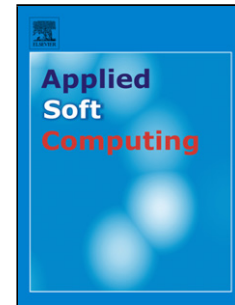


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## Augmented Grey Wolf Optimizer for Grid-connected PMSG-based Wind Energy Conversion Systems

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### Highlights

- We present a new improvement to the grey wolf algorithm.
- The new improvement is tested with twenty-three benchmark functions.
- The new improvement is compared with four published algorithms.
- The new improvement is applied to grid-connected wind power plants.
- The new improvement is verified by simulation results.

### Abstract

The grey wolf optimizer (GWO) is a new meta-heuristic algorithm inspired from the leadership and prey searching, encircling, and hunting of the grey wolves' community. The GWO algorithm has the advantages of simplicity (less control parameters), flexibility, and globalism. In this paper, a simple and efficient augmentation for the GWO (AGWO) algorithm is proposed for better hunting performance. The AGWO algorithm focuses on increasing the possibility of the exploration process over the exploitation process by modifying the behavior of the control parameter ( $a$ ) and position updating. The AGWO is suitable to the low number of search agents such as the electric power system application. The proposed AGWO algorithm is verified using twenty-three benchmark test functions and is applied to the grid-connected permanent magnet synchronous generator driven by variable speed wind turbine (PMSG-VSWT). The obtained results of the AGWO algorithm are compared with the results of the original GWO and other algorithms. The comparisons verified that the proposed AGWO is significantly augmented the performance of the original GWO algorithm without affecting its simplicity and easy implementation.

**Keywords:** Grey wolf optimizer; Exploration; Exploitation; wind energy conversion; proportional integral controller.

## 1 Introduction

The behavior of food searching and utilizing varies between the creatures in nature. The inspiration and imitating of these behaviors led to many efficient meta-heuristic algorithms for obtaining the global optimum solution of difficult functions and different engineering applications. Every time, a new algorithm emerges as a competitive algorithm to previous ones. The Particle Swarm Optimization (PSO) is inspired from birds swarm manners by Kennedy in 1995 [1]. The Ant Colony Optimization (ACO) is inspired from the shortest distance behavior from food to ant colony [2]. The Bat-inspired Algorithm (BA), where the Bats locate their food using echo [3]. The Cuckoo Search Algorithm (CS) is inspired from the memory mechanism of Cuckoo birds to register the local minima and search for the best among them [4]. The Artificial Bee Colony (ABC) algorithm is inspired from the honey bee swarm behavior [5]. On the other hand, many efficient meta-heuristic algorithms are inspired from evolution concept such as: Genetic Algorithm (GA) mimics the evolution process of natural selection and genetics [6], Biogeography-Based Optimizer (BBO) is inspired from The evolution of species (such as hunters and preys) over immigration and mutation to reach a steady state [7], and Differential Evolution (DE) is based on the weighted difference between two population vectors [8]. Furthermore, other meta-heuristic algorithms are physics-based techniques which imitates the physical rules such as: Gravitational Search Algorithm (GSA), which is based on the law of gravity of Newton and mass interactions [9], Ray Optimization (RO) that is based on the Snell's light refraction law, when light travels from a brighter medium to a darker medium, it refracts and its direction changes [10], charged system search (CSS) that is based on the Coulomb law and Newtonian laws of movement [11], and colliding bodies optimization is based on one-dimensional collisions between bodies [12]. Each heuristic algorithm has its coherent merits and demerits including the simplicity, robustness, the elapsing time, proper design, and computational burden. The great development of these heuristic algorithms is an incentive to the authors to implement an augmented version of the grey wolf optimizer (GWO).

A GWO is a recent efficient meta-heuristic algorithm which imitates the grey wolf social hierarchy behavior [13]. Grey wolves favor to live in a pack, where the average number of members is 5-12. Grey wolves are classified as top hunters and rely on the leadership chain and hunting manners. Detailed explanation about the GWO algorithm structure is presented in section 2. The GWO algorithm has been applied to solve many engineering disciplines especially in electrical power system and control such as : load frequency control [14], optimal real and reactive power dispatch [15,16], sizing of energy storage system [17], and tuning of fuzzy control systems [18].

All new algorithms are presented in its basic structure that can be improved and hybridized with other algorithms to solve either global or specific functions [19–21]. The simplicity, flexibility, and globalism

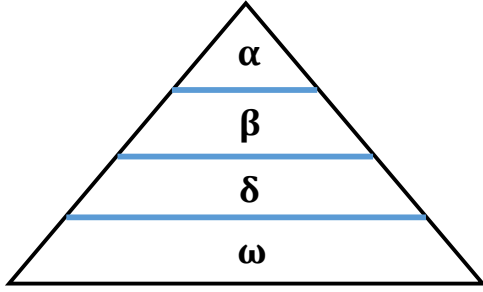
are the most characteristics of the proposed GWO algorithm. Many improvements are suggested for the GWO algorithm by scientific researchers in order to avoid the local optima trap. In [22], the GWO algorithm is proposed by integrating the GWO with Lévy Flight (LGWO) to avoid local optima stagnation. However, this integration affected the simplicity of original GWO algorithm. In [23], the improved GWO (IGWO) is proposed by changing the parameters of  $a_{min}$  and  $a_{max}$  for every test function. However, this improvement affected the globalism and flexibility of the GWO algorithm. In [24], the enhanced GWO (EGWO) algorithm is proposed by making the parameter  $a$  to be random number between 0 and 1 and using the alpha search agents only. This enhancement is the simplest among other modifications and simplified the structure of the GWO algorithm. However, using alphas only is not appropriate for the social hierarchy of grey wolves' behavior and will lead to stagnation in some local optima. In [25], the exploration of the GWO algorithm is enhanced (EEGWO) by adding many parameters to the position and parameter  $a$  updating. However, this enhancement increased the number of parameters in the GWO algorithm which make it more complicated than its original form.

In this paper, a simple augmentation has been proposed to the exploration and exploitation of the GWO algorithm (AGWO). The exploration is augmented by making the parameter  $a$  decrease nonlinearly from 2 to 1 to avoid stagnation. The exploitation is developed by updating the position of search agents by the average position of alphas (first best position) and betas (second best position). The AGWO algorithm is tested with twenty third benchmark functions using MATLAB, then the results show that the AGWO algorithm hit best minima more than the GWO, EGWO, LGWO, PSO, DE, CS, and GSA algorithms among the tested benchmark functions. The AGWO algorithm has many advantages: i) simple structure and easy implementation; ii) better exploration and exploitation than the original GWO; iii) better convergence to the global minimum; and iv) less computing time. The AGWO algorithm is applied to enhance the Maximum power point tracking (MPPT) and low voltage ride through (LVRT) capability performance of grid-connected permanent magnet synchronous generator driven by variable speed wind turbine (PMSG-VSWT). The enhancement can be achieved by obtaining the optimum gain parameters of multiple proportional-integral (PI) controllers used in the cascaded control of the full scale converter that used in grid-connected PMSG-VSWT. The AGWO, GWO, and PSO algorithm are coded in FORTRAN and applied to an online optimization of grid-connected PMSG-VSWT model in PSCAD/EMTDC environment.

## 2 Grey wolf optimizer algorithm

The GWO algorithm is a modern meta-heuristic algorithm presented by S. Mirjalili, et al [13], which mimics the community behavior of grey wolves, which live in a pack include 5-12 members. In the pack of grey wolves, strict dominant hierarchy is trained where the pack have a leader called alpha ( $\alpha$ ),

followed by secondary wolves called beta ( $\beta$ ) which assist alpha in decision making, followed by  $\delta$  and  $\omega$  as shown in Fig. 1.



**Fig. 1** Grey wolf hierarchy

The process of hunting a prey by grey wolves is: searching for the prey, encircling the prey, then hunting and attacking the prey. The mathematical model of encircling the prey is expressed as follows

$$\vec{D} = |\vec{C} \cdot \vec{X}_{pi} - \vec{X}_i| \quad (1)$$

$$\vec{X}_{i+1} = \vec{X}_{pi} - \vec{A} \cdot \vec{D} \quad (2)$$

where  $\vec{X}$  is the position vector of grey wolf,  $\vec{X}_p$  is the position vector of the prey,  $\vec{A}$  and  $\vec{C}$  are vectors computed as follows

$$\vec{a} = 2 - 2 \times t / Max\_iter \quad (3)$$

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (4)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (5)$$

where  $r_1$  and  $r_2$  are uniformly distributed random vectors between 0 and 1 and  $a$  is linearly decreased from 2 to 0 with iteration ( $t$ ) increased till reach maximum iteration ( $Max\_iter$ ). The exploration (searching) of the prey location can be achieved by the divergence of search agents, which can be achieved while  $|A| > 1$ . The exploitation (attacking) the prey can be achieved by the convergence of search agents, which is investigated when  $|A| < 1$ . The hunting is guided by  $\alpha$  agents and with support with  $\beta$  and  $\delta$  agents as in (6)-(8). A Pseudo code of the GWO algorithm is shown in Fig. 2.

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_{\alpha i} - \vec{X}_i|, \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_{\beta i} - \vec{X}_i|, \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_{\delta i} - \vec{X}_i| \quad (6)$$

$$\vec{X}_1 = \vec{X}_{\alpha i} - \vec{A}_1 \cdot \vec{D}_\alpha, \vec{X}_2 = \vec{X}_{\beta i} - \vec{A}_2 \cdot \vec{D}_\beta, \vec{X}_3 = \vec{X}_{\delta i} - \vec{A}_3 \cdot \vec{D}_\delta \quad (7)$$

$$\vec{X}_{i+1} = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (8)$$

```

Initialize the search agents positions  $X_i$ ,  $X_\alpha$ ,  $X_\beta$ , and  $X_\delta$ 
Calculate the fitness of each search agents
Initialize  $a$ ,  $A$ , and  $C$  by equations (3), (4), and (5)
while  $t < \text{Max\_iter}$ 
  for each search agent
    Update the position of current search agent by equation (8)
  end for
  Calculate the fitness of all search agents
  Update  $a$ ,  $A$ , and  $C$ 
  Update  $X_\alpha$ ,  $X_\beta$ , and  $X_\delta$ 
   $t = t + 1$ 
end while
return  $X_\alpha$ 

```

**Fig. 2** Pseudo code of the GWO algorithm

### 3 Augmented grey wolf optimizer algorithm

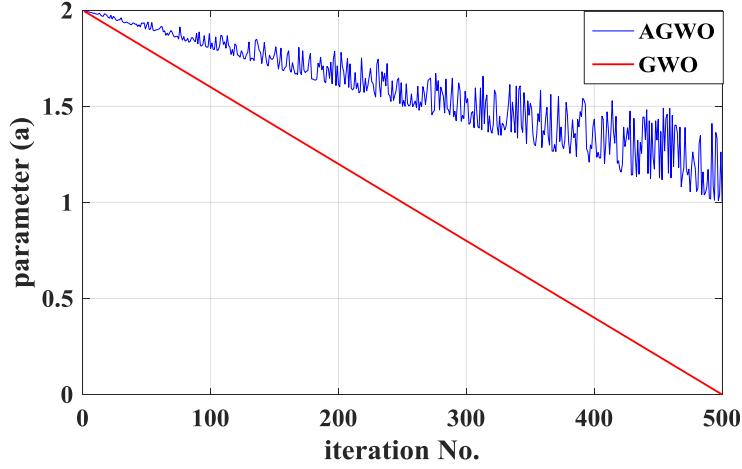
The large power system applications (e.g. grid-connected wind power plants) are nonlinear model and it is difficult to find the transfer function for optimum performance. Therefore, the online optimization for power system is the best alternative solution instead of the transfer function. The application of the GWO algorithm for online optimization of power system applications is limited with search agents' number, unlike the benchmark function optimization or transfer function optimization (offline optimization).

For global optimization and wide-range application, the GWO algorithm is presented in its simplest structure. Therefore, similar to the other proposed algorithms (e.g. PSO), the GWO algorithm can be improved and modified for better performance of exploration and exploitation in different discipline applications. In this paper, a new modification is proposed to augment the exploration of the GWO algorithm without affecting its simplicity, flexibility, and global optimization. As described in the previous section, the most parameter responsible for exploration and exploitation is parameter  $A$  which mainly depends on parameter  $a$  as in (4). The behavior of parameter  $a$  controls the exploration and exploitation of GWO algorithm, where parameter  $a$  changes linearly from 2 to 0 in the original GWO algorithm. In the proposed augmentation (AGWO) algorithm, parameter  $a$  changes nonlinearly and randomly from 2 to 1 as in (9), where the chances of exploration state is more than exploitation state as shown in Fig. 3.

$$\vec{a} = 2 - \cos(\text{rand}) \times t / \text{Max\_iter} \quad (9)$$

$$\vec{A} = 2\vec{a}\vec{r}_1 - \vec{a} \quad (10)$$

$$\vec{C} = 2\vec{r}_2 \quad (11)$$



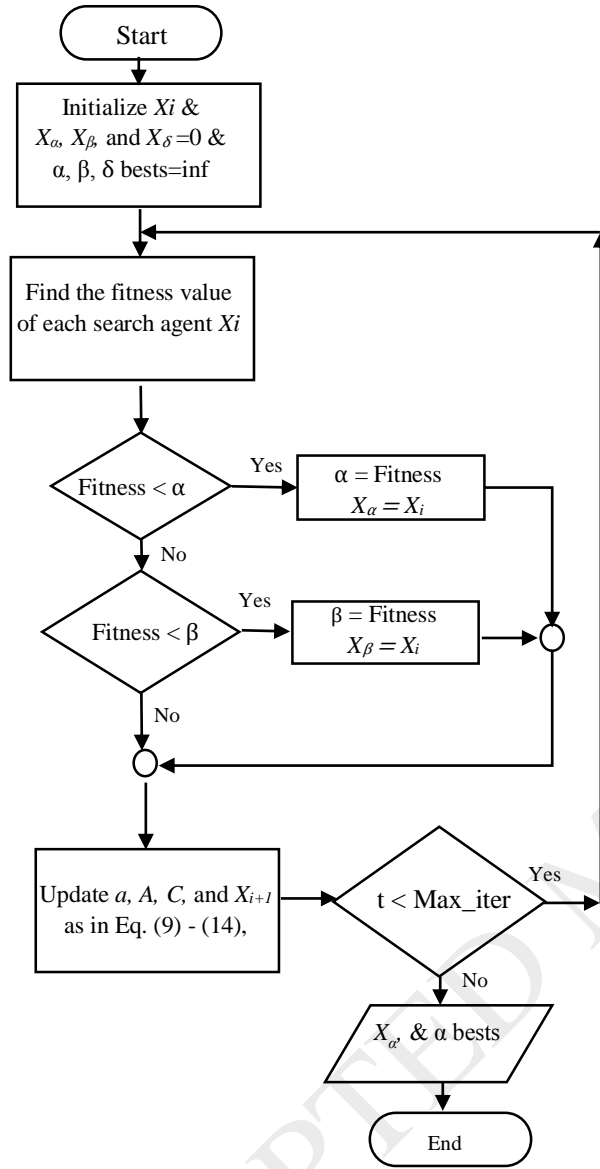
**Fig. 3** Behavior of parameter ( $a$ ) in GWO and AGWO algorithm.

The hunting and decision-making in the GWO algorithm depends on the updating of alphas ( $\alpha$ ), betas ( $\beta$ ), and deltas ( $\delta$ ) as in (6)-(8). However, in the proposed AGWO algorithm the hunting will depends only on  $\alpha$  and  $\beta$  as in (12)-(14). Fig. 4 shows the flowchart of the AGWO algorithm.

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_{ai} - \vec{X}_i|, \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_{\beta i} - \vec{X}_i| \quad (12)$$

$$\vec{X}_1 = \vec{X}_{ai} - \vec{A}_1 \cdot \vec{D}_\alpha, \vec{X}_2 = \vec{X}_{\beta i} - \vec{A}_2 \cdot \vec{D}_\beta \quad (13)$$

$$\vec{X}_{i+1} = \frac{\vec{X}_1 + \vec{X}_2}{2} \quad (14)$$



**Fig. 4** The flowchart of AGWO algorithm

#### 4 Verification of the AGWO

In this section, the proposed AGWO algorithm is tested with twenty three well known benchmark functions that are listed in three sets: uni-modal as shown in Table 1, multi-modal as shown in Table 2, and fixed-dimension multi-modal as shown in Table 3. Uni-modal functions will benchmark the exploitation state of algorithms and Multi-modal functions will benchmark the exploration state of algorithms.

The AGWO algorithm is compared with the EGWO, LGWO, the original GWO, PSO, DE, CSA, and GSA algorithms for all twenty three benchmark functions. The algorithms are coded in Matlab R2016b and all the experiments are done on a computer with core i7, 16 GB RAM, windows 7. For each



experiment, the search agents are 30, the maximum iterations number is 500, and the number of runs is 30 times to compare the mean and standard deviation of all algorithms as shown in Tables 4-6. According to the experimental results shown in Table 4, the proposed AGWO algorithm hit five best results out of seven results. Therefore, these results proved the exploitation ability of the AGWO algorithm among other compared algorithms. The results in Table 5 and 6 show that the AGWO algorithm is augmented in exploration state compared to other algorithms. From all Tables 4-6, the proposed improvement (AGWO) hit the best minimum solution of ten benchmark functions out of twenty three functions (9/23), then the LGWO and DE algorithms hit eight out of twenty three (8/23), then the PSO algorithm hit (4/23), then the GWO and GSO algorithms hit (3/23), Finally the EGWO and CS algorithms hit (2/23). Most of the tested benchmark functions are high-dimensional functions and the proposed (AGWO) shows better results than that obtained using other algorithms, as shown in Table 4. The convergence characteristics of the proposed AGWO algorithm is compared with the GWO and PSO algorithms as shown in Fig. 5. The PSO algorithm is the most used algorithm as a benchmark algorithm. The weight parameter  $\omega$  used in PSO is decreased linearly from 0.5 to 0.3,  $C_1$  and  $C_2$  are set to 2.

**Table 1** Uni-modal benchmark functions

Function	Dimension	Range	$f_{\min}$
$f_1 = \sum_{i=1}^n x_i^2$	30	[-100, 100]	0
$f_2 = \sum_{i=1}^n  x_i  + \prod_{i=1}^n  x_i $	30	[-10, 10]	0
$f_3 = \sum_{i=1}^n (\sum_{j=1}^i x_j)^2$	30	[-100, 100]	0
$f_4 = \max_i \{ x_i , 1 \leq i \leq n\}$	30	[-100, 100]	0
$f_5 = \sum_{i=1}^n [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[-30, 30]	0
$f_6 = \sum_{i=1}^n (x_i + 0.5)^2$	30	[-100, 100]	0
$f_7 = \sum_{i=1}^n ix_i^4 + random[0,1)$	30	[-1.28, 1.28]	0

**Table 2** Multi-modal benchmark functions

Function	Dim	Range	$f_{\min}$
$f_8 = \sum_{i=1}^n x_i \sin(\sqrt{ x_i })$	30	[-500, 500]	-418.9829×5
$f_9 = \sum_{i=1}^n [x_i^2 - 10 \cos(2\pi x_i) + 10]$	30	[-5.12, 5.12]	0
$f_{10} = -20 \exp(-0.2 \sqrt{\frac{1}{n} \sum_{j=1}^n x_j}) - \exp(\frac{1}{n} \cos(2\pi x_j)) + 20 + e$	30	[-32, 32]	0
$f_{11} = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos(\frac{x_i}{\sqrt{i}}) + 1$	30	[-600, 600]	0
$f_{12} = \frac{\pi}{n} \{10 \sin(\pi y_1) + \sum_{i=1}^n (y_i - 1)^2 [1 + 10 \sin^2(\pi y_{i+1})] + (y_n - 1)^2\} + \sum_{i=1}^n u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{x_i + 1}{4}$	30	[-50, 50]	0
$u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$			
$f_{13} = 0.1[10 \sin^2(3\pi x_1) + \sum_{i=1}^n (x_i - 1)^2 [1 + \sin^2(3\pi x_i + 1)] + (x_n - 1)^2 [1 + \sin^2(2\pi x_n)]]$ $+ \sum_{i=1}^n u(x_i, 5, 100, 4)$	30	[-50, 50]	0

**Table 3** Fixed-dimension multi-modal benchmark functions

Function	Dim	Range	$f_{\min}$
$f_{14} = (\frac{1}{500} + \sum_{i=1}^{25} \frac{1}{i + \sum_{j=1}^2 (x_i - a_{ij})^6})^{-1}$	2	[-65, 65]	1
$f_{15} = \sum_{i=1}^{11} [a_i - \frac{x_i(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4}]^2$	4	[-5, 5]	0.00030
$f_{16} = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	2	[-5, 5]	-1.0316
$f_{17} = (x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6)^2 + 10(1 - \frac{1}{8\pi})\cos(x_1) + 10$	2	[-5, 5]	0.398
$f_{18} = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)] \times [30 + (2x_1 - 3x_2)^2 \times (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	2	[-2, 2]	3
$f_{19} = -\sum_{i=1}^4 c_i \exp(-\sum_{j=1}^3 a_{ij}(x_j - p_{ij})^2)$	3	[1, 3]	-3.86
$f_{20} = -\sum_{i=1}^4 c_i \exp(-\sum_{j=1}^6 a_{ij}(x_j - p_{ij})^2)$	6	[0, 1]	-3.32
$f_{21} = -\sum_{i=1}^5 [(X - a_i)(X - a_i)^T + c_i]^{-1}$	4	[0, 10]	-10.1532
$f_{22} = -\sum_{i=1}^7 [(X - a_i)(X - a_i)^T + c_i]^{-1}$	4	[0, 10]	-10.4028
$f_{23} = -\sum_{i=1}^{10} [(X - a_i)(X - a_i)^T + c_i]^{-1}$	4	[0, 10]	-10.5363

**Table 4** Experimental results of uni-modal functions

$f$	index	AGWO (proposed)	EGWO	GWO	LGWO	PSO	GSA	DE	CS
$f_1$	mean	<b>6.69E-44</b>	1.30E-30	1.27E-27	3.17E-30	1.31E-05	2.53E-16	8.21E-14	5.78E-03
	std	1.33E-43	3.92E-30	3.11E-27	4.07E-20	2.39E-05	9.67E-17	5.32E-14	2.41E-03
$f_2$	mean	<b>8.35E-27</b>	9.27E-20	8.52E-17	5.39E-19	0.0076	5.57E-02	4.51E-08	2.08E-01
	std	9.41E-27	1.26E-19	6.62E-17	0.0107	0.0262	0.19407	3.32E-08	3.17E-02
$f_3$	mean	<b>2.98E-08</b>	4.68E-04	2.43E-05	8.12E-08	2.13E+03	8.97E+02	6.23E-07	2.63E-01
	std	1.08E-07	2.20E-03	8.14E-05	2.053	878.7605	318.96	2.31E-07	2.97E-02
$f_4$	mean	<b>1.25E-10</b>	0.14267	7.69E-07	1.17E-08	16.4104	7.35E+00	7.43E-06	1.43E-05
	std	5.70E-10	0.6166	6.51E-07	1.316	4.3603	1.74145	5.12E-07	4.83E-06
$f_5$	mean	26.9654	27.7802	27.1786	8.3507	106.6465	67.543	<b>0</b>	0.008
	std	0.6973	0.9073	0.814	5.336	104.3333	62.225	0	0.054
$f_6$	mean	1.4381	3.1384	0.70757	2.69E-04	5.59E-05	2.50E-16	<b>0</b>	6.17E-04
	std	0.3314	0.6103	0.3632	0.000023	1.42E-04	1.74E-16	0	2.8E-05
$f_7$	mean	<b>1.42E-03</b>	5.73E-03	1.72E-03	3.02E-03	6.05E-02	8.94E-02	1.71E-02	0.02855
	std	8.21E-04	0.0031	1.10E-03	0.0011	0.0206	0.04339	1.12E-03	0.001277
<b>Best <math>f_{min}</math></b>		<b>5/7</b>	<b>0/7</b>	<b>0/7</b>	<b>0/7</b>	<b>0/7</b>	<b>0/7</b>	<b>2/7</b>	<b>0/7</b>

Bold Values indicate the best result

**Table 5** Experimental results of multi-modal functions

$f$	index	AGWO (proposed)	EGWO	GWO	LGWO	PSO	GSA	DE	CS
$f_8$	mean	-3633.36	-6511.19	-5776.1208	-3365.86	<b>-9347.8</b>	-2821.07	-1538.15	-2128.913
	std	442.5815	786.8525	682.0101	296.13	754.4838	493.0375	582.45	0.0084
$f_9$	mean	0.91397	145.7781	3.1496	<b>0.094579</b>	58.0837	25.968	12.415	0.246
	std	5.006	39.4368	4.0294	21.58	13.1635	7.47	9.248	0.0018
$f_{10}$	mean	<b>1.93E-15</b>	3.40E-13	1.0273E-13	2.12E-15	0.9353	0.0621	2.85E-10	4.01E-10
	std	2.55E-15	1.76E-12	1.60E-14	0.0429	0.9909	0.2363	3.1E-08	5.21E-09
$f_{11}$	mean	1.18E-03	1.04E-02	6.08E-03	<b>0.000024</b>	1.97E-02	27.702	8.15E-04	0.1852
	std	0.0045	0.0201	0.0111	0.000084	0.0232	5.0403	1.41E-06	0.039
$f_{12}$	mean	0.1024	3.169	0.03669	<b>7.12E-04</b>	0.9099	1.79962	8.21E-03	0.01258
	std	0.0312	2.8708	0.0175	0.003	1.0678	0.9511	1.17E-04	4.12E-09
$f_{13}$	mean	1.1287	2.496	0.62239	<b>3.94E-07</b>	0.119	8.8991	5.15E-06	0.485
	std	0.2193	0.4061	0.2837	0.00021	0.2396	7.1262	1.52E-07	6.85E-08
<b>Best <math>f_{min}</math></b>		<b>1/6</b>	<b>0/6</b>	<b>0/6</b>	<b>4/6</b>	<b>1/6</b>	<b>0/6</b>	<b>0/6</b>	<b>0/6</b>

Bold Values indicate the best result

**Table 6** Experimental results of fixed-dimension multi-modal functions

$f$	index	AGWO (proposed)	EGWO	GWO	LGWO	PSO	GSA	DE	CS
$f_{14}$	mean	2.3104	6.6337	4.917	1.14938	<b>0.998</b>	5.8598	<b>0.998</b>	1.4236
	std	2.4804	4.657	4.125	2.91	0	3.83	2.56E-11	1.3E-02
$f_{15}$	mean	1.84E-03	1.03E-02	5.08E-03	2.53E-06	3.20E-03	0.003673	<b>4.5E-14</b>	5.03E-04
	std	0.005	0.0132	0.0086	3.95E-04	0.0071	1.65E-03	0.0003	1.11E-04
$f_{16}$	mean	<b>-1.0316</b>	<b>-1.0316</b>	<b>-1.0316</b>	<b>-1.0316</b>	<b>-1.0316</b>	<b>-1.0316</b>	<b>-1.0316</b>	<b>-1.0316</b>
	std	4.17E-06	5.80E-03	2.64E-08	3.2E-12	6.71E-16	4.88E-16	3.17E-11	1.49E-08
$f_{17}$	mean	<b>0.398</b>	0.39789	0.39789	0.3979	0.3979	0.397887	0.3979	0.3979
	std	1.39E-05	2.43E-07	8.86E-07	0	0	0	9.9E-09	3.24E-06
$f_{18}$	mean	<b>3</b>	12.9	<b>3</b>	<b>3</b>	<b>3</b>	<b>3</b>	<b>3</b>	3.0014
	std	3.07E-05	25.0522	4.27E-05	2.4E-02	1.26E-15	4.17E-15	1.58E-18	0.00258
$f_{19}$	mean	-3.859	<b>-3.8628</b>	-3.861	-3.8628	-3.8625	-3.86278	-3.268	-3.268
	std	0.0033	1.14E-05	0.0023	1.47E-05	0.0014	2.29E-15	1.51E-20	1.85E-05
$f_{20}$	mean	-3.1858	-3.2572	-3.2568	-3.3210	-3.2518	-3.31778	-3.217	<b>-3.32185</b>
	std	0.1199	0.0871	0.0885	0.0386	0.1086	0.02308	0.635	7.21E-03
$f_{21}$	mean	-6.7613	-5.2161	-9.3955	-10.15304	-6.2948	-5.95512	<b>-10.1532</b>	-9.728
	std	1.7626	2.9706	2	5.1404	2.9249	3.73708	0.0000025	0.2881
$f_{22}$	mean	-7.1128	-7.2367	-10.2241	<b>-10.4028</b>	-7.0398	-9.68447	-10.4029	-9.873
	std	1.9801	3.5259	0.9701	2.2005	3.5751	2.014	3.9E-07	0.32034
$f_{23}$	mean	-8.1292	-7.6685	-10.0838	<b>-10.5364</b>	-7.7011	<b>-10.5364</b>	<b>-10.5364</b>	-9.7822
	std	1.0174	3.6421	1.7514	2.0123	3.6189	2.6E-15	1.9E-07	0.5002
<b>Best <math>f_{min}</math></b>		<b>3/10</b>	<b>2/10</b>	<b>2/10</b>	<b>4/10</b>	<b>3/10</b>	<b>3/10</b>	<b>6/10</b>	<b>2/10</b>

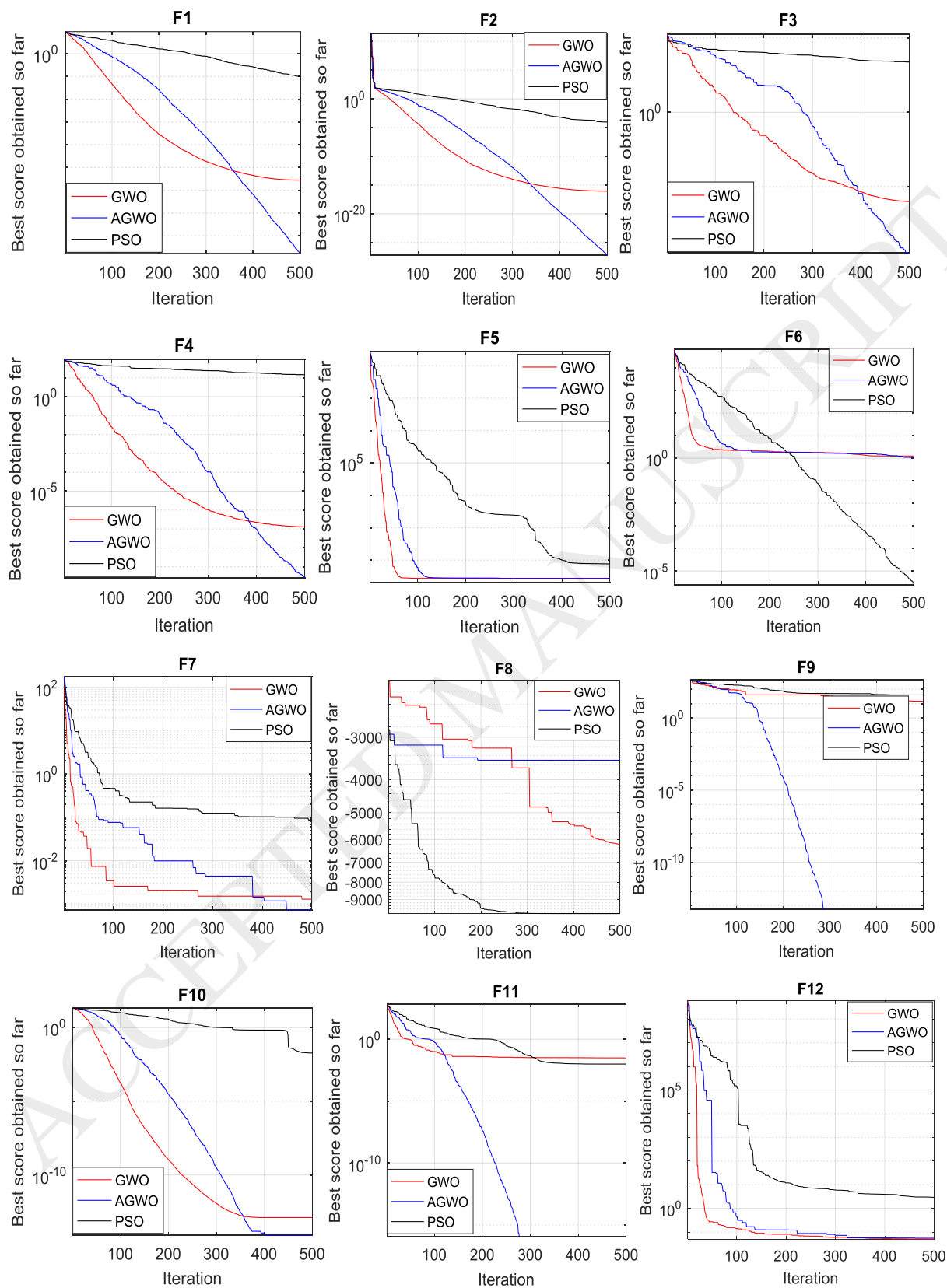
Bold Values indicate the best result

A statistical test based on the non-parametric sign test [26] is used to evaluate the improved algorithm (AGWO) versus to the other seven compared algorithms (EGWO, GWO, LGWO, PSO, GSA, DE, and CS). In Table 7, the non-parametric signs “+”, “-”, and “ $\approx$ ” show that the performance of the AGWO is statistically superior to, inferior to, and similar to the second optimizer, respectively. The last row in Table 7 shows that the number of “+” is 90 out of 161, the number of “-” is 59 out of 161, and the number of “ $\approx$ ” is 12 out of 161. Therefore, the results’ differences shown in Table 7 proved the superiority of the proposed AGWO algorithm compared to the other compared algorithms.

**Table 7** Non-parametric sign test results

	AGWO vs. EGWO	AGWO vs. GWO	AGWO vs. LGWO	AGWO vs. PSO	AGWO vs. GSA	AGWO vs. DE	AGWO vs. CS
f1	+	+	+	+	+	+	+
f2	+	+	+	+	+	+	+
f3	+	+	+	+	+	+	+
f4	+	+	+	+	+	+	+
f5	+	+	-	+	+	-	-
f6	+	-	-	-	-	-	-
f7	+	+	+	+	+	+	+
f8	-	-	+	-	+	+	+
f9	+	+	-	+	+	+	-
f10	+	+	+	+	+	+	+
f11	+	+	-	+	+	-	+
f12	+	-	-	+	+	-	-
f13	+	-	-	-	+	-	-
f14	+	+	-	-	+	-	-
f15	+	+	-	+	+	-	-
f16	≈	≈	≈	≈	≈	≈	≈
f17	+	+	+	+	+	+	+
f18	+	≈	≈	≈	≈	≈	+
f19	-	-	-	-	-	+	+
f20	-	-	-	-	-	-	-
f21	+	-	-	+	+	-	-
f22	-	-	-	+	-	-	-
f23	+	-	-	+	-	-	-
No. of (+)	18	12	8	15	16	10	11
No. of (-)	-4	-9	-13	-6	-5	-11	-11
Total number of (+)=90, Total number of (-)=59, and number of (≈)=12							

“+” means AGWO is better than,“-” is worse than,“≈” equal to the other algorithms



**Fig. 5** Convergence curves of the AGWO, GWO, and PSO algorithm on 23 benchmark functions

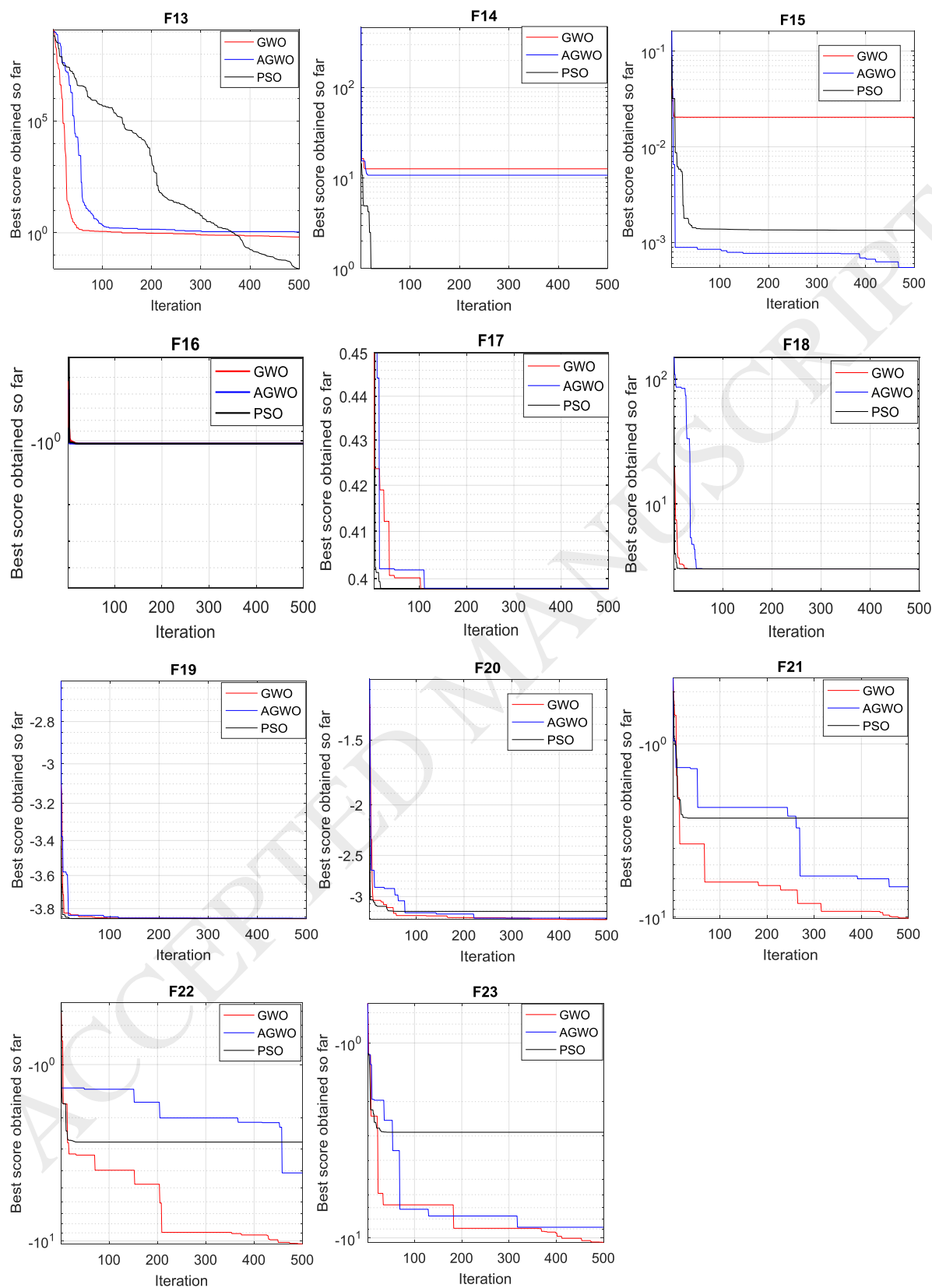


Fig. 5 continued

## 5 Grid-connected PMSG driven by variable speed wind turbine application

According to the global wind energy council, the wind power plants are dramatically increased in the electrical markets where at least 50 GW are expected to be installed every year till 2021 [27]. Because of the recent growth of wind power penetrations to the grid, transmission system operators (TSO) founded new grid codes to guarantee stability and reliability of grids [28]. The newly issued grid codes confirmed that wind farms should contribute to frequency and voltage regulations under steady state and low voltage ride through (LVRT) under transient operations [29,30].

The recent promising generator used in wind power plants is the permanent synchronous generator (PMSG). Many advantages for using PMSG such as: i) direct connection to the variable speed wind turbine (VSWT) without using the gearbox which means low rotation losses; ii) low speed operation because the high number of rotor poles of PMSG. PMSG-VSWT is connected to the grid through full scale power converter as shown in Fig. 6.

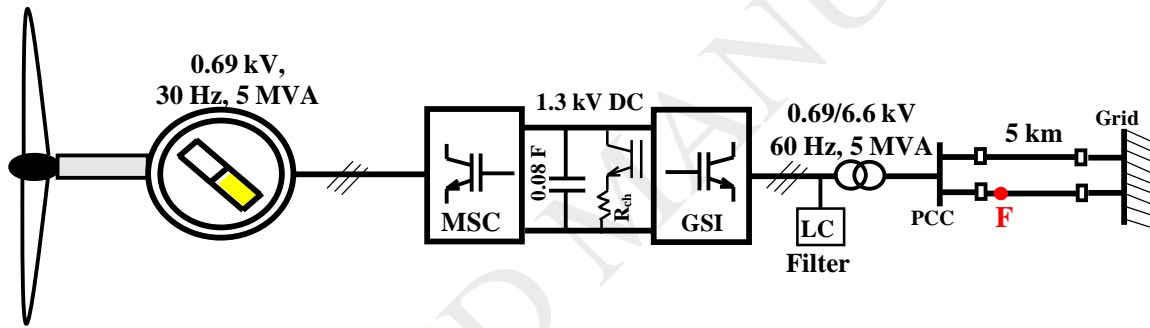


Fig. 6 Grid-connected PMSG-VSWT model

### 5.1 Wind turbine model

The captured mechanical power  $P_m$  by variable speed wind turbine is expressed as follows [31,32]

$$P_m = 0.5 \rho C_p(\lambda, \beta) A v^3 \quad (15)$$

$$C_p(\lambda, \beta) = 0.73 \left( \frac{151}{\lambda_i} - 0.58\beta - 0.002\beta^{2.14} - 13.2 \right) e^{-\frac{18.4}{\lambda_i}} \quad (16)$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.02\beta} - \frac{0.03}{1 + \beta^3} \quad (17)$$

$$\lambda = \frac{R\omega_m}{v} \quad (18)$$

where  $\rho$ ,  $C_p$ ,  $A$ ,  $v$ ,  $\lambda$ ,  $\beta$ ,  $R$  and  $\omega_m$  are the air density, the power coefficient, the swept area, the wind speed, the tip speed ratio (TSR), the pitch angle, the radius of blades, and the rotor mechanical speed, respectively. The maximum power, which can be traced by MPPT, is expressed as follows



$$P_{\max} = \frac{1}{2} \rho A \left( \frac{\omega_m R}{\lambda_{\text{opt}}} \right)^3 C_{P_{\text{opt}}} \quad (19)$$

where  $\lambda_{\text{opt}}$ ,  $C_{P_{\text{opt}}}$  are the optimum TSR and the optimum power coefficient.

## 5.2 PMSG Model

The stator voltages and electrical torque of PMSG are expressed in d-q framework as follows [33]

$$\begin{pmatrix} v_{sd} \\ v_{sq} \end{pmatrix} = -R_s \begin{pmatrix} i_{sd} \\ i_{sq} \end{pmatrix} - \frac{d}{dt} \begin{pmatrix} L_d i_{sd} \\ L_q i_{sq} \end{pmatrix} + \omega_e \begin{pmatrix} -L_q i_{sq} \\ L_d i_{sd} + \psi_f \end{pmatrix} \quad (20)$$

where  $v_{sd}$ ,  $v_{sq}$ ,  $i_{sd}$ , and  $i_{sq}$  are d-axis and q-axis stator voltages and currents,  $L_d$  and  $L_q$  are d-q inductance,  $R_s$  is the stator resistance, and  $\psi_f$  is the flux linkage developed by the permanent magnet. A single-mass shaft model is used in this study, because the DD-PMSG-VSWT is connected to grid through the full-scale power converter as follows

$$j \frac{d\omega_m}{dt} + B\omega_m = T_m - T_e \quad (21)$$

$$\omega_e = \frac{p}{2} \omega_m \quad (22)$$

where  $T_m$ ,  $j$ ,  $B$ ,  $T_e$ ,  $p$ , and  $\omega_e$  are the mechanical torque, the total inertia of the turbine and PMSG, the damping coefficient, the electromagnetic torque of the PMSG, the number of poles, and the electrical speed, respectively. Full scale converter is constructed from two voltage source converter (VSC) (Machine side converter (MSC) and Grid side inverter (GSI)) connected as a back-to-back converter. The cascaded control of the MSC and GSI are shown in Figs. 7 and 8. The total proportional-Integral (PI) controllers were used for both MSC and GSI control is 8, which means 16 gain parameters (proportional gain ( $K_p$ ) and integral time constant ( $T_i$ )) [34]. Many methods and algorithms are used to find the optimum gain parameters of PI controllers such as: Response surface methodology [35], Taguchi method [36], Affine projection algorithm [37], and artificial neural network (ANN) [38]

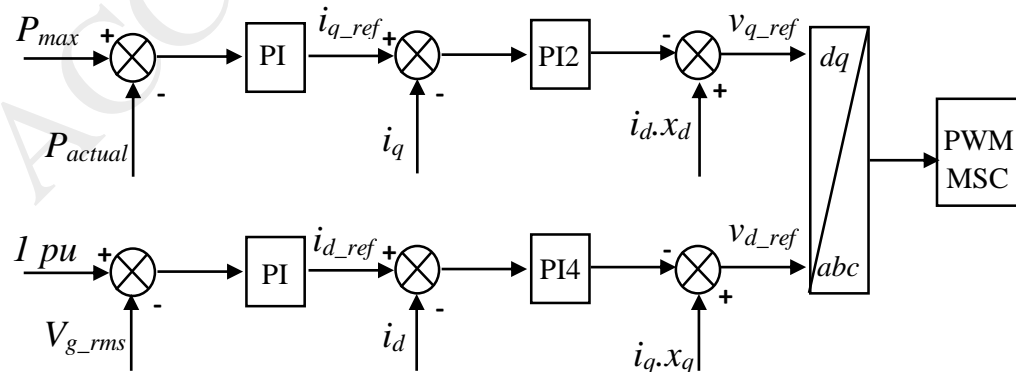
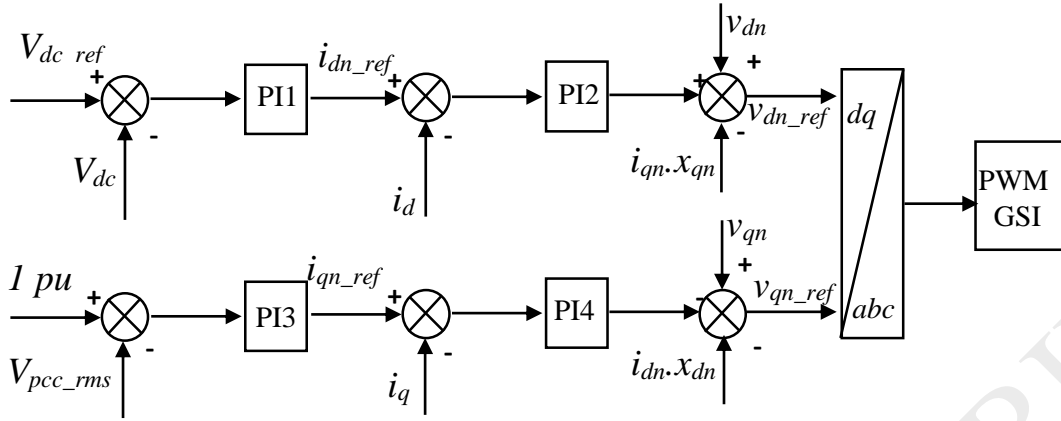


Fig. 7 Cascaded control of MSC



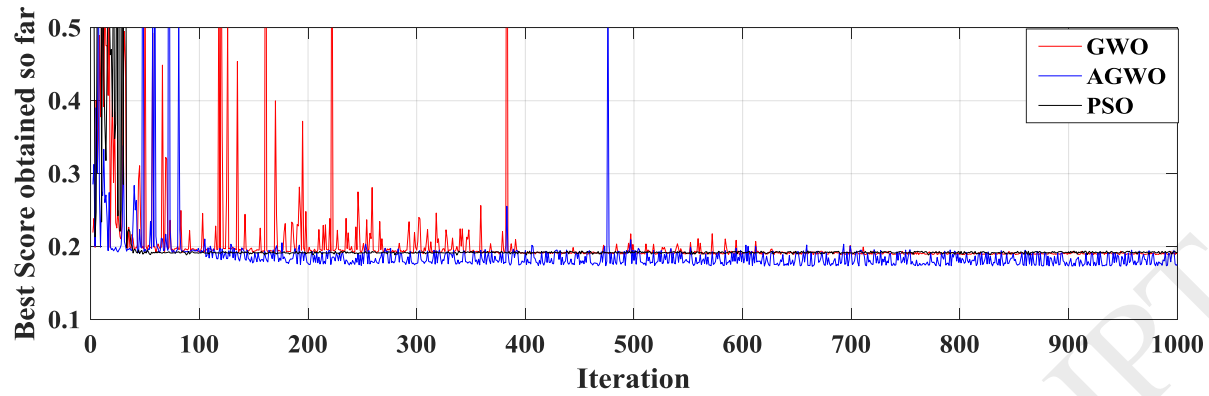
**Fig. 8** Cascaded control of GSI

### 5.3 Optimization Procedure

In this study, the AGWO, GWO, and PSO algorithms are coded by FORTRAN in PSCAD/EMTDC environment. The power system model shown in Fig. 6 is nonlinear system then it is difficult to find the mathematical model or transfer function of the power system model. The AGWO, GWO, and PSO algorithms are applied to an online optimization of 16 parameters ( $K_p$  and  $T_i$ ) for eight PI controllers existed in the cascaded control of MSC and GSI shown in Figs. 7 and 8. The purpose of the optimization is to enhance the maximum power point tracking (MPPT) and the LVRT capability of grid-connected PMSG-VSWT at worst fault case (three-line-to-ground (3LG) fault). The symmetrical 3LG fault is applied at location (F) in one transmission line (TL) of double circuit TL as shown in Fig. 6. The detailed data of studied model is listed in the appendix. The objective function is the sum of integral-squared error (ISE) of generated power  $P_g$  with reference  $P_{max}$  and RMS voltage at the PMSG terminal with reference 1 pu in the MSC control and the DC link voltage with reference 1 pu and RMS voltage at PCC location with reference 1 pu as follows

$$fitness = \sum ISE = \int (P_{max} - P_g)^2 dt + \int (1 - V_{grms})^2 dt + \int (1 - V_{dc})^2 dt + \int (1 - V_{rms\_PCC})^2 dt \quad (23)$$

For the AGWO, GWO, and PSO algorithms, the interval search of gain parameters  $K_p$  is [0.5, 5] and  $T_i$  is [0.001, 2]. The optimization is achieved by minimization the fitness function shown in (23). The number of multiple runs of PSCAD project is 1000 runs. Fig. 9 shows the optimization behavior of the AGWO, GWO, and PSO algorithms. Table 8 shows the best fitness value, mean and standard deviation of 10 individual runs. It is worthy for noting here that better statistical results are achieved by the proposed AGWO algorithm. Tables 9 and 10 show the optimum gain parameters of PI controllers in cascaded control of MSC and GSI, respectively.



**Fig. 9** Convergence curves of AGWO, GWO, and PSO algorithm with multiple run of PSCAD projects

**Table 8** Minimum ISE results

	Statistical analysis	
<b>GWO</b>	Fitness value (ISE)	0.1888847850
	Mean	0.189160502
	Std.	0.0007158687
<b>PSO</b>	Fitness value (ISE)	0.188412763
	Mean	0.188412763
	Std.	0
<b>AGWO</b>	Fitness value (ISE)	<b>0.173018205</b>
	Mean	<b>0.173018205</b>
	Std.	<b>0</b>

**Table 9** Optimum gain parameters of PI controllers of MSC control

	<b>PI1</b>		<b>PI2</b>		<b>PI3</b>		<b>PI4</b>	
	$K_p$	$T_i$	$K_p$	$T_i$	$K_p$	$T_i$	$K_p$	$T_i$
<b>GWO</b>	2.7989976 7	0.12620 4	0.79080811 9	1.018605 4	3.19568926 9	0.0022998 5	3.39508843 8	1.6654600 6
<b>PSO</b>	0.8567829 9	0.22762 6	0.56434525 8	0.001260 4	0.40434211 7	0.0045190 2	2.97435073 5	0.1460500 9
<b>AGWO</b>	1.0993255 4	0.00490 6	0.5	0.025099 0	1.82959847	0.0019952	5	0.0909401 0

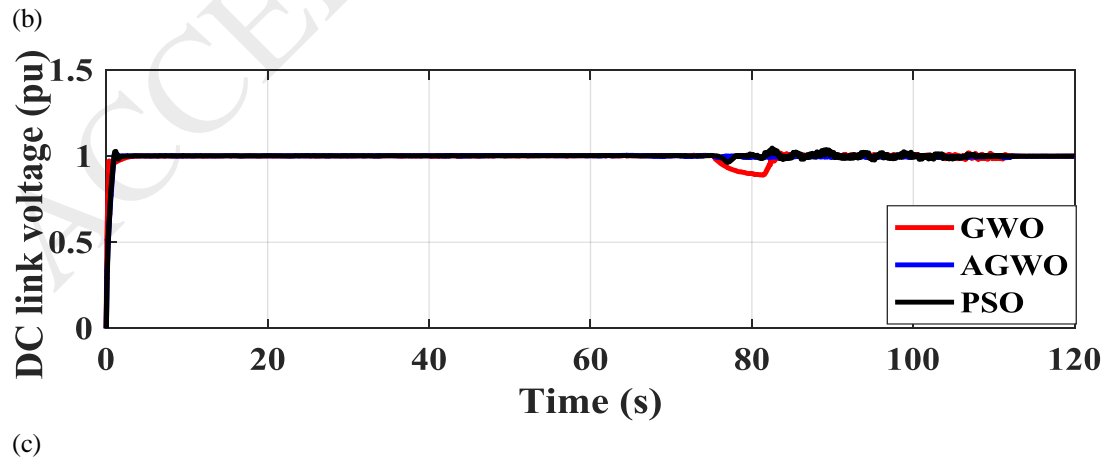
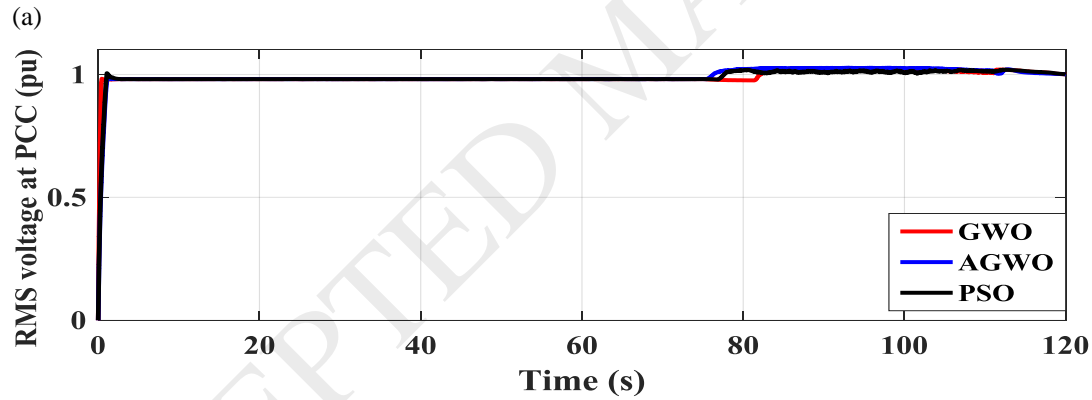
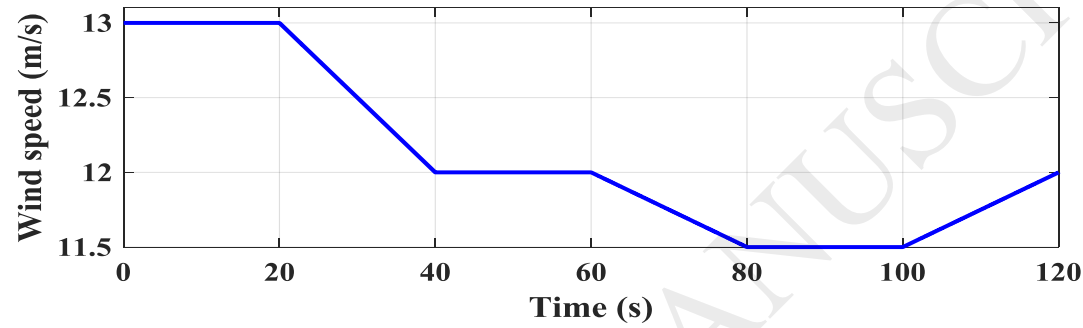
**Table 10** Optimum gain parameters of PI controllers of GSI control

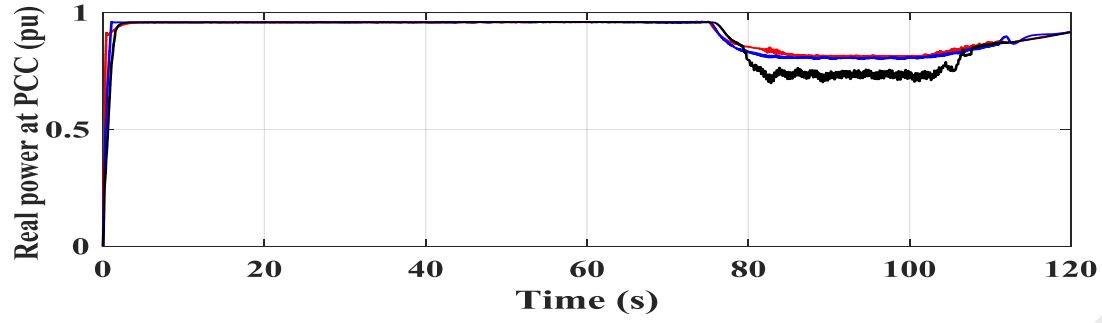
	<b>PI1</b>		<b>PI2</b>		<b>PI3</b>		<b>PI4</b>	
	$K_p$	$T_i$	$K_p$	$T_i$	$K_p$	$T_i$	$K_p$	$T_i$
<b>GWO</b>	1.4061725 1	0.73475802	0.528537	0.00170835	1.23771623 9	1.691676 7	0.56315565 5	1.12376
<b>PSO</b>	3.1148350 2	0.02264082 5	0.5	0.00321429	0.58688219 9	0.001	1.01299544 6	0.00280 9
<b>AGWO</b>	0.5	0.00377363 9	1.873589 8	0.06858595 9	5	0.198964 8	3.24936588 8	0.00131 5

#### 5.4 Simulation results

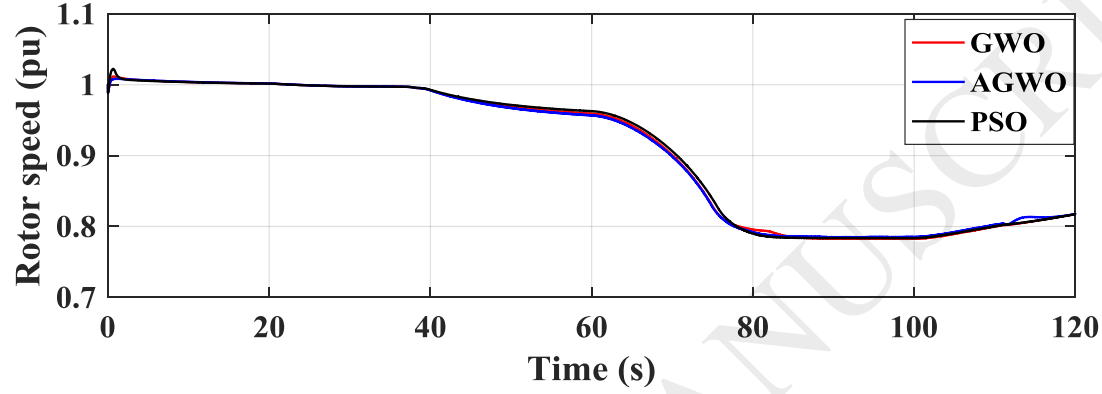
The obtained optimum gain parameters by the AGWO, GWO, and PSO algorithms are tested using PSCAD/EMTDC. The algorithms are compared during the dynamic and transient stability of the power system model shown in Fig. 6.

*Case1-dynamic stability:* the algorithms are tested under variable wind speed as shown in Fig. 10-(a) where the rated speed is 12 (m/s). The algorithms show similar response in the terminal RMS voltage at PCC location as shown in Fig. 10-(b). There is a dip in the DC link response for the GWO algorithm as shown in Fig. 10-(c). The real power response for the PSO algorithm is getting worst when the speed is under 12 m/s as shown in Fig.10-(d). The rotor speed response is shown in Fig. 10-(e), where there is overshoot for the PSO at  $t=0$ . The pitch angle response when the wind speed is more than the rated wind speed is shown in Fig. 10-(f), where there is an overshoot for PSO and GWO algorithms. According to the Fig. 10, the AGWO algorithm provided good responses for all variables (AC and DC voltage, power, rotor speed, and pitch angle).

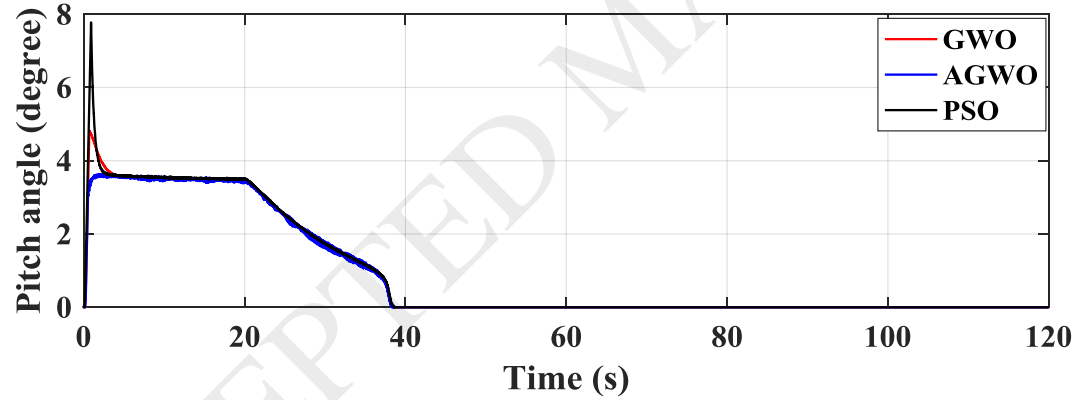




(d)



(e)

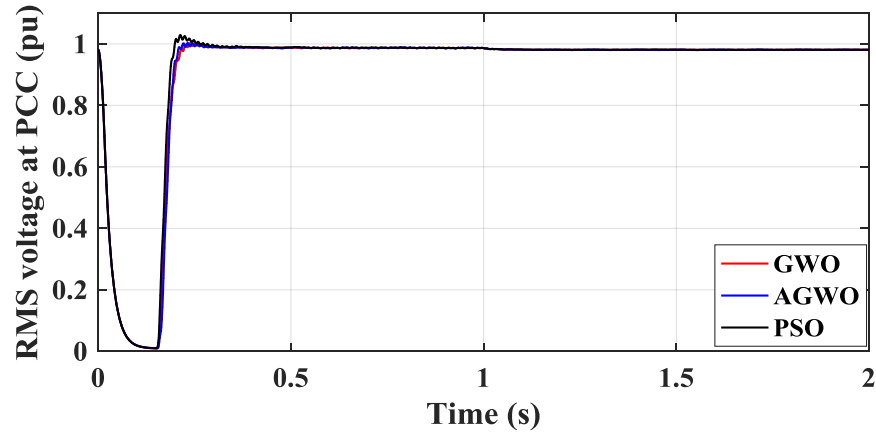


(f)

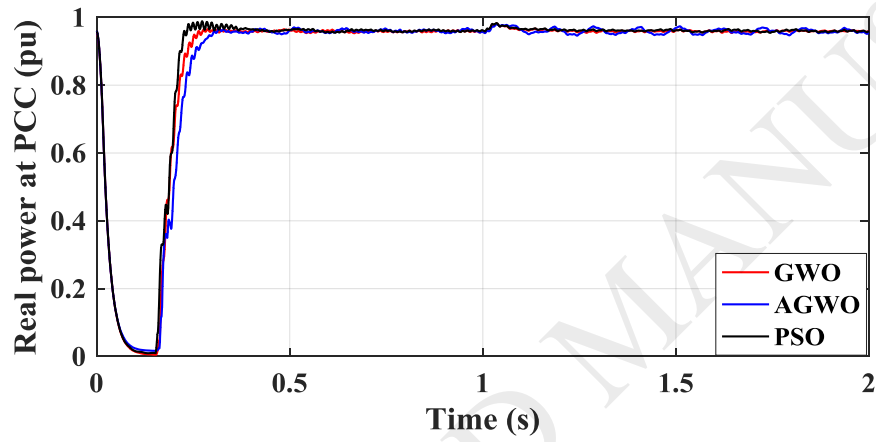
**Fig. 10** Dynamic stability response: a) wind speed; b) RMS voltage at PCC; c) DC link voltage; d) Real power at PCC; e) Rotor speed; f) Pitch angle.

*Case 2-transient stability:* the wind speed is considered not varying during the transient because the time is very small. The algorithms are test during 3LG fault, which is applied at F location as shown in Fig. 6. The 3LG fault is incepted at  $t=0$  with duration 0.15 (s), then the circuit breakers (CB) at the end of faulted TL were opened. At  $t=1$  s, the CBs were reclosed (proposing that the fault is cleared. The transient response of RMS voltage at PCC, real power, DC link voltage, and reactive power are shown in Figs. 11-(a)-(d). There is overshoot in the RMS voltage and real power for the PSO algorithm as shown in Figs. 11-(a) and (b). There is a little ripple for the AGWO algorithm in real power and DC link voltage at

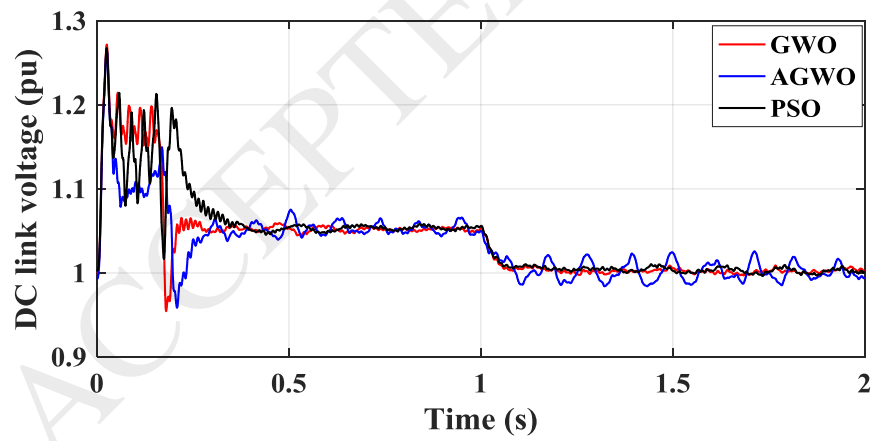
steady state which is for maximum power tracking as shown in Figs. 11-(b) and (c).



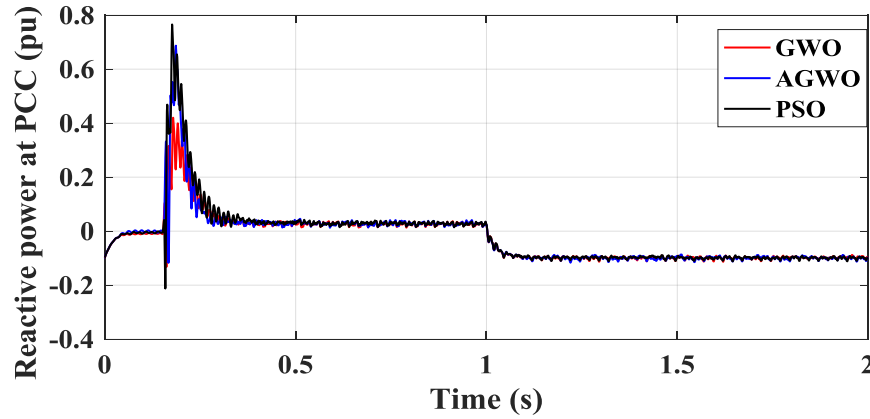
(a)



(b)



(c)



(d)

**Fig. 11** Transient response during 3LG fault: a) RMS voltage at PCC; b) Real power at PCC; c) DC link voltage; d) Reactive power at PCC.

## 6 Conclusion

In this paper, a new simple efficient augmentation is proposed for the GWO algorithm. The GWO algorithm is imitating the leadership hierarchy and prey tracking and hunting of the grey wolves. The AGWO is tested using twenty-three benchmark functions and compared with the original GWO, previous improvements (EGWO and LGWO), PSO, GSA, DE, and CS algorithms. The obtained results of uni-modal functions verified that the exploitation of the proposed AGWO algorithm is augmented among the compared algorithms. The obtained results of the multi-modal functions proved that the proposed AGWO algorithm is competitive in exploration when compared with other algorithms. The AGWO, GWO, and PSO algorithms are applied to enhance the performance of the grid-connected permanent magnet synchronous generator driven by variable speed wind turbine (PMSG-VSWT). The AGWO algorithm provided minimum integral squared error (ISE) for the input errors of PI controllers that are controlling the RMS voltage of PMSG and grid, the DC link voltage, and the generated real power. The optimum parameters for AGWO, GWO, and PSO are investigated using PSCAD simulation. The simulation results of dynamic and transient stability of grid-connected PMSG-VSWT proved that the AGWO algorithm is more efficient than GWO and PSO algorithms.

## Acknowledgement

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## Appendix

PMSG data

Rated power	5 MVA	No. of poles	150
Rated L-L voltage	0.69 kV	Inertia constant H	3 s
frequency	30 Hz	Stator resistance	0.01 pu
$X_d$	0.7 pu	$X_q$	0.7
Magnetic flux	1.4 pu		

The setting of frequency of carrier signal of MSC and GSI IGBTs are ( $55 \times 30 = 1650$  Hz) and ( $65 \times 60 = 3900$  Hz), respectively. Rated DC link voltage is 1.3 kV, DC link capacitor is 0.08 F, and chopper resistance is  $0.5 \Omega$ . The LC filter parameters are  $L = 0.0002$  H and  $C = 200 \mu\text{F}$ . The transformer reactance is 0.08 pu. The DC resistance of TL conductors is  $0.03712 \Omega/\text{km}$ . The grid inductance is 0.001 H.

**Code link of AGWO algorithm:** <https://www.mathworks.com/matlabcentral/fileexchange/67029>



## REFERENCES

- [1] J. Kennedy, R. Eberhart, Particle swarm optimization, in: *Neural Networks, 1995. Proceedings., IEEE Int. Conf.*, 1995: pp. 1942–1948. doi:10.1109/ICNN.1995.488968.
- [2] M. Dorigo, M. Birattari, T. Stutzle, Ant colony optimization, *IEEE Comput. Intell. Mag.* 1 (2006) 28–39. doi:10.1109/MCI.2006.329691.
- [3] X.-S. Yang, A New Metaheuristic Bat-Inspired Algorithm BT - *Nature Inspired Cooperative Strategies for Optimization (NISCO 2010)*, in: J.R. González, D.A. Pelta, C. Cruz, G. Terrazas, N. Krasnogor (Eds.), Springer Berlin Heidelberg, Berlin, Heidelberg, 2010: pp. 65–74. doi:10.1007/978-3-642-12538-6\_6.
- [4] X.S. Yang, S. Deb, Cuckoo Search via Levy flights, in: *2009 World Congr. Nat. Biol. Inspired Comput.*, 2009: pp. 210–214. doi:10.1109/NABIC.2009.5393690.
- [5] D. Karaboga, B. Basturk, A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm, *J. Glob. Optim.* 39 (2007) 459–471. doi:10.1007/s10898-007-9149-x.
- [6] J.H. Holland, Genetic algorithms, *Sci. Am.* 267 (1992) 66–72.
- [7] D. Simon, Biogeography-Based Optimization, *IEEE Trans. Evol. Comput.* 12 (2008) 702–713. doi:10.1109/TEVC.2008.919004.
- [8] R. Storn, K. Price, Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces, *J. Glob. Optim.* 11 (1997) 341–359. doi:10.1023/A:1008202821328.
- [9] E. Rashedi, H. Nezamabadi-pour, S. Saryazdi, GSA: A Gravitational Search Algorithm, *Inf. Sci. (Ny)*. 179 (2009) 2232–2248. doi:https://doi.org/10.1016/j.ins.2009.03.004.
- [10] A. Kaveh, M. Khayatizad, A new meta-heuristic method: Ray Optimization, *Comput. Struct.* 112–113 (2012) 283–294. doi:https://doi.org/10.1016/j.compstruc.2012.09.003.
- [11] A. Kaveh, S. Talatahari, A novel heuristic optimization method: charged system search, *Acta Mech.* 213 (2010) 267–289. doi:10.1007/s00707-009-0270-4.
- [12] A. Kaveh, V.R. Mahdavi, Colliding bodies optimization: A novel meta-heuristic method, *Comput. Struct.* 139 (2014) 18–27. doi:https://doi.org/10.1016/j.compstruc.2014.04.005.
- [13] S. Mirjalili, S.M. Mirjalili, A. Lewis, Grey Wolf Optimizer, *Adv. Eng. Softw.* 69 (2014) 46–61. doi:https://doi.org/10.1016/j.advengsoft.2013.12.007.
- [14] N.E.Y. Kouba, M. Mena, M. Hasni, M. Boudour, LFC enhancement concerning large wind power integration using new optimised PID controller and RFBs, *IET Gener. Transm. Distrib.* 10 (2016) 4065–4077. doi:10.1049/iet-gtd.2016.0385.
- [15] M.H. Sulaiman, Z. Mustaffa, M.R. Mohamed, O. Aliman, Using the gray wolf optimizer for

- solving optimal reactive power dispatch problem, *Appl. Soft Comput.* 32 (2015) 286–292.  
doi:<https://doi.org/10.1016/j.asoc.2015.03.041>.
- [16] A.A. El-Fergany, H.M. Hasanien, Single and Multi-objective Optimal Power Flow Using Grey Wolf Optimizer and Differential Evolution Algorithms, *Electr. Power Components Syst.* 43 (2015) 1548–1559. doi:10.1080/15325008.2015.1041625.
- [17] A. Fathy, A.Y. Abdelaziz, Grey Wolf Optimizer for Optimal Sizing and Siting of Energy Storage System in Electric Distribution Network, *Electr. Power Components Syst.* 45 (2017) 601–614. doi:10.1080/15325008.2017.1292567.
- [18] R.E. Precup, R.C. David, E.M. Petriu, Grey Wolf Optimizer Algorithm-Based Tuning of Fuzzy Control Systems With Reduced Parametric Sensitivity, *IEEE Trans. Ind. Electron.* 64 (2017) 527–534. doi:10.1109/TIE.2016.2607698.
- [19] P.K. Das, H.S. Behera, B.K. Panigrahi, A hybridization of an improved particle swarm optimization and gravitational search algorithm for multi-robot path planning, *Swarm Evol. Comput.* 28 (2016) 14–28. doi:<https://doi.org/10.1016/j.swevo.2015.10.011>.
- [20] S.S. Jadon, R. Tiwari, H. Sharma, J.C. Bansal, Hybrid Artificial Bee Colony algorithm with Differential Evolution, *Appl. Soft Comput.* 58 (2017) 11–24. doi:<https://doi.org/10.1016/j.asoc.2017.04.018>.
- [21] P. Savsani, R.L. Jhala, V. Savsani, Effect of hybridizing Biogeography-Based Optimization (BBO) technique with Artificial Immune Algorithm (AIA) and Ant Colony Optimization (ACO), *Appl. Soft Comput.* 21 (2014) 542–553. doi:<https://doi.org/10.1016/j.asoc.2014.03.011>.
- [22] A.A. Heidari, P. Pahlavani, An efficient modified grey wolf optimizer with Lévy flight for optimization tasks, *Appl. Soft Comput.* 60 (2017) 115–134. doi:<https://doi.org/10.1016/j.asoc.2017.06.044>.
- [23] A. Kaveh, P. Zakian, Improved GWO algorithm for optimal design of truss structures, *Eng. Comput.* (2017). doi:10.1007/s00366-017-0567-1.
- [24] H. Joshi, S. Arora, Enhanced Grey Wolf Optimization Algorithm for Global Optimization, *Fundam. Informaticae.* 153 (2017) 235–264.
- [25] W. Long, J. Jiao, X. Liang, M. Tang, An exploration-enhanced grey wolf optimizer to solve high-dimensional numerical optimization, *Eng. Appl. Artif. Intell.* 68 (2018) 63–80. doi:<https://doi.org/10.1016/j.engappai.2017.10.024>.
- [26] J. Derrac, S. García, D. Molina, F. Herrera, A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms, *Swarm Evol. Comput.* 1 (2011) 3–18. doi:<https://doi.org/10.1016/j.swevo.2011.02.002>.
- [27] Global Wind Report 2016, GWEC. (2017) 76. <http://gwec.net/publications/global-wind-report-2/>

(accessed December 1, 2017).

- [28] M. Tsili, S. Papathanassiou, A review of grid code technical requirements for wind farms, *IET Renew. Power Gener.* 3 (2009) 308–332. doi:10.1049/iet-rpg.2008.0070.
- [29] X. Liu, Z. Xu, K.P. Wong, Recent advancement on technical requirements for grid integration of wind power, *J. Mod. Power Syst. Clean Energy.* 1 (2013) 216–222. doi:10.1007/s40565-013-0036-9.
- [30] A.M. Howlader, T. Senju, A comprehensive review of low voltage ride through capability strategies for the wind energy conversion systems, *Renew. Sustain. Energy Rev.* 56 (2016) 643–658. doi:http://dx.doi.org/10.1016/j.rser.2015.11.073.
- [31] S.M. Mueeen, J. Tamura, T. Murata, *Stability augmentation of a grid-connected wind farm*, Springer Science & Business Media, 2008.
- [32] S. Heier, *Grid integration of wind energy: onshore and offshore conversion systems*, John Wiley & Sons, 2014.
- [33] O.P. Mahela, A.G. Shaik, Comprehensive overview of grid interfaced wind energy generation systems, *Renew. Sustain. Energy Rev.* 57 (2016) 260–281. doi:http://dx.doi.org/10.1016/j.rser.2015.12.048.
- [34] Bin Wu, Y. Lang, N. Zargari, S. Kouro, *Power conversion and control of wind energy systems*, 1st ed., John Wiley & Sons, 2011. http://onlinelibrary.wiley.com/book/10.1002/9781118029008.
- [35] H.M. Hasanien, S.M. Mueeen, Design optimization of controller parameters used in variable speed wind energy conversion system by genetic algorithms, *IEEE Trans. Sustain. Energy.* 3 (2012) 200–208. doi:10.1109/TSTE.2012.2182784.
- [36] H.M. Hasanien, S.M. Mueeen, A Taguchi approach for optimum design of proportional-integral controllers in cascaded control scheme, *IEEE Trans. Power Syst.* 28 (2013) 1636–1644. doi:10.1109/TPWRS.2012.2224385.
- [37] H.M. Hasanien, S.M. Mueeen, Affine projection algorithm based adaptive control scheme for operation of variable-speed wind generator, *IET Gener. Transm. Distrib.* 9 (2015) 2611–2616. doi:10.1049/iet-gtd.2014.1146.
- [38] T. Pajchrowski, K. Zawirski, K. Nowopolski, Neural Speed Controller Trained Online by Means of Modified RPROP Algorithm, *IEEE Trans. Ind. Informatics.* 11 (2015) 560–568. doi:10.1109/TII.2014.2359620.