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A novel modified dandelion optimizer with application in power system stabilizer

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ABSTRACT

This article presents a newly developed modification of the dandelion optimizer (DO). The proposed method is a chaotic algorithmic integrity and modification of the original dandelion optimizer. Dandelion is one of the plants that rely on wind for seed propagation. This article presents the tuning of the power system stabilizer with the method proposed in a case study of a single machine system. The validation of the proposed method uses the benchmark function and performance on a single engine system against transient response. The method used as a comparison in this article is the whale optimization algorithm (WOA), grasshopper optimization algorithm (GOA) and the original dandelion optimizer (DO). The simulation results show that the proposed method, which is a modified dandelion optimizer, provides promising performance.

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1. INTRODUCTION

The use of renewable energy and distributed generation integrated with various power semiconductor devices affects the stability of the power system [1]–[4]. The robustness of the interconnection of the electric power system will decrease because it is influenced by low-frequency oscillations that are not optimally submerged [5], [6]. This will cause electricity distribution disturbances which will indirectly burden the system technically and economically. So, the focus on attenuation of low-frequency oscillations becomes an important key in power systems.

A popular device in dealing with low-frequency oscillations is the power system stabilizer (PSS). This device is used in a variety of system conditions. Conventional PSS is modeled linearly as the basis of its design. This model considers the optimal working point as the basis for tuning PSS parameters. An electric power system that has non-linear and variable characteristics over a wide range. This makes conventional PSS not optimal. The development of technology and computational algorithms that are developing rapidly. This affects and penetrates into the power system stabilizer. Several studies have presented findings regarding this matter. In decades, computational approaches have been presented in tuning PSS parameters such as atomic search optimization (ASO) [7], moth search algorithm (MSO) [8], whale optimization algorithm (WOA) [9]–[12], Henry gas solubility optimization (HSO) [13], particle swarm optimization (PSO) [14]–[17], grey wolf optimization (GWO) [18]–[21] and JAYA algorithm (JA) [22]–[24].

This article presents the power system stabilizer tuning method using the modified dandelion optimizer (DO) method. Dandelion is one of the plants that rely on wind for seed propagation [25]. DO modification method is to integrate the chaotic algorithm and change one of the DO components. This is as a goal to increase the ability of DO. The contributions of this research are,

– Modify the dandelion optimizer method called CDO to get a new balance point of exploration and exploitation.
– Application of the CDO method to tune PSS parameters by measuring performance by comparing with conventional methods (PSS-Conv), PSS based on whale optimization algorithm (PSS-WOA), PSS based on grasshopper optimization algorithm (PSS-GOA) and PSS based on dandelion optimizer original (PSS-DO).

This article is structured: The second part describes the dandelion optimizer method, the dandelion modification method and the power system stabilizer. The third section presents the results and analysis. The last section provides conclusions from the research.

2. METHOD

2.1. Dandelion optimizer (DO)

Dandelion optimizer (DO) is a method adopted from the movement of plant seeds. Dandelion is one of the plants that rely on wind for seed propagation. Two important factors that affect the spread of dandelion seeds are wind speed and weather. The falling distance of dandelion seeds is affected by wind speed. Meanwhile, weather affects the ability of seedlings to grow near or far. DO can be modeled mathematically in 3 parts, namely the ascending section, descending section, and landing section. DO is like a population-based algorithm that assumes every dandelion seed is a candidate solution.

$$A = \begin{bmatrix} x_1^1 & \cdots & x_1^d \\ \vdots & \ddots & \vdots \\ x_p^1 & \cdots & x_p^d \end{bmatrix} \tag{1}$$

$$x_i = x_{min} + rand(x_{max} - x_{min}) \tag{2}$$

$$f_b = \min\left(f(x_i)\right) \tag{3}$$

$$x_e = x(find\ (f_b == f(x_i))) \tag{4}$$

Where population size is symbolized by p. Variable dimensions are represented by d. $rand$ denotes a random [0,1].

2.1.1. Ascending section

In the rising stage, sunny and windy weather brings dandelion seeds up. On the other hand, there is no wind over the seed when it rains. Local model search occurs in this section. Flying dandelion seeds are affected by wind speed and humidity. Dandelion seeds have the characteristic of being able to fly far considering the height. In this section the weather is modeled in two namely.

Condition 1: Sunny day conditions, lognormal distribution applied as wind speed. In this session, DO conducts exploration. The wind causes dandelion seeds to move randomly to various locations. The wind speed determines the height of the seed. Session 1 can be modeled,

$$x_{t=1} = x_t + \alpha \times v_x \times v_y \times \ln Y \times (x_s - x_t) \tag{5}$$

$$x_s = rand\ (1, dim\ ) \times rand(x_{max} - x_{min}) + x_{min} \tag{6}$$

$$lnY = \begin{cases} \frac{1}{y\sqrt{2\pi}} \exp[\frac{1}{2\sigma^2} (\ln y)^2] & y \geq 0 \\ 0 & y < 0 \end{cases} \tag{7}$$

$$\alpha = rand\ () \times \left(\frac{1}{T^2} t^2 - \frac{2}{T} t + 1\right) \tag{8}$$

$$v_x = r \times \cos\theta \tag{9}$$

$$v_y = r \times \sin\theta \tag{10}$$

$$r = \frac{1}{e^\theta} \tag{11}$$

$$\theta = (2 \times rand() - 1) \times \pi \tag{12}$$

Where the position of the dandelion seed during iteration is symbolized x_t. Randomly selected position in the search space during iteration is symbolized x_s. lnY is a lognormal distribution. The adaptive parameter used to adjust the search step length is α. The coefficient of the dandelion rising passage as a result of the action of the separate eddies symbolized v_x and v_y.

Condition 2: that is on a rainy day. Dandelion seeds have problems growing. In this condition, local exploitation is carried out. The mathematical equation of condition 2 is,

$$x_{t=1} = x_t \times k \tag{13}$$

$$q = \frac{1}{T^2-2T+1}t^2 - \frac{2}{T^2-2T+1}t + 1 + \frac{1}{T^2-2T+1} \tag{14}$$

$$k = 1 - rand() \times q \tag{15}$$

$$x_{t=1} = \begin{cases} x_t + \alpha \times v_x \times v_y \times \ln Y \times (x_s - x_t) & randn < 1.5 \\ x_t \times k & else \end{cases} \tag{16}$$

where k is applied to maintain the local seeking domain of an agent, $randn$ represented the random value that obeys the basic normal distribution.

2.1.2. Descending section

At this stage, the exploration phase is emphasized. The movement of dandelion seeds will decrease for sure after experiencing a peak at a certain value. The average information after the ascending stage is used to reflect the stability of the parental offspring. This is to provide support for the improvement of the overall population. The mathematical modeling of this stage is,

$$x_{t=1} = x_t - \alpha \times \beta_t \times (x_{mean\_t} - \alpha \times \beta_t \times x_t) \tag{17}$$

$$x_{mean\_t} = \frac{1}{pop}\sum_{i=1}^{pop} x_i \tag{18}$$

where β_t Points Brownian action. It is a random value from the standard normal distribution.

2.1.3. Landing section

Exploitation phase occurs in this section. The landing place of the dandelion seeds is chosen at random. The approximate position of the most viable dandelion seed was used as the optimal solution. Elite information is currently exploited in the local environment to obtain global optimum accuracy. This behavior can be modeled,

$$x_{t=1} = x_{elite} + levy(\lambda) \times \alpha \times (x_{elite} - x_t \times \delta) \tag{19}$$

$$levy(\lambda) = s\frac{\omega \times \sigma}{|t|^{\frac{1}{\beta}}} \tag{20}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{(\frac{\beta-1}{2})}}\right) \tag{21}$$

$$\delta = \frac{2t}{T} \tag{22}$$

where x_{elite} reflects the best position of the agent in every iteration. $levy(\lambda)$ deputizes the function of Levy flight.

2.2. A novel modified dandelion optimizer (CDO)

The proposed algorithm is an integration of the chaotic algorithm (CO) and the modified Dandelion Optimizer. This method is proposed to improve the DO optimization algorithm. CO applies chaotic variables instead of random variables. Chaos has non-reinforcement and ergodistic characteristics. In addition, the search system has a higher speed compared to search methods that are stochastic or rely on probability [26]. This study uses 1-D non-reversed maps, namely logitstics as a chaotic set algorithm. Modification is used to accelerate the level of the convergence curve to reach the optimal point.

$$ylog_{(i+1)} = a \times ylog_{(i)}\left(1 - ylog_{(i)}\right) \tag{22}$$

In (22) is used to replace the variable $rand()$ in (12). So, (12) becomes,

$$\theta = (2 \times ylog_{(i+1)} - 1) \times \pi \tag{23}$$

the second step is to change (19) to (24). This modification aims to sharpen the convergence curve obtained.

$$x_{t=1} = x_{elite} + levy(\lambda) \times \alpha \times (x_{elite} - x_t \times \delta) - x_{elite} \times rand() \tag{24}$$

2.3. Power system stabilizer

The damping torque on the engine rotor will be regulated by PSS with the aim of producing a compensation between the electric torque and the excitation input [27]. PSS will output a value proportional to the rotor speed. This maintains the stability of the electrical system. Figure 1 is a lead-lag PSS schematic.

2.4. Design of controllers

CDO is used to find the optimal point of attenuation by adjusting the PSS parameter. So that the requirements of the transient response criteria can be increased in the closed loop response. An illustration of PSS tuning with CDO can be seen in Figure 2 on Appendix. The initial step starts with making the required parameters. The results obtained are random parameters which are always corrected during the iteration process.

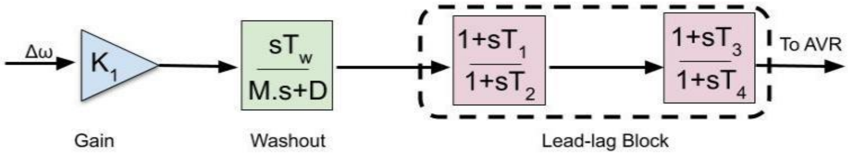


Figure 1. PSS lead-lag type

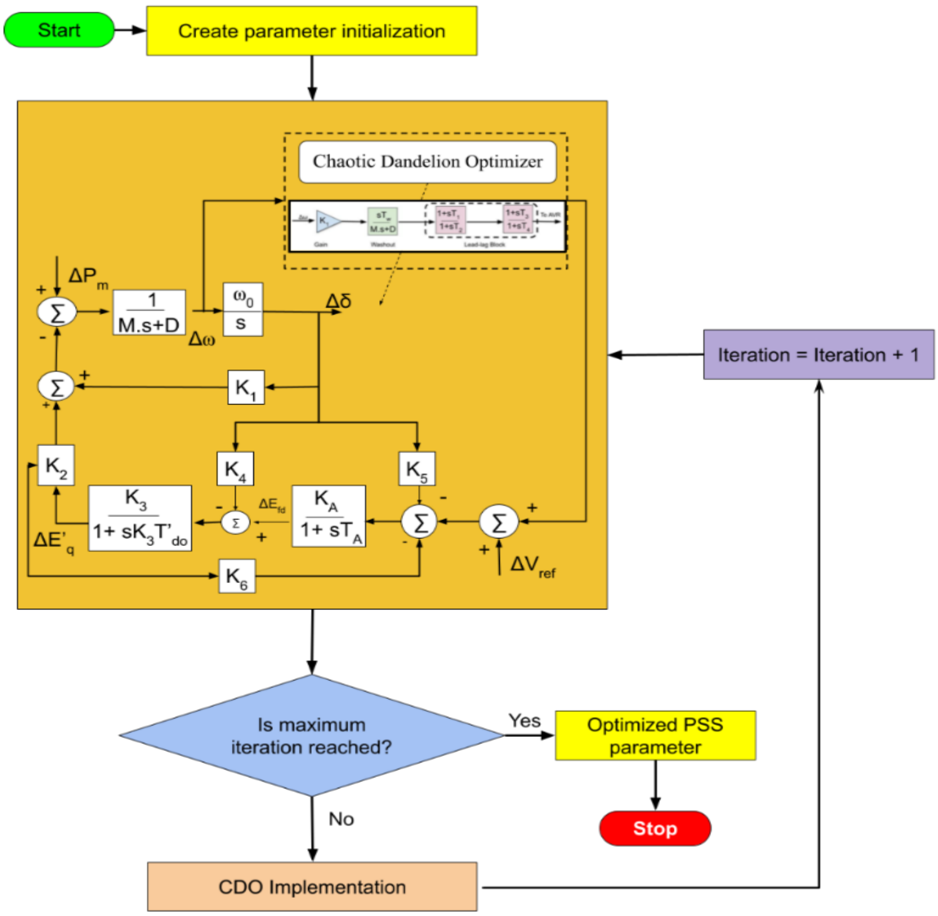


Figure 2. Block diagarm CDO-PSS

3. RESULTS AND DISCUSSION

3.1. Convergence curve profile

The performance of the CDO Algorithm is measured using the classical and CEC 2019 benchmark function. In this article, 12 classical benchmark functions are used which can be seen in detail in Table 1. The results of the classical benchmark function on CDO compared to the GOA, WOA, and DO methods can be seen in Figure 3. The Unimodal functions can be seen in Figure 3(a) to Figure 3(d), Multimodal can be seen in Figure 3(e) to Figure 3(h) and multimodal with fixed dimensions is presented in Figure 3(i) to Figure 3(l). The result of classical benchmark function can be seen in Table 2. This article also tests using CEC2019. The test results with CEC 2019 can be seen in Figure 3(m) to Figure 3(n). The Detail of CEC2019 Benchmark Function can be seen Table 3. From the results of trials using several functions from the CEC 2019 Benchmark function, the CDO method has a better average convergence value than the DO, WOA and GOA methods. The results of CEC 2019 Benchmark Function can ben seen in Table 4.

Table 1. The classical benchmark functions

ID	Test Function	Range	Type
F_1	$F_1(x) = \sum_{i=1}^{n} X_i^2$	$[-100,100]^n$	Unimodal
F_2	$F_2(x) = \sum_{i=1}^{n} \lvert X_i \rvert + \prod_{i=1}^{n} \lvert X_i \rvert$	$[-10,10]^n$	Unimodal
F_3	$F_3(x) = \sum_{i=1}^{n} (\sum_{j=1}^{n} \lvert X_i \rvert)^2$	$[-100,100]^n$	Unimodal
F_4	$F_4(x) = \max \{\lvert X_i \rvert, 1 \leq i \leq n\}$	$[-100,100]^n$	Unimodal
F_8	$F_8(x) = \sum_{i=1}^{n} -X_i \sin(\sqrt{\lvert X_i \rvert})$	$[-500,500]^n$	Multimodal
F_9	$F_9(x) = \sum_{i=1}^{n} [X_i^2 - 10\cos(2\pi X_i) + 10]$	$[-5.12,5.12]^n$	Multimodal
F_{10}	$F_{10}(x) = -20\exp(-0.2\sqrt{\frac{1}{n}\sum_{j=1}^{n} X_i^2}) - \exp(\frac{1}{n}\sum_{i=1}^{n} \cos(2\pi X_i)) + 20 + e$	$[-32,32]^n$	Multimodal
F_{11}	$F_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} X_i^2 + \prod_{i=1}^{n} \cos(\frac{X_i}{\sqrt{i}}) + 1$	$[-20,20]^n$	Multimodal
F_{18}	$F_{18}(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)] \times [30 + (2x_1 - 3x_2)^2 \times (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	$[-2,2]^2$	Multimodal with fixed dimensions
F_{19}	$F_{19}(x) = -\sum_{i=1}^{4} C_i \exp(-\sum_{i=1}^{3} a_{ij}(X_i - p_{ij})^2)$	$[0,1]^3$	Multimodal with fixed dimensions
F_{20}	$F_{20}(x) = -\sum_{i=1}^{4} C_i \exp(-\sum_{i=1}^{6} a_{ij}(X_i - p_{ij})^2)$	$[0,1]^6$	Multimodal with fixed dimensions
F_{21}	$F_{21}(x) = -\sum_{i=1}^{5} [(X - a_i)(X - a_i)^T + C_i]^{-1}$	$[0,10]^4$	Multimodal with fixed dimensions

3.2. Transient response validation

In this article, small signal stability analysis is applied to the Heffron-Philips model. The non-linear set of PSS parameters is solved by CDO. The parameters obtained are used to reduce wave oscillations as best as possible. This study uses a comparison method, namely conventional PSS, WOA, GOA and DO as a validation of the performance of the CDO. The PSS parameters that have been obtained are tested with the system under 100% loading conditions. Performance validation is carried out by comparing the CDO method with other algorithms and can be seen in Figure 4. The analysis of the transient response is detailed in Table 5. The simulation results using the MATLAB/simulink application with a laptop that has an Intel I5-5200 2.19 GHz processor specification and 8 GB RAM memory where the PSS-CDO method is able to reduce overshoot from a speed of 96.48% from PSS-Conv. It can be seen in Figure 4(a). Meanwhile, the undershoot of the PSS-Conv method can be reduced by 75.99%, by implementing PSS-CDO. The Rotor angel comparison results can be seen in Figure 4(b).

Table 2. Results of the benchmark function

ID		CDO	DO	GOA	WOA
F1	Best	1.23E-11	642.4311	530.3973	0.001318
	Worst	3.25E-10	2404.2	1185.804	0.3713
	Mean	1.29E-09	4219.987	2217.168	3.4714
	Std Deviation	3.24E-10	982.7503	409.3191	0.67814
F2	Best	3.16E-07	8.6321	8.567	0.005495
	Worst	4.75E-06	23.2267	27.9892	0.084016
	Mean	1.16E-05	76.2167	85.1458	0.27367
	Std Deviation	2.61E-06	13.9029	21.4767	0.074365
F3	Best	1.95E-10	8200.342	1427.746	49283.88
	Worst	5.30E-09	16207.47	5290.209	100263
	Mean	2.52E-08	23853.42	15021.57	189167.9
	Std Deviation	7.40E-09	4707.366	3251.914	31384.76
F4	Best	4.02E-06	35.8668	9.596	16.9667
	Worst	1.31E-05	49.8996	15.224	66.0116
	Mean	2.73E-05	69.733	23.7969	89.2632
	Std Deviation	5.96E-06	9.14	3.7136	20.5823
F8	Best	-3437.92	-8086.5344	-7407.9610	-11917.8502
	Worst	-2491.49	-6574.3898	-6332.4420	-9133.0283
	Mean	-1578.35	-5285.6636	-4765.8226	-7066.2870
	Std Deviation	469.98	770.5834	653.0869	1191.3498
F9	Best	1.24E-11	74.7104	111.4599	0.0042695
	Worst	1.09E-10	132.3206	180.5123	54.3783
	Mean	3.59E-10	202.8456	243.5834	269.2653
	Std Deviation	8.60E-11	33.0798	29.7397	84.7164
F10	Best	1.09E-06	8.3848	6.5252	0.010797
	Worst	3.41E-06	12.2815	8.9729	0.11812
	Mean	9.98E-06	16.0868	11.8267	0.43745
	Std Deviation	2.27E-06	2.5945	1.5671	0.12948
F11	Best	8.27E-12	7.2046	4.1278	0.011716
	Worst	4.84E-10	21.5406	10.2899	0.28451
	Mean	2.08E-09	47.1931	19.3694	1.0244
	Std Deviation	5.79E-10	9.2638	3.5281	0.3107
F18	Best	3.00	3.0000	3.0000	3.0000
	Worst	13.69	11.6400	3.0000	7.3665
	Mean	92.20	84.0001	3.0000	30.6394
	Std Deviation	29.54	23.0161	0.0000	10.2109
F19	Best	-3.86	-3.8628	-3.8628	-3.8623
	Worst	-3.76	-3.8627	-3.8037	-3.8290
	Mean	-3.46	-3.8619	-2.9627	-3.6659
	Std Deviation	0.11	0.0002	0.1861	0.0544
F21	Best	-3.55	-10.1532	-10.1532	-9.8812
	Worst	-1.97	-5.3342	-5.0476	-6.4502
	Mean	-0.60	-2.6303	-2.6305	-2.5763
	Std Deviation	0.89	3.2221	3.0965	2.4101

Table 3. CEC 2019 benchmark function [28]

ID	Function	Range	D
Cec01	Storn 's Chebyshev Polynomial Fitting	[−8192, 8192]	9
Cec02	Inverse Hilbert Matrix	[−16,384, 16,384]	16
Cec03	Lennard-Joes Minimum Energy Cluster	[−4.4]	18

Table 4. Results of the CEC 2019 benchmark function

ID		CDO	DO	GOA	WOA
Cec01	Best	53455.03	496325170.4257	2801884356.8928	4114376128.4504
	Worst	69042.86	35323431917.2154	46367185532.8617	344838981298.6600
	Mean	103213.64	145361857875.7400	163343949975.5400	2016913382426.1000
	Std Deviation	12794.30	34144248607.8775	50100680407.7947	440383992017.2400
Cec02	Best	18.56	18.3468	23.2134	18.3932
	Worst	18.80	18.4452	57.6369	19.1504
	Mean	19.11	18.7158	300.7714	21.2557
	Std Deviation	0.14	0.1080	60.5416	0.8178
Cec03	Best	13.70	13.7024	13.7024	13.7024
	Worst	13.70	13.7026	13.7029	13.7025
	Mean	13.71	13.7049	13.7062	13.7038
	Std Deviation	0.00	0.0007	0.0011	0.0003

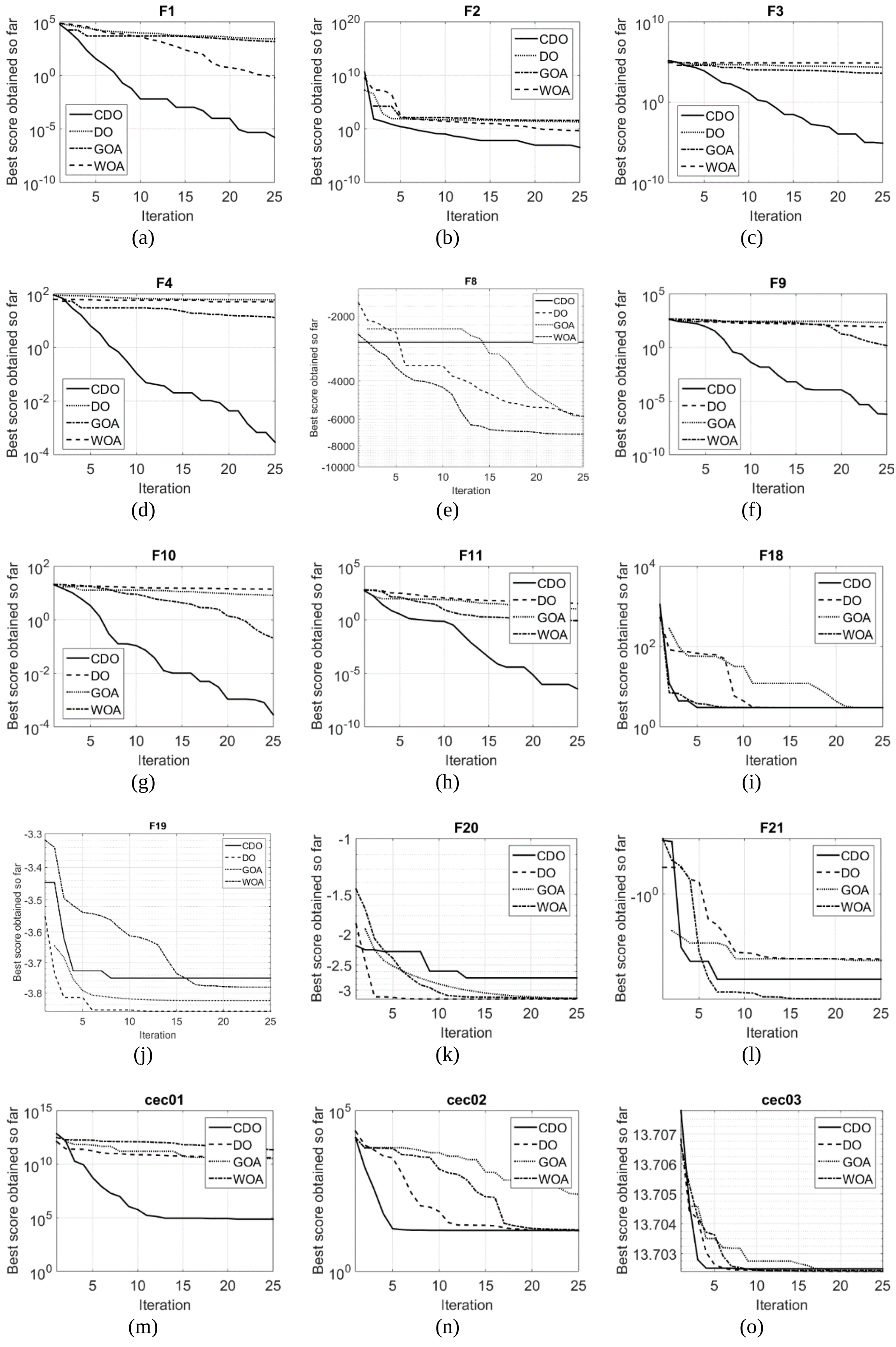
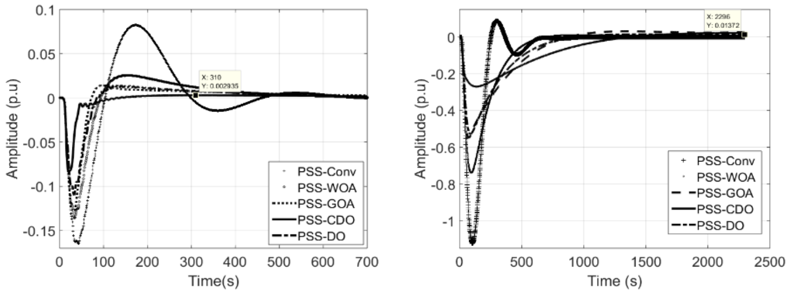


Figure 3. The convergence curve of benchmark function (a) F1, (b) F2, (c) F3, (d) F4, (e) F8, (f) F9, (g) F10, (h) F11, (i) F18, (j), F19, (k) F20, (l) F21, (m)cec01, (n)) cec02, (o)) cec03

Table 5. Transient response

Algorithm	Rotor Angle Output			Speed Output		
	Overshoot	Undershoot	Settling Time(s)	Overshoot	Undershoot	Settling Time(s)
PSS-CDO	No Overshoot	-0.27	785	0.0029	-0.0837	609
PSS-DO	0.01372	-0.527	649	0.0139	-0.11	977
PSS-GOA	0.308	-0.55	980	0.0141	-0.1287	681
PSS-WOA	0.011	-0.7395	607	0.0257	-0.1359	543
PSS-Conv	0.0887	-1.1244	593	0.0823	-0.1647	602



(a) (b)

Figure 4. Transient response; (a) Speed response, and (b) Rotor angle response

4. CONCLUSION

This article proposes a modification of the Dandelion Optimizer method by integrating the chaotic algorithm and modification of the original Dandelion Optimizer (DO) to obtain optimal parameters from the power system stabilizer (PSS). DO is a method adopted from the movement of dandelion seeds. Dandelion is one of the plants that rely on wind for seed propagation. The experimental results show that the performance of the CDO method can increase the ability of PSS with a fully loaded system condition. PSS optimized with CDO can reduce overshoot speed by 96.48% and undershoot rotor angle by 75.99% compared to conventional methods.

REFERENCES

[1] 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 Transactions on Smart Grid*, vol. 12, no. 6, pp. 4616–4626, 2021, doi: 10.1109/TSG.2021.3096638.

[2] J. J. Kim and J. H. Park, "A novel structure of a power system stabilizer for microgrids," *Energies*, vol. 14, no. 4, 2021, doi: 10.3390/en14040905.

[3] W. Aribowo, "Slime mould algorithm training neural network in automatic voltage regulator," *Trends in Sciences*, vol. 19, no. 3, 2022, doi: 10.48048/tis.2022.2145.

[4] M. Rohman, F. Baskoro, W. Aribowo, Y. S. Nugroho, A. P. Nurdiansyah, and L. E. C. Ningrum, "Selection of the modulation, distance, and number of hop nodes parameters to determine the minimum energy in the wireless sensor network," *2022 5th International Conference on Vocational Education and Electrical Engineering: The Future of Electrical Engineering, Informatics, and Educational Technology Through the Freedom of Study in the Post-Pandemic Era, ICVEE 2022 - Proceeding*, pp. 118–123, 2022, doi: 10.1109/ICVEE57061.2022.9930396.

[5] I. M. Alotaibi, S. Ibrir, M. A. Abido, and M. Khalid, "Nonlinear power system stabilizer design for small signal stability enhancement," *Arabian Journal for Science and Engineering*, vol. 47, no. 11, pp. 13893–13905, 2022, doi: 10.1007/s13369-022-06566-2.

[6] H. Z. A. Kareem, H. H. Mohammed, and A. A. Mohammed, "Robust tuning of power system stabilizer parameters using the modified harmonic search algorithm," *IIUM Engineering Journal*, vol. 22, no. 1, pp. 47–57, 2021, doi: 10.31436/IIUMEJ.V22I1.1276.

[7] D. Izci, "A novel improved atom search optimization algorithm for designing power system stabilizer," *Evolutionary Intelligence*, vol. 15, no. 3, pp. 2089–2103, 2022, doi: 10.1007/s12065-021-00615-9.

[8] N. Razmjooy, S. Razmjooy, Z. Vahedi, V. V. Estrela, and G. G. de Oliveira, "A new design for robust control of power system stabilizer based on moth search algorithm," *Lecture Notes in Electrical Engineering*, vol. 696, pp. 187–202, 2021, doi: 10.1007/978-3-030-56689-0_10.

[9] B. Dasu, M. Sivakumar, and R. Srinivasarao, "Interconnected multi-machine power system stabilizer design using whale optimization algorithm," *Protection and Control of Modern Power Systems*, vol. 4, no. 1, 2019, doi: 10.1186/s41601-019-0116-6.

[10] P. R. Sahu, P. K. Hota, and S. Panda, "Modified whale optimization algorithm for coordinated design of fuzzy lead-lag structure-based SSSC controller and power system stabilizer," *International Transactions on Electrical Energy Systems*, vol. 29, no. 4, 2019, doi: 10.1002/etep.2797.

[11] N. A. M. Kamari, I. Musirin, Z. Othman, and S. A. Halim, "PSS based angle stability improvement using whale optimization approach," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 8, no. 2, pp. 382–390, 2017, doi: 10.11591/ijeecs.v8.i2.pp382-390.

[12] R. Devarapalli, B. Bhattacharyya, and A. Kumari, "Enhancing oscillation damping in a power network using EWOA technique," *Lecture Notes in Electrical Engineering*, vol. 693 LNEE, pp. 27–36, 2021, doi: 10.1007/978-981-15-7675-1_3.

[13] S. Ekinci, D. Izci, and B. Hekimoglu, "Implementing the henry gas solubility optimization algorithm for optimal power system stabilizer design," *Electrica*, vol. 21, no. 2, pp. 250–258, 2021, doi: 10.5152/electrica.2021.20088.

[14] 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," *Electronics (Switzerland)*, vol. 11, no. 6, 2022, doi: 10.3390/electronics11060946.

[15] S. Kondattu Mony, A. J. Peter, and D. Durairaj, "Gaussian quantum particle swarm optimization-based wide-area power system stabilizer for damping inter-area oscillations," *World Journal of Engineering*, vol. 20, no. 2, pp. 325–336, 2023, doi: 10.1108/WJE-05-2021-0303.

[16] F. Rodrigues, Y. Molina, C. Silva, and Z. Ñaupari, "Simultaneous tuning of the AVR and PSS parameters using particle swarm optimization with oscillating exponential decay," *International Journal of Electrical Power and Energy Systems*, vol. 133, 2021, doi: 10.1016/j.ijepes.2021.107215.

[17] T. Hussein Elmenfy, "Design of velocity PID-fuzzy power system stabilizer using particle swarm optimization," *WSEAS Transactions on Systems*, vol. 20, pp. 9–14, 2021, doi: 10.37394/23202.2021.20.2.

[18] P. Dhanaselvi, S. S. Reddy, and R. Kiranmayi, "Optimal tuning of multi-machine power system stabilizer parameters using grey wolf optimization (GWO) algorithm," *Lecture Notes in Electrical Engineering*, vol. 569, pp. 347–355, 2020, doi: 10.1007/978-981-13-8942-9_29.

[19] R. K. Sharma, D. Chitara, S. Raj, K. R. Niazi, and A. Swarnkar, "Multi-machine power system stabilizer design using grey wolf optimization," pp. 331–343, 2022, doi: 10.1007/978-981-16-4103-9_28.

[20] A. H. Khader, A. H. Yakout, and M. El-Sharkawy, "Damping interarea oscillations using PID power system stabilizer with grey wolf algorithm and particle swarm algorithm," *2019 21st International Middle East Power Systems Conference, MEPCON 2019 - Proceedings*, pp. 330–336, 2019, doi: 10.1109/MEPCON47431.2019.9007977.

[21] J. Chen, T. Jin, X. Zhu, Z. Li, and K. Zhang, "Parameter optimization of a power system stabilizer based on SOGWO," *Dianli Xitong Baohu yu Kongzhi/Power System Protection and Control*, vol. 48, no. 22, pp. 159–164, 2020, doi: 10.19783/j.cnki.pspc.202030.

[22] B. M. Alshammari, A. Farah, K. Alqunun, and T. Guesmi, "Robust design of dual-input power system stabilizer using chaotic JAYA algorithm," *Energies*, vol. 14, no. 17, 2021, doi: 10.3390/en14175294.

[23] A. Farah, A. Kahouli, T. Guesmi, and H. H. Abdallah, "Dual-input power system stabilizer design via JAYA algorithm," *2018 15th International Multi-Conference on Systems, Signals and Devices, SSD 2018*, pp. 744–749, 2018, doi: 10.1109/SSD.2018.8570632.

[24] Y. Welhazi, T. Guesmi, and H. H. Abdallah, "Jaya optimization approach for PSSs and TCSC based coordinated controller design in power system," *2019 10th International Renewable Energy Congress, IREC 2019*, 2019, doi: 10.1109/IREC.2019.8754647.

[25] S. Zhao, T. Zhang, S. Ma, and M. Chen, "Dandelion Optimizer: A nature-inspired metaheuristic algorithm for engineering applications," *Engineering Applications of Artificial Intelligence*, vol. 114, 2022, doi: 10.1016/j.engappai.2022.105075.

[26] B. Hekimoglu, "Optimal tuning of fractional order PID controller for DC motor speed control via chaotic atom search optimization algorithm," *IEEE Access*, vol. 7, pp. 38100–38114, 2019, doi: 10.1109/ACCESS.2019.2905961.

[27] W. Aribowo, "A novel improved sea-horse optimizer for tuning parameter power system stabilizer," *Journal of Robotics and Control (JRC)*, vol. 4, no. 1, pp. 12–22, 2023, doi: 10.18196/jrc.v4i1.16445.

[28] P. N. S. K. V. Price, N. H. Awad, M. Z. Ali, "The 100-digit challenge: Problem definitions and evaluation criteria for the 100-digit challenge special session and competition on single objective numerical optimization," *Technical Report Nanyang Technological University, Singapore*, no. November, p. 22, 2018, [Online]. Available: http://www.ntu.edu.sg/home/EPNSugan/index_files/CEC2019.

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