [8] A. Menati, K. Lee and L. Xie, "Modeling and Analysis of Utilizing Cryptocurrency Mining for Demand Flexibility in Electric Energy Systems: A Synthetic Texas Grid Case Study," *IEEE Transactions on Energy Markets, Policy and Regulation*, vol. 1, no. 1, pp. 1-10, 2023, doi: 10.1109/TEMPR.2022.3230953.
- [9] M. E. Javanmard, Y. Tang, Z. Wang, and P. Tontiwachwuthikul, "Forecast energy demand, CO2 emissions and energy resource impacts for the transportation sector," *Appl. Energy*, vol. 338, p. 120830, 2023.
- [10] J. Lee and Y. Cho, "National-scale electricity peak load forecasting: Traditional, machine learning, or hybrid model?," *Energy*, vol. 239, p. 122366, 2022.
- [11] A. A. Eladl, M. I. Basha, and A. A. ElDesouky, "Techno-economic multi-objective reactive power planning in integrated wind power system with improving voltage stability," *Electr. Power Syst. Res.*, vol. 214, p. 108917, 2023.
- [12] J. J. Opperman et al., "Balancing renewable energy and river resources by moving from individual assessments of hydropower projects to energy system planning," *Front. Environ. Sci.*, vol. 10, 2023.
- [13] H. Xie et al., "IntelliSense technology in the new power systems," *Renew. Sustain. Energy Rev.*, vol. 177, p. 113229, 2023.
- [14] R. Abdulkader et al., "Soft Computing in Smart Grid with Decentralized Generation and Renewable Energy Storage System Planning," *Energies*, vol. 16, no. 6, p. 2655, 2023.
- [15] V. Priya, V. Praveena, and L. R. Sujithra, "A parallel optimization and transfer learning approach for summarization in electrical power systems," *Automatika*, vol. 64, no. 4, pp. 1225–1233, 2023.
- [16] S. Yu, S. Zhou, and J. Qin, "Layout optimization of China's power transmission lines for renewable power integration considering flexible resources and grid stability," *Int. J. Electr. Power Energy Syst.*, vol. 135, p. 107507, 2022.
- [17] F. Quinteros, D. Carrión, and M. Jaramillo, "Optimal Power Systems Restoration Based on Energy Quality and Stability Criteria," *Energies*, vol. 15, no. 6, p. 2062, 2022.
- [18] V. A. Kabirov, V. D. Semenov, D. S. Torgaeva, and A. I. Otto, "Miniaturization of spacecraft electrical power systems with solar-hydrogen power supply system," *Int. J. Hydrogen Energy*, vol. 48, no. 24, pp. 9057–9070, 2023.
- [19] B. Sharma and A. Shrestha, "Petroleum dependence in developing countries with an emphasis on Nepal and potential keys," *Energy Strateg. Rev.*, vol. 45, p. 101053, 2023.
- [20] V. Rai, "Integration, coordination, and regulatory resources: Keys to electricity system resilience," *The Electricity Journal*, vol. 36, no. 2–3, p. 107256, 2023.
- [21] P. Venkatesh and N. Visali, "Investigations on hybrid line stability ranking index with polynomial load modeling for power system security," *Electr. Eng. Electromechanics*, no. 1, pp. 71–76, 2023.
- [22] Z. Rafique, H. M. Khalid, S. M. Muyeen, and I. Kamwa, "Bibliographic review on power system oscillations damping: An era of conventional grids and renewable energy integration," *Int. J. Electr. Power Energy Syst.*, vol. 136, p. 107556, 2022.
- [23] A. Shetgaonkar, L. Liu, A. Lekić, M. Popov, and P. Palensky, "Model predictive control and protection of MMC-based MTDC power systems," *Int. J. Electr. Power Energy Syst.*, vol. 146, p. 108710, 2023.
- [24] Z. Li, Y. Xu, P. Wang, and G. Xiao, "Coordinated preparation and recovery of a post-disaster multi-energy distribution system considering thermal inertia and diverse uncertainties," *Appl. Energy*, vol. 336, p. 120736, 2023.
- [25] S. Xu, H. Tu, and Y. Xia, "Resilience enhancement of renewable cyber-physical power system against malware attacks," *Reliab. Eng. Syst. Saf.*, vol. 229, p. 108830, 2023.
- [26] H. Liu, C. Sun, X. Zhang, N. Wang, and J. Wang, "Design of Energy Recovery Control for General Virtual Synchronous Machines Based on Various Forms of Energy Storage," *Appl. Sci.*, vol. 13, no. 14, p. 8059, 2023.
- [27] Y. G. Landera, O. C. Zevallos, R. C. Neto, J. F. da C. Castro, and F. A. S. Neves, "A Review of Grid Connection Requirements for Photovoltaic Power Plants," *Energies*, vol. 16, no. 5, p. 2093, 2023.
- [28] X. Zhang, B. Lin, K. Xu, Y. Zhang, S. Hao, and Q. Hu, "An Improved Over-Speed Deloading Control of Wind Power Systems for Primary Frequency Regulation Considering Turbulence Characteristics," *Energies*, vol. 16, no. 6, p. 2813, 2023.
- [29] N. A. Mohammed and A. Al-Bazi, "An adaptive backpropagation algorithm for long-term electricity load

- forecasting," *Neural Comput. Appl.*, vol. 34, no. 1, pp. 477–491, 2022.
- [30] R. Devarapalli, N. K. Sinha, and F. P. García Márquez, "A review on the computational methods of power system stabilizer for damping power network oscillations," *Arch. Comput. Methods Eng.*, vol. 29, no. 6, pp. 3713–3739, 2022.
- [31] A. F. Rashwan et al., "Explicit adaptive power system stabilizer design based an on-line identifier for single-machine infinite bus," *Ain Shams Eng. J.*, vol. 13, no. 2, p. 101544, 2022.
- [32] I. M. Alotaibi, S. Ibrir, M. A. Abido, and M. Khalid, "Nonlinear Power System Stabilizer Design for Small Signal Stability Enhancement," *Arab. J. Sci. Eng.*, vol. 47, no. 11, p. 13893–13905, 2022, doi: 10.1007/s13369-022-06566-2.
- [33] G. Penchalaiah and R. Ramya, "An EnGRFA control scheme based power system stabilizers (PSS) for the stability analysis with wind energy integration," *Artif. Intell. Rev.*, vol. 56, pp. 8437–8468, 2023.
- [34] N. M. A. Ibrahim, H. E. A. Talaat, A. M. Shaheen, and B. A. Hemade, "Optimization of Power System Stabilizers Using Proportional-Integral-Derivative Controller-Based Antlion Algorithm: Experimental Validation via Electronics Environment," *Sustainability*, vol. 15, no. 11, p. 8966, 2023.
- [35] V. Snášel, R. M. Rizk-Allah, D. Izci, and S. Ekinici, "Weighted mean of vectors optimization algorithm and its application in designing the power system stabilizer," *Appl. Soft Comput.*, vol. 136, p. 110085, 2023.
- [36] D. U. Sarkar and T. Prakash, "A Recent Review on Approaches to Design Power System Stabilizers: Status, Challenges and Future Scope," *IEEE Access*, vol. 11, pp. 34044–34061, 2023, doi: 10.1109/ACCESS.2023.3244687.
- [37] D. Butti, S. K. Mangipudi, and S. Rayapudi, "Model order reduction based power system stabilizer design using improved whale optimization algorithm," *IETE J. Res.*, vol. 69, no. 4, pp. 2144–2163, 2023.
- [38] C. Gu, E. Chi, C. Guo, M. M. Salah, and A. Shaker, "A New Self-Tuning Deep Neuro-Sliding Mode Control for Multi-Machine Power System Stabilizer," *Mathematics*, vol. 11, no. 7, p. 1616, 2023.
- [39] R. K. Sharma, D. Chitara, S. Raj, K. R. Niazi, and A. Swarnkar, "Multi-machine Power System Stabilizer Design Using Grey Wolf Optimization," *Proceedings of International Conference on Computational Intelligence and Emerging Power System*, pp. 331–343, 2022, doi: 10.1007/978-981-16-4103-9_28.
- [40] J. J. Kim and J. H. Park, "A novel structure of a power system stabilizer for microgrids," *Energies*, vol. 14, no. 4, p. 905, 2021, doi: <https://doi.org/10.3390/en14040905>.
- [41] A. Nocon and S. Paszek, "A Comprehensive Review of Power System Stabilizers," *Energies*, vol. 16, no. 4, p. 1945, 2023.
- [42] Y. Yang et al., "Parameter coordination optimization of power system stabilizer based on similarity index of power system state-BP neural network," *Energy Reports*, vol. 9, pp. 427–437, 2023.
- [43] A. Sheykhsarraf, M. Abedini, and M. Davarpanah, "A novel method for optimal placement and tuning of the power system stabilizer in the multi-machine system," *Electr. Power Syst. Res.*, vol. 221, p. 109451, 2023.
- [44] E. Solomon et al., "Mitigating Low-Frequency Oscillations and Enhancing the Dynamic Stability of Power System Using Optimal Coordination of Power System Stabilizer and Unified Power Flow Controller," *Sustainability*, vol. 15, no. 8, p. 6980, 2023.
- [45] M. R. Djalal, I. Robandi and M. A. Prakasa, "Stability Enhancement of Sulselbar Electricity System Using Mayfly Algorithm Based on Static Var Compensator and Multi-Band Power System Stabilizer PSS2B," *IEEE Access*, vol. 11, pp. 57319–57340, 2023, doi: 10.1109/ACCESS.2023.3283598.
- [46] A. A. Alsakati, C. A. Vaithilingam, J. Alnasseir and A. Jagadeeshwaran, "Transient Stability Improvement of Power System using Power System Stabilizer Integrated with Excitation System," *2021 11th IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*, pp. 34–39, 2021, doi: 10.1109/ICCSCE52189.2021.9530970.
- [47] K. M. Sreedivya, P. A. Jeyanthi, and D. Devaraj, "Improved design of interval type-2 fuzzy based wide area power system stabilizer for inter-area oscillation damping," *Microprocess. Microsyst.*, vol. 83, p. 103957, 2021, doi: 10.1016/j.micpro.2021.103957.
- [48] W. Aribowo, B. Suprianto, U. T. Kartini, and A. L. Wardani, "Optimal tuning proportional integral derivative controller on direct current motor using reptile search algorithm," *Int. J. Electr. Comput. Eng.*, vol. 13, no. 5, pp. 4901–4908, 2023.
- [49] K. Guo, Y. Qi, J. Yu, D. Frey, and Y. Tang, "A Converter-Based Power System Stabilizer for Stability Enhancement of Droop-Controlled Islanded Microgrids," *IEEE Trans. Smart Grid*, vol. 12, no. 6, pp. 1–11, 2021, doi: 10.1109/TSG.2021.3096638.
- [50] M. A. El-Dabah, S. Kamel, M. Khamies, H. Shahinzadeh, and G. B. Gharehpetian, "Artificial Gorilla Troops Optimizer for Optimum Tuning of TID Based Power System Stabilizer," *2022 9th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS)*, pp. 1–5, 2022, doi: 10.1109/CFIS54774.2022.9756463.
- [51] M. Izdebski, R. Małkowski, and P. Miller, "New Performance Indices for Power System Stabilizers," *Energies*, vol. 15, no. 24, p. 9582, 2022.
- [52] I. Davut, "A novel modified arithmetic optimization algorithm for power system stabilizer design," *Sigma J. Eng. Nat. Sci.*, vol. 40, no. 3, pp. 529–541, 2022, doi: 10.14744/sigma.2022.00056.
- [53] E. S. Bayu, B. Khan, Z. M. Ali, Z. M. Alaas, and O. P. Mahela, "Mitigation of Low-Frequency Oscillation in Power Systems through Optimal Design of Power System Stabilizer Employing ALO," *Energies*, vol. 15, no. 10, p. 3809, 2022, doi: 10.3390/en15103809.
- [54] N. Agrawal, F. A. Khan, and M. Gowda, "LQR based Power System Stabilizer for Damping Oscillations with Frequency Response Analysis," *J. Control Syst. its Recent Dev.*, vol. 6, no. 1, pp. 1–15, 2023.
- [55] D. Acharya and D. K. Das, "An Optimizer to Tune Fractional-Order Power System Stabilizer for Synchronous Generator Considering Governor Effect and Exciter Voltage Fluctuation," *J. Control. Autom. Electr. Syst.*, vol. 34, no. 2, pp. 407–419, 2023.
- [56] M. A. El-Dabah, M. H. Hassan, S. Kamel, M. A. Abido, and H. M. Zawbaa, "Optimal Tuning of Power System Stabilizers for a Multi-Machine Power Systems Using Hybrid Gorilla Troops and Gradient-Based Optimizers," *IEEE Access*, vol. 11, pp. 27168–27188, 2023.
- [57] J. H. Tayeb, M. R. Islam, M. Shafiullah, S. M. A. Gani, and M. I. Hossain, "Robust Power System Stabilizer for Multi-machine Power Networks using Tunicate Swarm Algorithm," in *2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS)*, pp. 1761–1766, 2022, doi: 10.1109/ICAIS53314.2022.9741828.
- [58] W. Aribowo, S. Muslim, B. Suprianto, and S. I. H. Joko, "Tunicate swarm algorithm-neural network for adaptive power system stabilizer parameter," *Sci. Technol. Asia*, vol. 26, no. 3,

- pp. 50–63, 2021, doi: 10.14456/scitechasia.2021.46.
- [59] M. A. El-Dabah, M. H. Hassan, S. Kamel, and H. M. Zawbaa, "Robust Parameters Tuning of Different Power System Stabilizers Using a Quantum Artificial Gorilla Troops Optimizer," *IEEE Access*, vol. 10, pp. 82560–82579, 2022.
- [60] D. Izci, "A novel improved atom search optimization algorithm for designing power system stabilizer," *Evol. Intell.*, vol. 15, no. 3, pp. 2089–2103, 2022, doi: 10.1007/s12065-021-00615-9.
- [61] E. Akbari et al., "Improved salp swarm optimization algorithm for damping controller design for multimachine power system," *IEEE Access*, vol. 10, pp. 82910–82922, 2022.
- [62] S. Ekinici and B. Hekimoglu, "Parameter optimization of power system stabilizer via Salp Swarm algorithm," *2018 5th International Conference on Electrical and Electronic Engineering (ICEEE)*, pp. 143-147, 2018, doi: 10.1109/ICEEE2.2018.8391318.
- [63] A. A. Alsakati, C. A. Vaithilingam, K. Naidu, G. Rajendran, J. Alnasseir, and A. Jagadeeshwaran, "Particle Swarm Optimization for Tuning Power System Stabilizer towards Transient Stability Improvement in Power System Network," in *2021 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAJET)*, pp. 1-6, 2021, , doi: 10.1109/IICAJET51634.2021.9573534.
- [64] S. Latif, S. Irshad, M. Ahmadi Kamarposhti, H. Shokouhandeh, I. Colak, and K. Eguchi, "Intelligent Design of Multi-Machine Power System Stabilizers (PSSs) Using Improved Particle Swarm Optimization," *Electron.*, vol. 11, no. 6, p. 946, 2022, doi: 10.3390/electronics11060946.
- [65] T. Hussein Elmenfy, "Design of velocity PID-fuzzy power system stabilizer using particle swarm optimization," *WSEAS Trans. Syst.*, vol. 20, pp. 9-14, 2021, doi: 10.37394/23202.2021.20.2.
- [66] S. N. Shahbazova and D. Ekmekci, "Tuning of Fuzzy Control Systems by Artificial Bee Colony with Dynamic Parameter Values Algorithm for Traction Power System," in *Recent Developments and the New Directions of Research, Foundations, and Applications: Selected Papers of the 8th World Conference on Soft Computing, 2022*, vol. 2, pp. 233–248, 2023.
- [67] A. E. Ezugwu, J. O. Agushaka, L. Abualigah, S. Mirjalili, and A. H. Gandomi, "Prairie dog optimization algorithm," *Neural Comput. Appl.*, vol. 34, no. 22, pp. 20017–20065, 2022, doi: 10.3390/s22030855.
- [68] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, "Marine Predators Algorithm: A nature-inspired metaheuristic," *Expert Syst. Appl.*, vol. 152, p. 113377, 2020, doi: 10.1016/j.eswa.2020.113377.
- [69] F. Jamsheed and S. J. Iqbal, "Design of an Adaptive Power System Stabilizer using Robust System-Response Prediction," *2020 IEEE International Conference on Power Electronics, Smart Grid and Renewable Energy (PESGRE2020)*, pp. 1-6, 2020, doi: 10.1109/PESGRE45664.2020.9070516.